Image Fusion Using Biomedical Images

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Abstract- *Personalized therapies play an increasingly critical role in cancer care: Image guidance with multimodality image fusion facilitates the targeting of specific tissue for tissue characterization and plays a role in drug discovery and optimization of tailored therapies. Magnetic Resonance Imaging (MRI), and Contrast-Enhanced Computed Tomography (CT) may offer additional information not otherwise available to the operator during minimally invasive image-guided procedures, such as Biopsy and Ablation. With use of multimodality image fusion for image-guided interventions, navigation with advanced modalities does not require the physical presence of the MRI, or CT imaging system. Computed Tomography (CT) provides the best information on denser tissue with less distortion. Magnetic Resonance Image (MRI) provides better information on soft tissue with more distortion*

Several commercially available methods of image-fusion and device navigation are reviewed along with an explanation of common tracking hardware and software. An overview of current clinical applications for multimodality navigation is provided.

Medical image fusion covers a broad number of hot topic areas, including Image Processing, Computer Vision, Pattern Recognition, Machine Learning and Artificial Intelligence. And medical image fusion has been widely used in clinical for physicians to comprehend the lesion by the fusion of different modalities medical images

I. INTRODUCTION

Multi-modal medical image fusion is the combination of multiple images from single or multiple imaging modalities. The purpose of the medical image fusion is to improve imaging quality with preserving the specific features for increasing the clinical applicability of images for diagnosis and assessment of medical problems. Medical image fusion methods cover a broad number of areas, including image processing, computer vision, pattern recognition, machine learning and artificial intelligence with wide applications in clinical for physicians to comprehend the lesion by fusing different modalities medical images. Medical image fusion mainly concentrates on Magnetic Resonance Imaging (MRI), Computerized Tomography (CT) Modalities. Computed Tomography (CT) provides the best information on denser tissue with less distortion. Magnetic Resonance Image (MRI) provides better information on soft tissue with more distortion hole for logic 1 and lifts up in air for logic zero & actuator changes it position for next commands execution. As in future plan, it can use for laser cutting and Printing also.

It can also be used for Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) modalities. MRI images provide better soft tissue definition and higher spatial resolution, but they are short of movement information such as body metabolism. CT images gain importance as a three dimensions (3D) imaging technique with the characteristic of short scan times and high imaging resolutions. Nevertheless, tissue characterization is limited and the restrictions of CT scan equipment to invert slices of images to one image in the short scan times. Furthermore, the PET images have the property of high sensitivity due to the molecular imaging technique, but they are with lower resolution. SPECT images are used to study the blood flow of tissues and organs by the imaging technique of nuclear. In summary, every modality of imaging has its own characteristics and practical limitations. This enforces to explore new imaging technologies or new fusion methods for combining information from multiple imaging modalities. The latter seems to be more meaningful because of lower cost and shorter time, compared with the former. The multi-modal medical image fusion traditionally centres on three categories: MRI-CT,MRI-PET and MRI-SPECT images fusion.

Multi-modal medical image fusion plays a major role in biomedical research. In general, the purpose of multi-modal medical image is to improve the imaging quality for removing the physical limitations of the imaging technology. The availability of a large number of multi-modal fusion approaches, including image decomposition, image reconstruction, fusion rules and image quality assessments, makes the field of image fusion appealing to be employed by medical imaging community. The main challenge is the gap between the image fusion algorithms and the patient case in hospital. Image fusion is primarily concerned with image decomposition and reconstruction methods, image fusion rules and image quality assessment resulting from the framework of image fusion. The major problems of the three parts are caused by the additional noise, colour distortion, missing features, artificial effects.

II. PROBLEM STATEMENT

To Implement Project in such a way that it Fuses Images from Two different Modalities to form a Single Enhanced Image that give more clear information about the Image (Report of MRI & CT SCAN).

OBJECTIVE

- To combine information from multiple images of the same scene in to a single image retaining the important and required features from each of the original image.
- The basic idea is to improve the image content by fusing images taken from different imaging tools like Computed Tomography (CT), Magnetic Resonance Imaging (MRI).
- MRI gives info about Soft tissue & CT Scan gives info about Dense tissue. In this case, only one kind of image may not be sufficient to provide accurate clinical requirements for the physicians.

LITERATURE SURVEY

IEEE Base Paper: Multi-Sensor Image Fusion using Wavelet Transform; Hui Li: HNC Software Inc.5930 Cornerstone Court West San Diego, CA 92121., B.S. Manjunath and Sanjit K. Mitra: Dept. of Electrical &Computer Engineering. University of California Santa Barbara, CA 93106. In the Image Fusion Scheme presented in this Paper, Wavelet transforms of the Input Images are appropriately combined and the New Image is obtained by taking the Inverse Transform of the Fused Wavelet Coefficients. An area based maximum selection rule and a consistency verification steps are used for feature selection. A performance measure using specially generated test images is also suggested.

Manchanda and Sharma (2016) proposed fuzzy based approach for Multimodal IF. Edge strength is reported 0.8816, fusion loss0.1141, fusion artefacts 0.0043,Entropy 4.6591,fusion factor 4.4413,&structural similarity value 0.7781for MR-SPECT IF. Dictionary based technique is used to combine image patches together in frame using segmentation and framing methods by ZHU et al.(2016).
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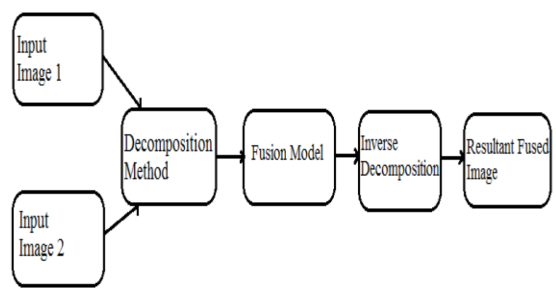
Multi-modal medical image fusion is the process of merging multiple images from single or multiple imaging modalities to improve the imaging quality with preserving the specific features. Medical image fusion covers a broad number of hot topic areas, including image processing, computer vision, pattern recognition, machine learning and artificial intelligence. And medical image fusion has been widely used in clinical for physicians to comprehend the lesion by the fusion of different modalities medical images. In this review, methods in the field of medical image fusion are characterized by (1) image decomposition and image reconstruction, Image fusion rules, (3) image quality assessments, and (4) experiments on the benchmark dataset. In addition, this review provides a factual listing of scientific challenges faced in the field of multi-modal medical image fusion.

III. BLOCK DIAGRAM



DESCRIPTION

Image decomposition and reconstruction

In terms of multi-modal medical image fusion, scheme for image decomposition and reconstruction closely relates to the quality extracted from the images. Characteristic of approaches in this frame aims at decomposing the original image into a sequence of images and then reconstructing the decomposition images into a single image. It is of interest to look at a snapshot of five different key methodologies: 1) colour space , 2)pyramid , 3) wavelet, 4) sparse representation andsalient feature. The methods of image decomposition and reconstruction are compared with the indexes of spatial domain, frequency domain, multi-scale, scale invariance, dictionary and directive filter. Due to the images shown in pseudo-colour, colour space based fusion method is employed to multi-modal medical image fusion. Unlike other methods, colour space methods are used to process input images in spatial domain. Then multi-scale decomposition (MSD) is used to extract and combine salient features of medical images at different scales .The advantages of wavelet methods are scale invariance and directive filter. Moreover, salient feature methods are used as the MSD tool in spatial domain. In addition, the sparse representation methods, inspired from the compressed sensing algorithms, construct a dictionary of input images.

Wavelet transformation based methods

Wavelet transformation (WT) based fusion methods for multi-modal medical image fusion is regarded as multi-scale geometric analysis tools. Firstly, the input image is decomposed into low and high frequency components. Secondly, different image fusion rules are selected to fuse different frequency components. Finally, the fused image is obtained by inversed transformation. In 2001, discrete wavelet transformation (DWT) is applied for fusing multi-modal medical images. DWT preserves different frequency information in a stable form and permits perfect localization both in time and spatial frequency domain. However, the method fails to meet the requirements of shift-invariance. Then redundant DWT (RDWT) aims to overcome the shift-variance problem of DWT through removing down-sampling operation from traditional critically sample DWT. Since multi-wavelet filter banks have no strict division of low-pass and high-pass, multi-wavelet (MWT) has an advantage of preserving more details and texture information with purpose to overcome the shortcomings of the scalar wavelet. Lifting wavelet transformation (LWT) is also famous as the second generation wavelet transformation with the properties of reducing the computational complexity of wavelet transformation. The construction of LWT is divided into three phases: split, prediction and update.

Image fusion rules:

Image fusion rules refer to algorithms that seek to highlight the features of interest in images and restrain the features of insignificance. The main contribution of image fusion rules is the combination of multiple original images into a single image. Traditionally, an image fusion rule includes four components activity-level measurement, coefficient grouping, coefficient combination and consistency verification. In our work we focused on the following image fusion techniques:

1. Select Minimum
2. Select Maximum
3. Average Method
4. Discrete Wavelet Transformation -- using Daubechies (DWT Daub)

1. Mean Fusion Rule:

A number of fusion rules have been proposed for pixel-based fusion. Averaging is generally used only for the low-pass coefficients since averaging of the high-pass sub-bands tends to blur images and reduce the contrast of features appearing in only one image. Fusion rules applied to high-pass sub-bands include:

1.1Select Minimum:

In the select minimum image fusion algorithm, it compares everyCorresponding pixel intensity value from each input image and selects the minimum value andthat value in inserted in the final fused image

$$I_{fused}(i,j) = \min_{0\le i\le m,\ 0\le j\le n}[I_1(i,j), I_2(i,j)]$$

Where $Ifused$ is the final fused image and $I1$and $I2$ are the two input images m is the height of the image in terms of pixels, which is also the number of rows in thatimage & n is the width of the image in terms of pixels, which is also the number ofcolumns in that image.

Steps to perform select minimum algorithm :

1) Compare the intensity value at pixel location (imp) in all input images
2) Assign the minimum intensity value to the corresponding pixel of the output fused image.
3) Repeat step 1 and 2 for all pixel locations
4) After going through the entire images pixel locations, the resulting matrix would be the final fused image.

1.2 Select Maximum:

In the select maximum image fusion algorithm, it compares every corresponding pixel intensity value from each input image and selects the maximum value and thatvalue in inserted in the final fused image This simple and efficient fusion rule wasinitially suggested in . The maximum-selection scheme selects the largest absolutewavelet coefficient at each location from the input images as the coefficient at thatlocation in the fused image. This is motivated by wavelets tending to pick out the salient features in an image. Maximum-selection results full most of therequirements for fused results. Relevant information is generally preserved in thefused image and few noticeable artefacts are introduced.

$$I_{fused}(i,j) = \max_{0\le i\le m,\ 0\le j\le n}[I_1(i,j), I_2(i,j)]$$

Where $Ifused$ is the final fused image and $I1$and $I2$ are the two input images m is the height of the image in terms of pixels, which is also the number of rowsin that image & n is the width of the image in terms of pixels, which is also the number of columns in that image.

Steps to perform select Maximum Algorithm :

1) Compare the intensity value at pixel location (imp) in all input images.
2) Assign the maximum intensity value to the corresponding pixel of the output fused image.
3) Repeat step 1 and 2 for all pixel locations.
4) After going through the entire images pixel locations, the resulting matrix would be the final fused image.

1.3 Model-based Average Method:

In the average image fusion algorithm, which is a more advanced version than the select maximum and minimum, it calculates the average of the sum of each corresponding pixel intensity value from each input image and inserts the result in the corresponding location in the final fused image. The resultant coefficient for reconstruction is calculated via a weighted average of input image coefficients. As wavelet coefficients exhibit non-Gaussian characteristics, the families of generalised Gaussian distribution (GGD) and symmetric alpha-stable distribution have been used for modelling image wavelet coefficients. The fusion results of visible/IR images show improvement over conventional weighted average. The Meridian distribution is employed in for medical images. The weights in the two latter techniques are optimised via Maximum Likelihood (ML) estimation. Recently, the shrinkage function for de-noising has been combined with the model-based weighted average using bivariate Laplacian-based and bivariate Cauchy-based techniques. This method produces excellent fusion results in many applications, including medical imaging and various multiband sensors.

$$I_{fused}(i,j) = \frac{I_1(i,j)+I_2(i,j)}{2} \text{ , } for\ 0 \le i \le m \ \ and \ \ 0 \le j \le n$$

Where $Ifused$ is the final fused image and $I1$and $I2$ are the two input images m is the height of the image in terms of pixels, which is also the number of rows in that image & n is the width of the image in terms of pixels, which is also the number of columns in that image.

Steps to perform Model-based Average Method Algorithm:

1) extract the intensity value at pixel location (i, j) in all input images.
2) compute the average of these extracted intensity values from step 1 and assignit to the corresponding pixel of the output fused image.
3) Repeat step 1 and 2 for all pixel locations
4) After going through the entire images pixel locations, the resulting matrix would be the final fused image

1.4 Discrete wavelet transformation using Daubechies:

In the discrete wavelet transformation using Daubechies algorithm, there are three main steps to be performed to successfully fuse the input images. Decompose, fuse and reconstruct but before starting the user needs to choose how many levels, k,will the algorithm implement. This needs to be predetermined before starting the algorithm.

a) Image decomposition:

The first step in applying discrete wavelet transform image fusion is decomposing each input image. By treating images as a signal and decomposing them using a Daubechies wavelet transform based low pass filter ,g(n) and a Daubechies wavelet transform based high pass filter h(n).

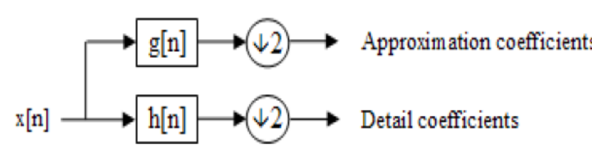


Fig.1.4.1.Daubechies wavelet transform.

And then repeat that decomposition steps K times to reach to the final decomposition level. This series of decomposition is represented as a tree is known as a filter bank.

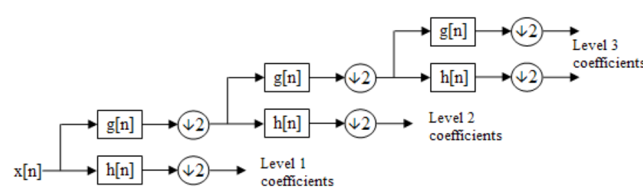


Fig.1.4.2Daubechies filter bank.

b) Fuse the multiscale Images:

Secondly, after getting the final decomposition level for each level image, we will end up with two coefficients for each image; the approximation coefficient and the detail coefficients. So the next step would be to fuse them, there are three different fusing methods to use

1) Select Maximum
2) Select minimum
3) Average

In the Select Maximum, we compare each matrix element value in a matrix and choose the maximum value while in the minimum we choose the smaller out of the two values and finally the average method we calculate the average of both values.

c) Image Reconstruction of the Fused Image:

Finally, after getting the fused approximation coefficient and the detail coefficients values, we can get the final fused image by applying inverse wavelet transform on these values k times to reach the original starting level.

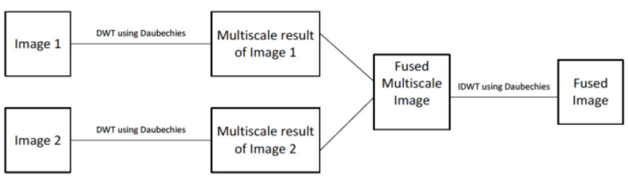


Fig.1.4.3 DWT using Daubechies

Steps to perform Discrete Wavelet Transformation – Daubechies Algorithm:

1) Choose the level, k, of decomposition required to apply to the images for fusion.
2) Decompose the input images using discrete wavelet transformation with Daubechies wavelet filter.
3) Repeat step 2 K times, decided upon from step 1, to reach the targeted level of decomposition.
4) After obtaining the final level of decomposed images matrices from step 3, afused decomposed matrix is created using one of the following methods:
    a. Model-based Average Method.
    b. Select Maximum Method
    c. Select Minimum Method.

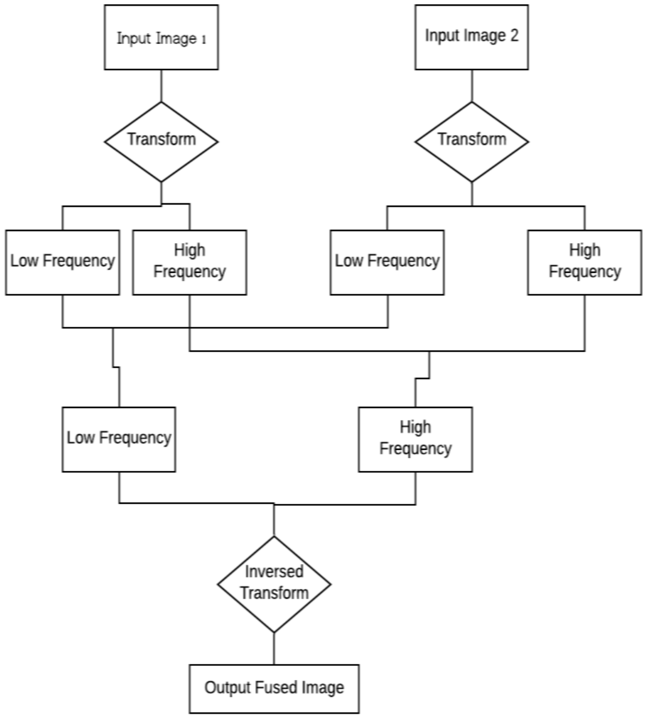
Subjective quality assessment:

Subjective quality metric is easy to obtain within a nonlinear questionnaire since it is convenient for people to compensate survey. In addition, the survey is close with dependent of the subjective validation application scope and methodology. The traditional way of subjective quality assessment is to calculate scores for each subject with normalized by the mean and variance of scores for that subject from a number of people ranging from 1 to 100. Firstly, five indexes marked with adjectives of bad, poor, fair, good and excellent are with the value assignments of 1, 2, 3, 4 and 5. Secondly, human subjects are asked to assign each image with a score for their perception of quality indicating their assessment of that image, defined as the extent to which the artefacts were visible and annoying. The raw scores are altered to scores between the test and the reference images and then converted to Z-scores with 1-100 ranges. Finally a difference mean opinion score for each test image is computed. Finally, a double stimulus methodology for more accurate measurement of quality for realignment purposes is proposed.

Objective quality assessment:

Quality metric for image fusion is a pertinent quality assessment tool to evaluate the visual quality degradation of images suffering from various distortions during fusion procedure. Objective image quality measure is foremost in various image processing applications. There are basically three classes known as full-reference, reduced-reference and no-reference of objective quality or distortion assessment approaches according to the availability of an original image with which the test image is to be compared. In full-reference image metric, the reference image is assumed to be known. And in reduced-reference quality assessment, the reference image is only partially available to help evaluate the quality of test image. No-reference image metric means that the reference image is not available. The most widely used objective quality assessments for multi-modal medical image fusion are full-reference quality metrics. The simplest full-reference metrics are based on signal distortion and HVM. The metrics based on signal distortion defined with strict mathematical theory is incorporated with entropy (EN), difference of entropy (DEN), overall cross entropy(OCE), standard deviation (STD), sharpness (SP), RMSE, peak signal to noise ratio(PSNR), etc. The second class based on HVS is to measure the information of salient feature transferred from the input images to the fused image, such as SSIM, the phase congruency based index (QG), the gradient based index (QAB/F), etc. It is meaningful to compute the error between test and reference images with loss in salient information of gradient, contrast and edge between different image components.

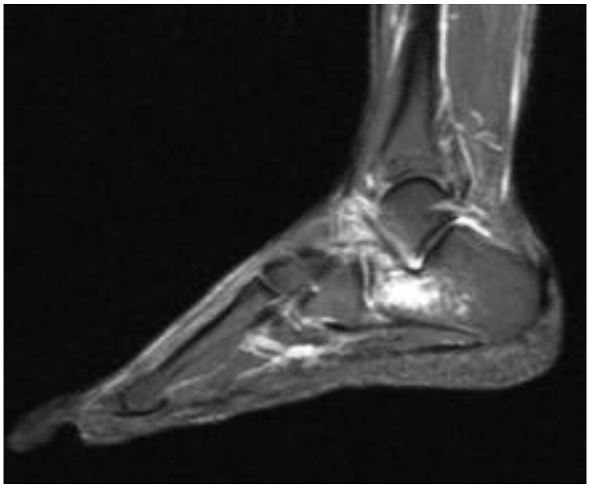
FLOWCHART:



Experiments on database:

Experiment was performed on CT Scan and MRI Report on the Database of a Patient whose Left Ankle had to undergo Treatment to overcome the Injury who had met with severe Accident. Images were Fused and resultant image is shown in Fig(c). which was Fused using Average Method of Fusion Rule.

Fig.1 (a)CT Scan image (Ankle).



(b) MRI image (Ankle).

(c)Fused Image by Average Method.

V. RESULT

A good image decomposition and reconstruction approach is tightly linked to the scale and rotation invariance on medical image fusion. Point of interest is that when addressing the medical image decomposition strategy, the emphasis has been in the direction of developing algorithms that try to extract features at different scales and orientations within images. The methods are introduced from other fields of fusion, such as multi-focus image fusion, remote sensing image fusion, etc.

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