Medical image processing by hybrid image fusion Technique

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Abstract : Medical image fusion techniques are extensively used to aid medical diagnosis by combining features of two or more images of various modalities such as Computed Tomography (CT) , Magnetic Resonance Image (MRI) ,and positron emission tomography (PET) into a single output image that contains salient features from all inputs. This paper proposes a hybrid fusion algorithm is applied on a CT and MRI images. The largest Eigen value of the covariance matrices of each image are used to obtain weights for next stage image by Principal component analysis (PCA) and different frequency components of input image are separated by Discrete Cosine Transform (DCT), noise in output images from first two stages. Performance evaluation of CT-MRI image fusion with hybrid algorithm BY Discrete Wavelet Transform (DWT) improves the image quality compared to established methods. Overall, the non-linear fusion rule holds strong potential to help improve image fusion applications in medicine and indeed other fields.

Keyterms – fusion, PCA, DCT, DWT

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I. INTRODUCTION

Image fusion is a process of merging two or more images, which preserves important features from each input in order to generate a fused output image of a higher visual quality. The concept has extensive applications in medical imaging, where various image acquisition systems tend to exist such as magnetic resonance imaging (MRI), computed tomography (CT), the difference and complementary nature of each system has led to the idea that combining images acquired with more comprehensive information. For instance, CT images give more information of strong structure like bones while MRI will give information of soft tissues. On the other hand, modalities possessing low spatial resolution like positron emission tomography (PET) and single photoemission computed tomography (SPECT) contain functional records which help in providing information about visceral metabolism and blood circulation in the scanned subject. Therefore Fusion is deemed important in enhancing image results, which can lead to better detection of anomalies, reducing uncertainties and generally aid in better observation making by the medical practitioner.

Numerous techniques have been implemented to perform fusion on medical images over the years, one of the most popular being the wavelet-based approach.[2]By the use of signal decomposition techniques divide the input image into a series of low-pass and high-pass filtered representations, by obtained the respective wavelet coefficients for each of the two input images, fusion is then performed by a fusion operator or rule that selects the preferred coefficients. From the choice of feature extraction, fusion rule is a key factor that influences the quality of fused image.

PRINCIPLE COMPONENT ANALYSIS (PCA)

The principal component analysis image fusion algorithm is to reorganize the image dataset to be able to be used in the calculation. It is to convert the input images matrix I_1 and I_2 of a dimension **m** by **n** to one by **m** multiplied **n** matrix, essentially a one column matrix. This will be repeated for all input images.

The next step is to calculate the covariance between the two new datasets **X** and **Y** which are created from the input images matrices I_1 and I_2.

$$C = (X, Y) = [(X - E[X])(Y - E[Y])] \tag{1}$$

Where E[X] and E[Y] are the expected value of X and Y respectively.

So to find the covariance, first find the E[X] and E[Y], which is basically calculating the empirical mean of each datasets **X** and **Y** and then subtracting these values from the X and Y datasets to get the deviations from the mean which essentially means (X-E[X]) and (Y-E[Y]) .

By using the covariance matrix **C**, find the Eigenvector and Eigen value such that

$$Cv = Dv . \tag{2}$$

Where **C** is the covariance matrix, **v** is the Eigenvector matrix and **D** is the Eigen value.

After getting the Eigenvector V and Eigen value D of matrix C, we sort them by decreasing Eigen value. The Resulting V and D are of dimension two by two, and the first column of V will correspond to larger Eigen value and then can be used to compute the final PCA value (weighted value) of each picture p_1 and p_2.

$$p_1 = \frac{v(1)}{\Sigma v} , \quad p_2 = \frac{v(2)}{\Sigma v} \tag{3}$$

Where **v** is the Eigenvector matrix.

To get the fused image, multiply each weighted average to the original picture and sum the result together to get the final fused image.

$$I_{fused} = p_1 * I1 + p_2 * I2 \tag{4}$$

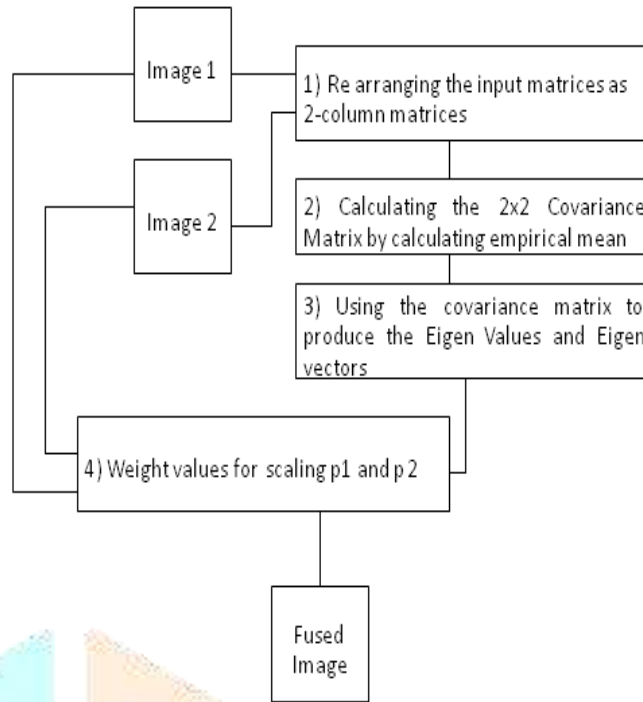Where I_{fused} is the final fused image and I_1 and I_2 are the two input images

Figure :   PCA algorithm

Steps to perform PCA algorithm:

1. Generate the column vectors, respectively, from the input images matrices.

2. Calculate the covariance matrix of the column vectors formed in step 1.

3. Calculate the Eigen vectors and Eigen values of that covariance matrix.

4. Normalize the column vector corresponding to the larger Eigen value.

5. Create the weight values datasets which are the values of the normalized.

6. Eigenvector from step 4 divided by the mean of the Eigenvector.

7. Multiply the weight values datasets from step 5 with each pixel of the input images and summing them together to get the final fused image matrix.

DISCRETE COSINE TRANSFORM (DCT)

The discrete cosine transforms is a technique for converting a signal into elementary frequency components. It represents an image as a sum of sinusoids of varying magnitudes and frequencies.

With an input image, x, the DCT coefficients for the transformed output image, y, are computed according to the fallowing Equation.

$$y(u,v) = \sqrt{\frac{2}{M}} \sqrt{\frac{2}{N}} \alpha_u \alpha_v \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} x(m,n) \cos \frac{(2m+1)u\Pi}{2M} \cos \frac{(2n+1)v\Pi}{2N}$$

(5)

Where

$$\alpha_u = \begin{cases} \dfrac{1}{\sqrt{2}} \ldots\ldots\ldots u = 0 \\ 1 \ldots\ldots\ldots\ldots u = 1,2,3\ldots N-1 \end{cases}$$

$$\alpha_v = \begin{cases} \dfrac{1}{\sqrt{2}} \ldots\ldots\ldots v = 0 \\ 1 \ldots\ldots\ldots\ldots v = 1,2,3,\ldots N-1 \end{cases}$$

In the equation, x is the input image having N x M pixels, x (m, n) is the intensity of the pixel in row m and column n of the image, and y (u, v) is the DCT coefficient in row u and column v of the DCT matrix.

The block-based DCT transform segments image as non-overlapping blocks and applies DCT to each block. These results in giving three frequency sub-bands: low frequency sub-band, mid-frequency sub-bands and high frequency sub-band. DCT-based watermarking is based on two facts. The first fact is that much of the signal energy lies at low-frequencies sub-band which contains the most important visual parts of the image. Then the high frequency components of the image are removed. The image is reconstructed by applying inverse DCT operation according to the fallowing Equation.

$$X(m,n) = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}} \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} \alpha_u \alpha_v\, y(u,v) \cos\frac{(2m+1)u\Pi}{2M} \cos\frac{(2n+1)v\Pi}{2N}$$

(6)

PROPERTIES OF DCT:

De-correlation:

As discussed previously, the principle advantage of image transformation is the removal of redundancy between neighboring pixels. This leads to uncorrelated transform coefficients which can be encoded independently. Let us consider our example from Figure 2 to outline the de-correlation characteristics of the 2-D DCT. The normalized autocorrelation of the images before and after DCT. Clearly, the amplitude of the autocorrelation after the DCT operation is very small at all lags. Hence, it can be inferred that DCT exhibits excellent de-correlation properties.

Energy Compaction:

Efficiency of a transformation scheme can be directly gauged by its ability to pack input data into as few coefficients as possible. This allows the quantizer to discard coefficients with relatively small amplitudes without introducing visual distortion in the reconstructed image. DCT exhibits excellent energy compaction for highly correlated images. Let us again consider the two example images of Figure 2(a) and (b). In addition to their respective correlation properties discussed in preceding sections, the uncorrelated image has more sharp intensity variations than the correlated image. Therefore, the former has more high frequency content than the latter. Figure 6 shows the DCT of both the images. Clearly, the uncorrelated

image has its energy spread out, whereas the energy of the correlated image is packed into the low frequency region (i.e., top left region).

DISCRETE COSINE TRANSFORM BASED LAPLACIAN PYRAMID :

In the discrete cosine transform based Laplacian pyramid 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 cosine transform based Laplacian pyramid image fusion is to decompose each input image using discrete cosine transform (DCT) and then we need to construct a Laplacian pyramid representing how many levels, k, for algorithm would apply.

The two-dimensional discrete cosine transform $Z(u,v)$ of an image $I(i, j)$ of dimensional size is m by n is calculated using the following equation.

$$Z(u,v) = \alpha(u)\, \alpha(v) \sum_{i=0}^{m} \sum_{j=0}^{n} I(i,j) \cos\left(\frac{\pi(2i+1)u}{2m}\right) \cos\left(\frac{\pi(2j+1)v}{2n}\right) \qquad (7)$$

Where

$$\alpha(u) = \begin{cases} \dfrac{1}{\sqrt{m}}, & u = 0 \\ \dfrac{2}{\sqrt{m}}, & 1 \le u \le m \end{cases}$$

$$\alpha(v) = \begin{cases} \dfrac{1}{\sqrt{n}}, & v = 0 \\ \dfrac{2}{\sqrt{n}}, & 1 \le v \le n \end{cases}$$

And then repeat that decomposition steps K times to reach to the final decomposition level. This series of decomposition is represented as a pyramid and is known as a Laplacian pyramid.
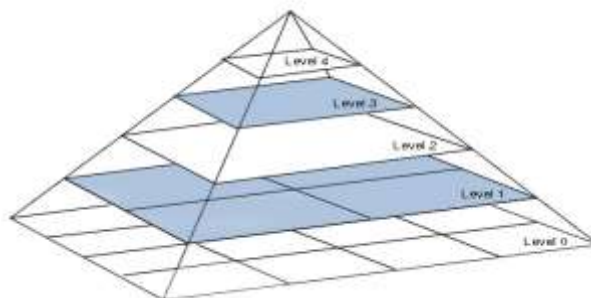

Figure : Laplacian Pyramid

b)   Fuse the multi-scale images.

Secondly, after getting the final decomposition level for each image, we will end up with a multi-scale image for each image. So the next step would be to fuse them and to do that 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 multi-scale image, we can get the final fused image by applying inverse discrete cosine transform on the image k times to reach the original starting level which is the base of our Laplacian pyramid model.
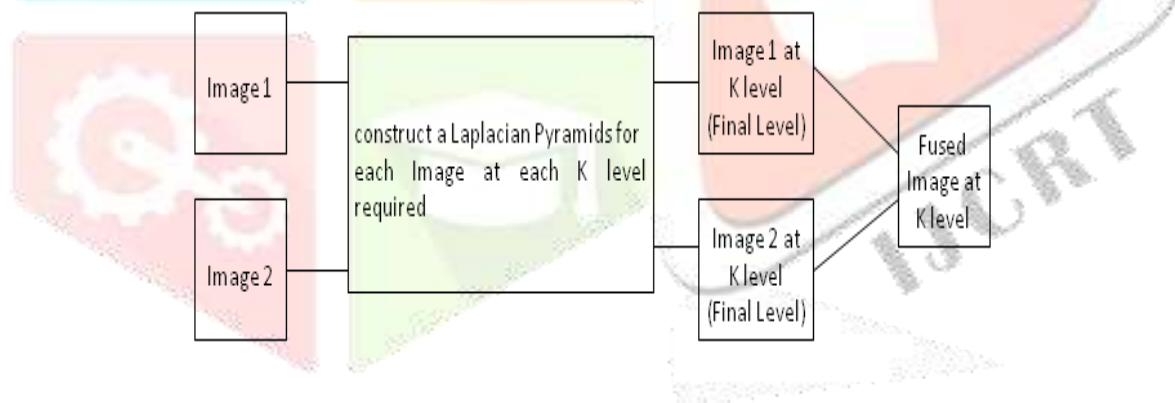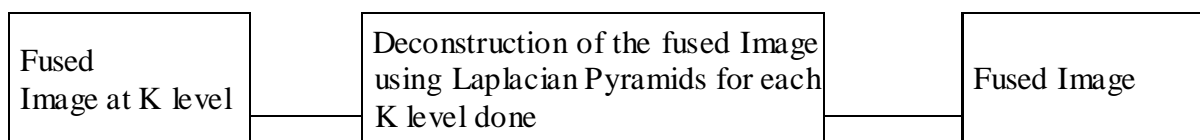

Figure : DCTLP

Steps to perform discrete cosine transform & Laplacian pyramid algorithm:

1) Choose the level, k, of decomposition required to apply to the images for fusion

2) Decompose the input images using a Laplacian pyramid of the discrete cosine transform

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, a fused decomposed matrix is created using one of the following methods

   a. Average

   b. Select Maximum

   c. Select Minimum

5) Reconstruct a matrix by applying the inverse of a Laplacian pyramid of the discrete cosine transform to the fused decomposed matrix obtained in step- 4

6) Repeat Step K times, decided upon from step 1, till we reach the original level

7) The resulting matrix from step 6 will be the final fused image.

DISCRETE WAVELET TRANSFORM (DWT)

The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies. Multi-resolution: analyses the signal at different frequencies giving different resolutions. Multi-resolution analysis is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. Good for signal having high frequency components for short durations and low frequency components for long duration, e.g. images and video frames.

The fundamental idea behind wavelets is to analyse according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mind-set are perspective in processing data. However, in wavelet analysis, this scale that we use to look at data plays a special role. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a small "window," we could notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak. This makes wavelets interesting and useful. For many decades, scientists have wanted more appropriate functions than the sine and cosines which comprise the bases of Fourier analysis, to appropriate choppy signals. By their definition, these functions are non-local (and stretch out to infinity). They therefore do a very poor job in approximating sharp spikes. But with wavelet analysis, we can use approximating functions that are contained neatly in finite domains. Wavelets are well-suited for approximating data with sharp discontinuities.

The wavelet analysis procedure is to adopt a wavelet prototype function, called an analysing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet

coefficients. And if you further choose best wavelets adapted to your data, or truncate the coefficients below a threshold, your data is sparsely represented. This spares coding makes wavelets an excellent tool in the field of data compression.

Other applied fields that are making use of wavelets include astronomy, acoustics, nuclear engineering, sub band coding, signal and image processing, neurophysiology, music, magnetic resonance imaging, speech discrimination, optics, fractals, turbulence, earthquake-prediction, radar, human vision and pure mathematics application such as solving partial differential equation.

Wavelet definition

A wavelet is a small wave which has its energy concentrated in time. It has an oscillating wave like characteristics but also has the ability to allow simultaneous time and frequency analysis and it is suitable tool for transient, no stationary or time-varying phenomenon.
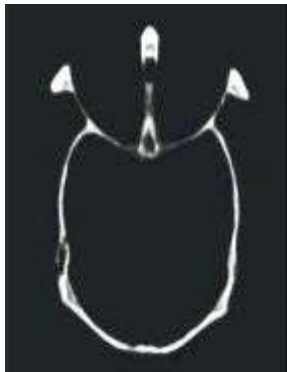
FUSION ALGORITHM:

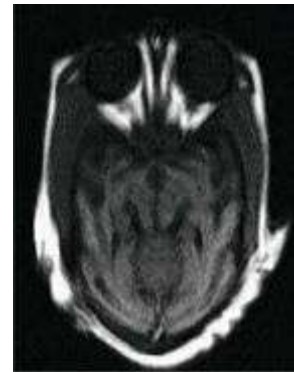Following algorithm has been developed and implemented in MATLAB software.

STEPS:

1. Read the image I1 and find its size.

2. Read the second image I2 and find its size.

3. Compute and match the size if not same, make it same.

4. Convert both images from grayscale to indexed image to perform various wavelet functions. If the color map is smooth, wavelet transform can be directly applied to the indexed image; otherwise the indexed image should be converted to grayscale format.

5. Perform discrete wavelet transform and obtain the fused image by DWT.

6. Generate the coefficient matrices of the level-three approximation and horizontal, vertical and diagonal details.

7. Construct and display approximations and details from the coefficients.

8. Regenerate an image by principle component analysis(PCA).

9. Repeat the same with second image.

10. Now fuse the wavelet coefficients using either of averaging, maximum or minimum technique.

11. Generate a final matrix of fused wavelet coefficients.

12. Compute the entropy values of each technique and tabulate them.

13. Finally display the results of the hybrid model.
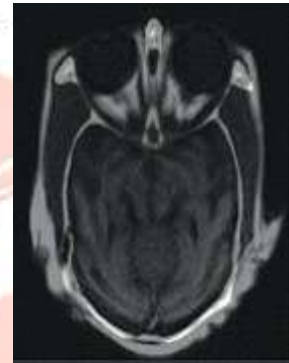
RESULTS AND DISCUSSION:

INPUT IMAGES

CT IMAGE

MRI IMAGE

OUTPUT IMAGES

PCA FUSED IMAGE

DCT FUSED IMAGE

HYBRID IMAGE BY DWT

S no	Input Images/fusion methods	Entropy
1	Image 1(CT)	4.2698
2	Image 2(MRI)	6.8741
3	PCA	7.0703
4	DCT	6.3910
5	DWT(hybrid model)	8.9230

The proposed medical image fusion techniques were implemented using MATLAB. The medical image fusion was performed by taking two input images i.e. MRI image and CT image. For the purpose of fusion we are using the discrete cosine transform and principal component analysis techniques. To get the better quality image we are using the hybrid technique by using discrete wavelet transform (DWT). The fused image was verified based on the entropy (E) value. This medical image fusion algorithm uses discrete cosine transform (DCT),Principal component analysis(PCA),and discrete wavelet transform(DWT). This hybrid technique gives better quality image by referring the entropy value. There is also a different image fusion techniques were carried out of which discrete wavelet transform gives better results in entropy value is high.

Although selection of fusion algorithm is problem dependent but this review results that spatial domain provide high spatial resolution. But spatial domain have image blurring problem. The Wavelet transforms is the very good technique for the image fusion provide a high quality spectral content. But a good fused image have both quality so the combination of DWT & spatial domain fusion method (like PCA) fusion algorithm improves the performance as compared to use of individual DWT and PCA algorithm. Finally this review concludes that a image fusion algorithm based on combination of DWT and PCA with DCT hybrid model will improve the image fusion quality and may be the future trend of research regarding image fusion.

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