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# Image Reconstruction Algorithm Based on Patch Dictionary Method for CT and MRI Images

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*Abstract*—***Image fusion is a process, used for mixing the common sorts of set of images into a single image. Medical imaging is a most significant source to find out the presence of assured diseases. The fusion of these medical images provides the useful clinical information for doctors for their analysis. In this paper, we are fusing CT (Computer Tomography) and MRI (Magnetic Resonance Imaging) using Patch extraction. Patch extraction is nothing but the Dictionary Learning of the input images. Further, Interpolation and Adaptive Histogram Equalization (AHE) methods are used for feature extraction of the input images. By using these features a high resolution image is reconstructed, which consist of features of both the input images. The proposed work is a benefit to the medical society as it provides enhanced information in the resultant image.***

***Keywords—CT, MRI, Patch Extraction, Interpolation, AHE, High Resolution.***

## I. Introduction

Medical image fusion is a blending of data fusion. The fusion of medical images acquired from different instruments such as MRI (magnetic resonance imaging), CT (computed tomography) and X-rays of the same objects is often needed. The most familiar image fusion method is based on multiresolution analysis, such as the discrete wavelet transform, complex wavelet transform etc. The input images are first decomposed, and the resultant coefficients are fused by various fusion rules. Finally, by performing the inverse transformation of multi resolution analysis, the fused image will be reconstructed from the fused multi resolution coefficients. Different from the multi resolution analysis approach, a new approach image fusion of medical images constructed on the use of patch extraction is proposed. However, in medical applications the source images have limited resolution. To improve the resolution of the scanned image, a separate high resolution step has to be performed. The proposed method aims to produce a high resolution image from one or more low-resolution images. Some of the widely held interpolation techniques may include Bilinear, Bi-cubic, and edge-guided image interpolation. The interpolation techniques are simple and have low calculation cost. However, they are not worthy at reconstructing high-frequency information. Therefore, another category of obtaining the high resolution image is based on Dictionary learning.

The proposed method in this paper is based on patch extraction and the work is explained in four steps viz., preprocessing, patch extraction, feature extraction and reconstruction. In preprocessing step the input images are resized. In second step the source images dictionaries are learned. In feature extraction step the interpolation and Adaptive histogram equalization (AHE) is applied to the source image. And also a difference image of interpolation and AHE images are taken for comparison of missing pixel values. Then finally all the features obtained from the above steps are fuse together to form a reconstructed image which will be having both the features of input images in a single image with high resolution.

MRI images provide greater contrast of soft tissues of brain than CT images, but the brightness of hard tissues such as bones is higher in CT images. CT and MRI images individually have some shortcoms such as MRI images not concentrate on hard tissues & in CT image soft tissues can't be clearly visible. In this paper, image fusion of CT & MRI images has been carried out so that the fused image which is the combination of soft & hard tissues proven as the focused image for doctors & their clinical analysis. This paper further quantitatively evaluates the reconstructed images quality through four performance measures Standard Deviation (SD), Entropy (EN), Mean Square Error (MSE) and the Peak Signal-to-Noise Ratio (PSNR).

This paper is organized as follows;section -II elaborates the image fusion based on patch extraction. Section-III details the system implemetation. In section-IV Results of the proposed work is discussed. In Section-V Provides the Performance evaluation. Further conclusion and future scope of the proposed work is mentioned in Section -V.

## II. IMAGE FUSION BASED ON PATCH EXTRACTION

The objective of the proposed system is to develop an algorithm for patch extraction and reconstruction of medical images that will provide the high resolution reconstructed image, which will be having the more information than the reference images. With this objective in mind a block diagram is proposed in Fig 1.

As discussed in the previous section, this paper mainly revolves around an image fusion method which makes use of patch extraction for dictionary creation and features of Interpolation and AHE are extracted to reconstruct the final image.

Listed below are the major functionalities of this paper carried out.

1. Pre-processing of the input images.
2. Patch extraction of the pre-processed images.
3. Feature extraction of the input images.
4. Reconstruction of the image.

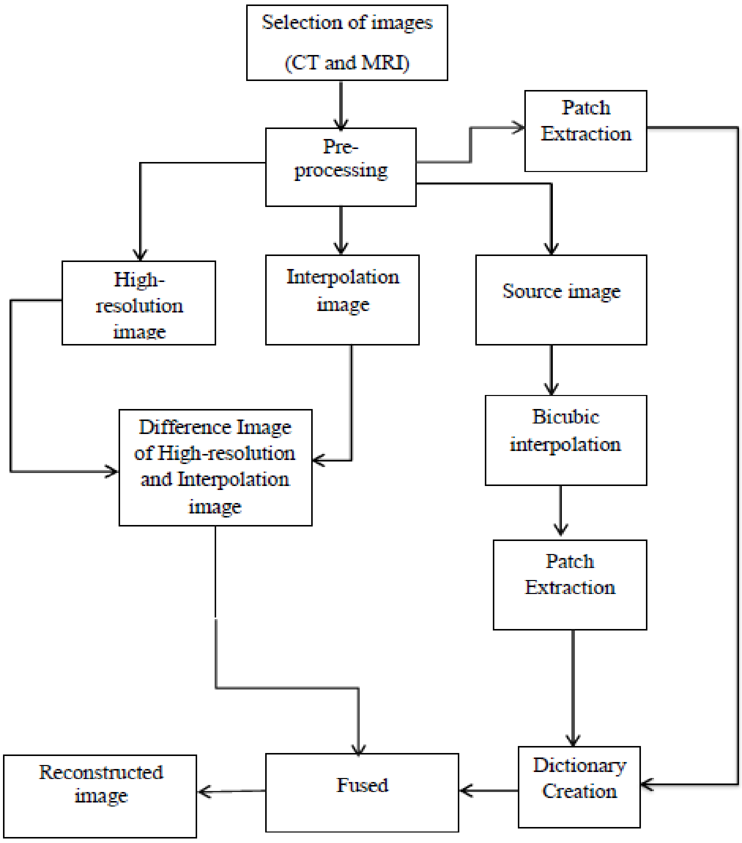


Fig 1: Block diagram of the proposed work.

### A. Pre-processing

Pre-processing is the process of aligning two or more images of the same scene acquired at different times, or with different sensors, or from different viewpoints. Before the pre-processing block, the input images CT and MRI are selected. Then both the input images are resized to a standard size 256X256 and if the input image is in color, then RGB to gray conversion is performed by channel extraction and separation. If the given input is in gray format then directly it is given to next steps.

### B. Patch Extraction

Patch corresponding to an edge or a point in the image. In patch extraction, the source images are divided into small boxes or patches for feature extraction. Learning the basis set is called as dictionary, to adjust it to specific data, a methodology that has recently recognized to be very effective for signal reconstruction and classification in the audio and image processing domains. The patch extraction is used for learning the dictionaries of images. Patch extraction is applied to source images, which are resized in the pre-processing step, by initializing the patch size to 8. For every patch size, patch is extracted from the whole image and displays it on the image.

### C. Feature Extraction

The feature is defined as a task of one or more quantities, each of which specifies some quantifiable assets of an object, and is computed such that it computes some significant characteristics of the object. The extraction task renovates rich content of images into various content features. Visual features such as shape, color and texture are mined to describe the images.

In this paper, the features of CT and MRI images are extracted by using Interpolation and AHE methods to reconstruct the fused image which will be having the both information of CT and MRI images in a single image, with better information and which will be helpful for the doctors to find out the disease.

#### 1. Interpolation

The interpolation is one of the fundamental operations in image processing. Interpolation is the process of converting discrete samples to continuous values. Interpolation determines the continuous range of values for given some values at some points. Image interpolation refers to the "guess" of intensity values at missing locations and reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function. Mainly, two types of interpolation techniques are used in this paper.

a) Bicubic Interpolation

Bicubic interpolation solves for the value at a new point by evaluating the 16 data points neighboring the interpolation region. It considers the closest 4×4 neighborhood of known pixels for a total of 16 pixels. When these are at various distances from the unknown pixel, closer pixels are taken for the calculation of a higher weighting. Bicubic produces sharper images than the nearest neighbor and bilinear methods.

b) Cubic Spline Interpolation

A cubic spline is a spline created of piecewise third-order polynomials which pass over a set of control points. The second derivative of each polynomial is commonly set to be zero at the endpoints, since this delivers a boundary condition that completes the system of equations.

#### 2. Adaptive Histogram Equalization (AHE)

Adaptive Histogram Equalization enriches the contrast of images by converting the values in the intensity image. Histogram Equalization operates on small data tiles but AHE operates on the entire image. Each tile's contrast is enriched, so that the histogram of the output region approximately equals the specified histogram. The neighboring tiles are then joined using bilinear interpolation in order to remove falsely induced boundaries. The contrast, especially in similar areas, can be limited in order to avoid increasing the noise which might be present in the image.

3. Difference of High-resolution and Interpolation image

The difference of high-resolution image and interpolation image is taken. The difference image gives the details of missing pixels between interpolation and AHE images, which will be added to the final reconstruction image. The difference image given as,

$$diffImg(x,y) = interImg(x,y) - hiInterImg(x,y) \quad \text{- - - - - - - (1)}$$

### D. Dictionary Learning and Reconstruction

The dictionary learning of source images $(D_1)$ $(D_2)$, Interpolation image $(D_I)$, and Difference image $(D_{IH})$, is used for final image reconstruction.

First, we introduce the procedure used to construct the training sets $(D_1)$ and $(D_2)$. An input image is upscale by using Bicubic interpolation and again AHE is applied to input image. Since the interpolation image lacks high pixel component, it can be regarded as the low resolution input image; while the missing high pixel component can be obtained by subtracting this low resolution from AHE image. The four dictionaries are learned by using following equations.

$$\{D_1, D_2, D_I, D_{IH}, A\} = K_1 + K_2 + K_3 + K_4$$

***Where,***

$$K_1 = arg \min_{\{D_1, D_2, D_I, D_{IH}, A\}} \sum_{i=1}^{K} \| Z_i^1 - D_1 \alpha_i \|_2^2 \quad \text{-- - - - - -(2)}$$

$$K_2 = \sum_{i=1}^{K} \| Z_i^2 - D_2 \alpha_i \|_2^2 \quad \text{-- - - - - - (3)}$$

$$K_3 = \sum_{i=1}^{K} \| Z_i^I - D_I \alpha_i \|_2^2 \quad \text{-------(4)}$$

$$K_4 = \sum_{i=1}^{K} \| Z_i^{IH} - D_{IH} \alpha_i \|_2^2 \quad \text{---- ------(5)}$$

*Subject to* $\forall_i, \| \alpha_i \|_0 \leq \tau_1$

Where $A = [\alpha_1, \alpha_2, \ldots \ldots \alpha_K]$ is the matrix containing the sparse coefficients, and $\tau_1$ controls the sparsity level. By introducing auxiliary variables

$Z^1 = [Z_1^1, Z_2^1 \ldots \ldots . Z_K^1] \in \mathbb{R}^{n \times K}$,

$Z^2 = [Z_1^2, Z_2^2 \ldots \ldots . Z_K^2] \in \mathbb{R}^{n \times K}$,

$Z^I = [Z_1^I, Z_2^I \ldots \ldots . Z_K^I] \in \mathbb{R}^{n \times K}, Z^{IH} = [Z_1^{IH}, Z_2^{IH} \ldots \ldots . Z_K^{IH}] \in \mathbb{R}^{n \times K}$,

$Z = [(Z^1)^T, (Z^2)^T, Z^I)^T (Z^{IH})^T]^T \in \mathbb{R}^{4n \times K}$,

$D = [(D_1)^T, (D_2)^T, (D_I)^T (D_{IH})^T]^T \in \mathbb{R}^{4n \times m}$ (where T denotes matrix transpose).

The final function is the reconstruction of the high resolution fused image, which is reconstructed by using all feature extraction methods as mentioned in the above sections. In reconstruction, Averaging (mean) and maximum (max) are usually used as the fusion rules. Thus the local mean of each patch is combined by averaging technique which is used for $D_1, D_2, D_I$ and $D_{IH}$. First, the mean of $D_1$, $D_I$ and $D_2$ ,$D_I$ are obtained. Then max rule is applied to both mean of $D_1$, $D_I$ and $D_2$ ,$D_I$. Finally, the difference image and fused image patches are averaged to obtain the final reconstructed image.

## III. System Implementation

The proposed work is implemented in Matlab version R2015a, which is shown in Fig 3.1. The detailed description is explained below.

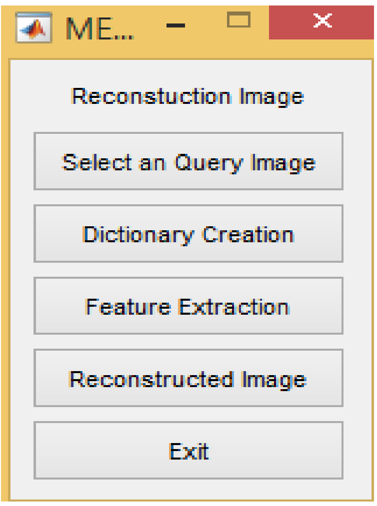


Fig 2: Main tool box.

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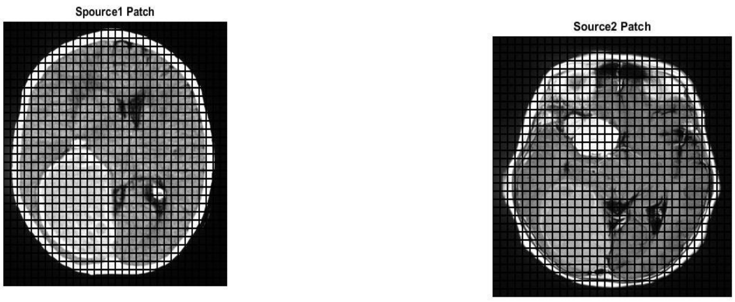
The two input images are selected by clicking the Select an query image. Here both input images are resized. The patches of resized input images are extracted by selecting the Dictionary creation. The features of interpolation, AHE and Difference image are extracted by selecting the Feature extraction. Then finally, will get the reconstructed image by selecting the reconstructed image.

## IV RESULT

Case1: Hyper dense intracranial tumor on CT (Fig 4.1 (a)) and Heterogeneities (Hyper intense at peripherally and Hypo intense at center). Lesion on MRI (Fig 4.1 (b)) in right frontal region with midline shift and causing effacement of ipsilateral lateral ventricle. Tumor margins are well delineated in reconstructed image (Fig 4.4) and it helps in accurate measurement of tumor size.

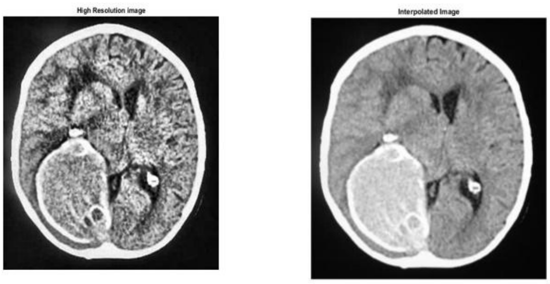

(a)CT Image (b)MRI Image

Fig 3:Input Image




( c)CT patch (d)MRI patch

Fig 4: Dictionary Creation of CT and MRI images.




(e) Interpolation (f) AHE

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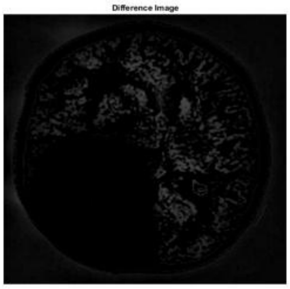



(g) Difference image

Fig 5: Feature Extraction images

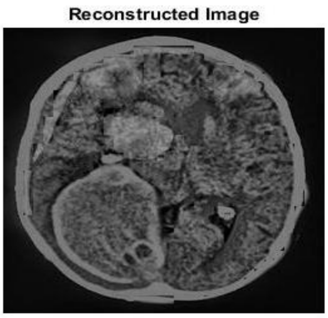
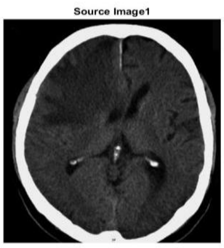
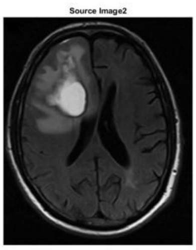



Fig6: Reconstructed Image

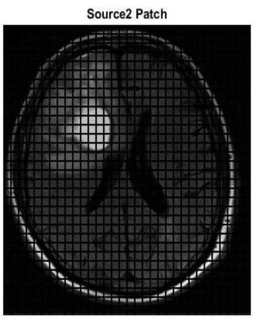
Case 2: Hypodense area in CT (Fig 4.5(a)) and Hyperintence lesion in MRI (Fig 4.5(b)) seen right frontal parietal lobe, which is a subacute intracerebral hemorrhage mimicking brain tumor. Hemorrhage is well delineated from surrounding edema in reconstructed image (Fig 4.8), which helps in accurate measurement of hemorrhage, and made of treatment in terms of medical management or surgery.




(a) CT image (b) MRI image

Fig 7: Input images


(c) CT patch (d) MRI patch

Fig 8: Dictionary Creation of CT and MRI images.

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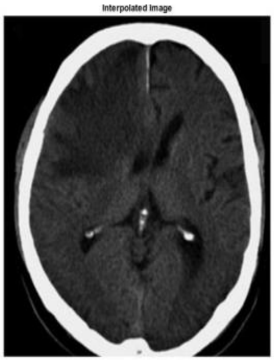
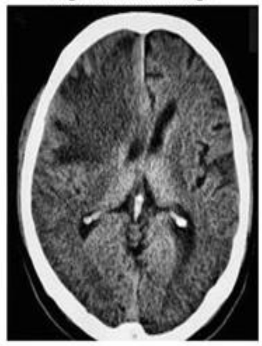
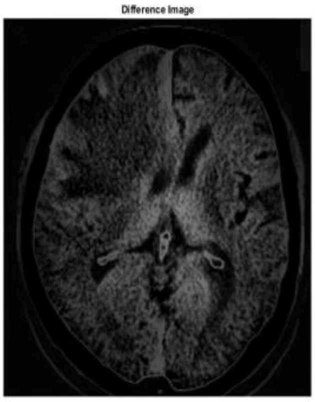



(e) Interpolation (f) AHE




(f) Difference image

Fig 9: Feature extraction images.

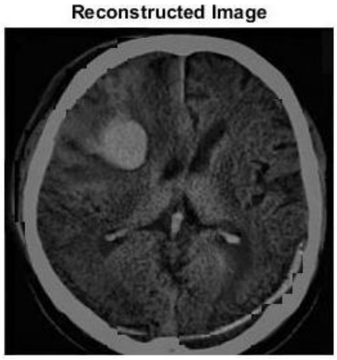



Fig 10: Reconstructed image.

## V PERFORMANCE ASSESSMENT

In order to quantitatively evaluate the image resolution quality, we utilize an evaluation measure based on the Standard Deviation (SD), Entropy (EN), Mean Square Error (MSE) and the Peak Signal-to-Noise Ratio (PSNR). This provides quantitative comparison among different cases. It focuses mainly at the definition of image.

### A. Standard Deviation(SD)

SD evaluates how widely spread the gray values in an image and measures the fused image contrast. SD denotes the deviation degree of the estimation and the average of the random variable. SD produces best results in the absence of noise. An image, which is having high contrast would have a high standard deviation value. For better results SD should be at the higher end. The SD of the image can be evaluated as

$$SD = \sqrt{\frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y) - \bar{I})^2} \quad (7)$$

M is the width of the image, N is height. I(x,y) represents the pixel value in (x,y), $\bar{I}$ is average value of image.

### B. Entropy(EN)

Entropy can represent how much information is contained in signals. It's also widely used to show the average amount of information of images in image processing field. For a image, grayscale value of every pixel can be considered as mutual independent. The Entropy of the image can be evaluated as

$$EN = -\sum_{i=0}^{L-1} P_i \log_2(P_i) \quad (8)$$

Where $P_i$ represents the probability that the grayscale value of pixels in the image $i$, i.e. the ratio between the number of pixels whose grayscale values are $i$, and The total number of image pixels . L is the total number of gray levels.

### C. Mean Square Error (MSE) and the Peak Signal-to-Noise Ratio (PSNR).

The MSE is used to measure the amount of data loss through the pixel value comparison. As the PSNR is derived from MSE, it is used to measure the image quality. The PSNR index indicates the ratio between the maximum possible pixel value of the original image and the pixel value by noise. The equation is as the following:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (9)$$

Where *R* is the maximum possible pixel value of the input image (*R* is 255 represented by 8 bits) and MSE represents the MSE between the given input image *Iinp* and the original image *Igor* which can be obtained by the following:

$$MSE = \frac{\sum_{i,j}(I_{inp}(i,j) - I_{org}(i,j))^2}{M \times N} \quad (10)$$

Where, *M* and *N* are the rows and column dimension of the image respectively.

| Cases | Case 1 | Case 2 |
|---|---|---|
| SD | 41.07 | 36.89 |
| EN | 0.0198 | 0.041 |
| PSNR | 19.39 | 29.32 |
| MSE | 6972.9 | 2223.2 |

Table1: Performance Assessment of Reconstructed Images.

## VI Conclusion and Future Scope

In this proposed work, image fusion is performed based on patch extraction. The proposed method has some advantages, they are-It reduces image error, it gives the fast and accurate results. It gives high contrast reconstructed image. An experiment on different types of input images determines the advantage of our method over existing fusion strategies based on interpolation and sparse representation. This image can be used to improve image quality of medical images and reduces the image error, which is very useful for diagnosis purposes.

The target of the simulation is to propose more effective fusion method applied on medical image fusion which is with important significance to modern medical imaging. More investigation will focus on fusion method optimization and evaluation criteria

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