Hybrid PCA-DCT Based Image Fusion For Medical Images

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ABSTRACT: The purpose of image fusion is to merge relevant information from multiple images right into a single image. In this paper, by conducting the review it has been discovered that the majority of the existing techniques are based upon transform domain therefore it could results in some artifacts which might decrease the execution of the transform based vision fusion techniques. Moreover it is already been discovered that the issue of the uneven illuminate has already been neglected in the absolute most of existing focus on fusion. Therefore to overcome these issues, a fresh method which integrates the larger valued Alternating Current (AC) coefficients calculated in iterative block level principal component averaging (IBLPCA) domain base fusion with illuminate normalization and fuzzy enhancement has been proposed in this paper. The experimental results show the efficiency of proposed algorithm over existing work.

Keywords: Image Fusion, PCA, DCT.

1. INTRODUCTION

Image fusion is the method of merging information from several images of a scene right into a single composite image, which will be more informative and worthy for human visual perception or computer processing. There are numerous advantages in using image fusion viz. wider spatial and temporal coverage, improved reliability, decreased ambiguity and increased robustness of system performance. Fused images can give information that sometimes can't be observed in the person input images. With the recent, rapid developments in the field of sensing technologies, multisensor imaging systems are now being found in an increasing amount of fields, like in remote sensing, medical and military applications [1]. Multisensor image fusion, that will be referred as the method of combining relevant information from several images right into a single image, has been receiving increasing attention in the remote sensing research community as a result of increasing accessibility to spaceborne imaging sensors. The key aim of multisensor image fusion would be to merge complementary information from multisensory images of the exact same scene right into a single image to acquire data that's more useful compared to data from some of the individual source images by reducing imprecision and uncertainty in the spatial properties and maintaining completeness of the spectral information. Such fused images should become more ideal for further image processing tasks such as for instance image segmentation, object identification, and regional change detection [2]. Medical image fusion is the strategy of registering and merging different images from one or more than two imaging modalities to boost the imaging class and reduce randomness and redundancy to possess the capability to enhance the clinical use of medical images for diagnosis. Multi-modal medical image fusion process reveals notable accomplishments in improving clinical accuracy of decisions specialized in medical image. It describe the medical image fusion research predicated on (a) the reliable image fusion methods, (b) imaging modalities, and (c) imaging of organs which are under study. This review concludes that the fusion of medical images has turned out to be great for advancing the clinical reliability by facing numerous scientific challenges [3]. Yang et al. [8] proposed a story multiscale geometric analysis tool, contourlet indicate many advantages over the standard image representation methods. In this method, a fresh fusion algorithm for multimodal medical images centred on contourlet transform is presented. All fusion functions are performed in contourlet domain. **Han et al.** [9] works for palmprint identification. Palmprint is widely utilized in personal identification for an exact and robust recognition. To boost the prevailing palmprint systems, the proposed system, which will be the initial on-line multispectral palmprint recognition system ever designed before, uses multispectral capture system to sense images under different illumination, including red, green, blue and infrared. Yang et al. [10] proposed a book objective quality metric for image fusion. The interest with this metric is based on the truth that the regions like redundant and the complementary/conflicting are examined based on the structural similarity between the origin images. Zhang et al. [11] proposed a straight forward and effective multi-focus image fusion approach. When it comes to multi-focus images, these are obtained from the exact same scene with various focuses. This new fusion technique can significantly decrease the total amount of distortion artifacts and the increasing loss of contrast information. They're usually observed in fused images in the standard fusion strategies. Yang et al. [12] present sparse representation-based multifocus image fusion method. In this method, first, the origin image is represented with sparse coefficients having an over complete dictionary. Second, the coefficients are merged with choose-max fusion rule. Then the final fused image is reconstructed from the merge sparse coefficients and the dictionary. Wang et al. [13] proposed a new method known as dual-channel pulse coupled neural networks (dual-channel PCNN) for multi-focus image fusion. PCNN is given input by two parallel source images directly. Source images are subjected to focus measures. Based on results of focus measure, weighted coefficients are automatically modified. Li et al. [15] compared various multi-resolution decomposition algorithms, especially the most recent developed image decomposition methods, such as curvelet and contourlet, for

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image fusion. By comparing fusion results, it gives the most effective outcome for multi-focus images, infrared–visible images, and medical images. Tian et al. [16] aims to merge a couple of images which are captured from exactly the same scene but with various focuses for generating another sharper image. Inspired by the observation that the marginal distribution of the wavelet coefficients is significantly different for images with various focus levels, a new statistical sharpness method is presented by exploiting the allocation of the wavelet coefficients distribution to determine the amount of the image's blur. Liu **et al.** [17] conducted a relative study on 12 particular image fusion metrics over six multiresolution image fusion algorithms for just two different fusion schemes and input images with deformation. Image fusion is a well known selection for diverse image enhancement applications such as for example refinement of image resolutions for alignment, overlay of two image products etc. Zhao et al. [19] gave a notion that gray image is accepted as a two-dimensional surface, and the neighbour distance inferred from the oriented distance in differential geometry can be used as a way of measuring pixel's sharpness, where in fact the smooth image surface is restored by kernel regression. On the basis of the assumed neighbour distance filter, a multi-scale image analysis framework is constructed, and proposes a multi-focus image fusion method on the basis of the neighbour distance.

2. IMAGE FUSION TECHNIQUES

2.1 Neural network based methods

Artificial Neural Networks (ANN) are motivated from the fact that biological neural network is having the potential to learn from inputs for processing attributes and for making global decisions. To identify set of parameters for the input training set, weights are referred for artificial neural network models. The scope of the neural network models to approximate, analyze and deduce information from a given data without going through a rigorous mathematical solution is often seen as a benefit. This makes the neural network more striking to image fusion as the nature of variability between the images is subjected to change every time a new modality is used [4]. The potential to prepare the neural network to accept to these changes permit several applications for medical image fusion such as solving the problems of feature generation, classification , data fusion image fusion, breast cancer detection, medical diagnosis, cancer diagnosis, natural computing methods and classifier fusion. Although ANN recommends generality in terms of having the capability to apply the notion of training, the robustness of ANN methods is limited by the superiority of the training data and the accuracy of convergence of the training algorithm. In order to improve the quality of the features and thereby to improve the strength of the ANN, hybrids of neural networks and sequential processing with other fusion techniques can be employed [5].

2.2 Fuzzy logic based method

The disjunctive, conjunctive and compromise attributes of the fuzzy logic have been widely traversed in image processing and have manifested to be useful in image fusion. For image fusion process, fuzzy logic is applied both as a decision operator or a feature transform operator. There are numerous uses of fuzzy logic base image fusion such as deep brain stimulation, brain tumor segmentation , image retrieval, spatial weighted entropy, brain diagnosis, cancer treatment, image segmentation and integration , maximization mutual information, feature fusion, multimodal image fusion, ovarian cancer diagnosis , sensor fusion , natural computing methods and gene expression. The preference of fuzzy sets and membership functions that result in the optimal image fusion is an open issue. The improvements of feature processing and analysis can be improved to fit the fuzzy space better when merged with probabilistic approaches such as fuzzy-neural network, fuzzy–genetic-neural network– rough set , fuzzy-probability and neuro-fuzzy– wavelet [5].

2.3 DCT based Method

The objective of image fusion is to merge relevant information from different images into a single composite image. Methods based on DCT for image fusion are more time-saving in real-time mechanisms by applying DCT based standards of still image or video. Presently some methods based on DCT are having unwanted issues such as blurring or blocking artifacts which affects resultant image [2]. Additionally, some of these methods are rather complicated and this challenge the concept of the principle used in DCT based algorithms. In this method, a suitable technique based on variance calculated in DCT domain for fusion of multi-focus images is conducted. Due to easy accessibility of this approach it offers high degree of reliability in real-time applications [6]. The resultant outcome verifies the efficiency improvement of this technique in contrast with numerous recent proposed techniques.

2.4 PCA based Method

In this method, hierarchical PCA algorithm is used for fusion. Image fusion is a method of merging two or more images (which are registered) of the same scene to get the more informative image. Principal component analysis provides a powerful tool for data analysis and pattern recognition which is used in image processing as a technique for data dimension reduction or their decorrelation of variables and data compression as well**.** Principal component analysis is appropriate when you have obtained measures on a number of observed variables and wish to develop a smaller number of artificial variables (called principal components) that will account for most of the variance in the experimental variables. PCA involves decorrelation and reduces the number of components. The first principal component gives description for as much of the variance in the data as possible. Remaining components accounts for lesser variance than first [7].

4. PROPOSED METHODOLOGY

Steps of proposed algorithm are:

1. Consider two partially blurred images which are passed to the system. Read both images.
2. Apply level shifting by 8 to them.
3. Divide images into 8*8 blocks.
4. Now apply DCT.

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5. DCT transform of an N*N image block f(x,y) is given by:

$$F(u,v)=\frac{2}{N}c(u)(v)\sum_{y=0}^{N-1}\sum_{x=0}^{N-1}f(x,y)\cos\left[{(2x+1)u\Pi}/{2N}\right]*\cos\left[{(2y+1)v\Pi}/{2N}\right]$$

(a)Extract AC coefficients from both images.

(b)Initialize $C^t_n = 0$, where C^t_n represents number of maximum valued ac coefficient found in a particular block.

6 Evaluate principle component value, i.e. maximum ac value.

7. Check for consistency verification value.
8. Apply consistency verification.
9. If CV = -1,

   Take block from image 1

   Else CV = 1

   Take block from image 2
10. Return fused image.

5. RESULTS AND DISCUSSIONS

5.1 Experimental Set - up

In order to implement the proposed algorithm, design and implementation has been done in MATLAB using image processing toolbox. In order to do cross validation we have also implemented the enhanced DCT and PCA based image fusion using fuzzy enhancement. Table 1 is showing the various medical images which are used in this research work. Images are given along with their formats. All the images are of same kind and passed to proposed algorithm.

TABLE 1

Images taken for experimental analysis

Image name	Extension	Size in K.Bs (Partially blurred 1)	Size in K.Bs (Partially blurred 2)
Image 1	.jpg	61.8	61.7
Image 2	.jpg	82.5	82.8
Image 3	.jpg	67.8	68.0
Image 4	.jpg	41.9	45.2
Image 5	.jpg	62.7	65.5
Image 6	.jpg	68.8	65.5
Image 7	.jpg	115	117
Image8	.jpg	246	242
Image9	.jpg	35.6	41.1
Image10	.jpg	71.2	73.5

For the purpose of cross validation we have taken 10 different images and passed to proposed algorithm. Following segment encloses a result of one of the 10 particular images to demonstrate the enhancement of the proposed algorithm over the other technique.

5.2 Experimental Results

Fig 1 represents the input image for experiments. Fig 1(a) is showing the partially left blurred image and Fig 1(b) is showing right partially blurred image. The overall goal is to merge relevant information from different images into a single image that is more instructive and appropriate for both visual perception and further computer processing.

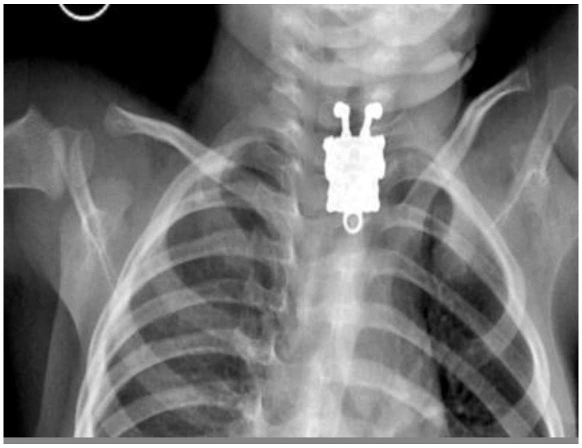

Fig 1: *Input Image 1*

Fig 1(a): *Left partially blurred image*

Fig 1(b): *Right partially blurred image*

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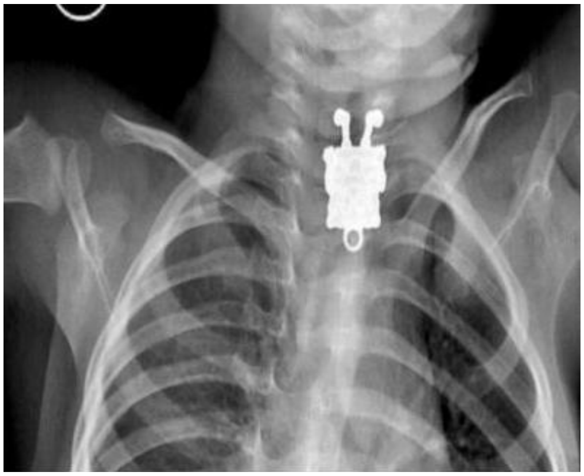

Fig 2: *Output for DCT technique.*

Fig 2 has shown the output image taken by DCT. The output image has contained too much brightness and has artifacts as compare to original blurred images to be fused.

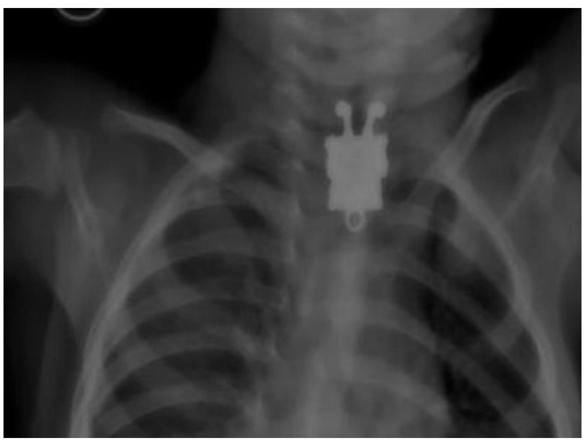

Fig 3: *Output for PCA technique.*

Fig 3 has shown the output image taken by PCA. The output image has contained low brightness and low contrast as compare to original blurred images to be fused which have degraded the quality of the image.

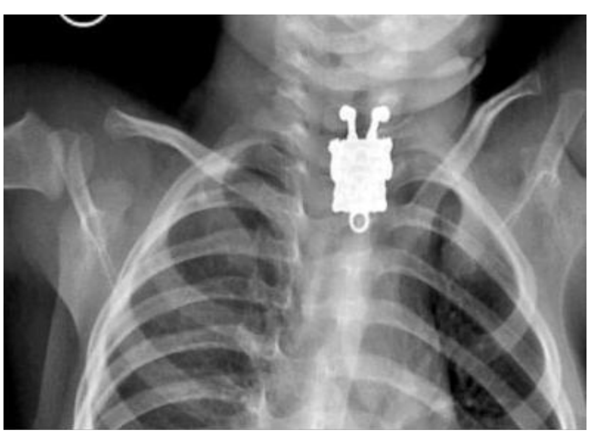

Fig 4: *Output for Proposed technique.*

Fig 4 has shown the output image taken by the integrating DCT and PCA based image fusion with fuzzy enhancement. The image has contained the balanced color and brightness as the original images to be fused. The quality of output image is quite good with proposed method with respect to all the techniques discussed.

6. PERFORMANCE EVALAUTION

6.1 Peak Signal to Noise Ratio (PSNR)

The PSNR block calculates the peak signal-to-noise ratio, between two images. As a quality measurement between reference and final fused image, PSNR ratio is used. The higher the PSNR shows the better the quality of the fused or reconstructed image. PSNR value is computed by following equation:

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad \text{... (6.1)}$$

Table 2 shows the comparison of DCT, PCA and proposed technique in terms of peak signal to noise ratio. From the table it is clear that as PSNR of proposed is more as compared to DCT and PCA, therefore the proposed technique performs effectively as compared to DCT and PCA.

TABLE 2

PSNR EVALUATION

Medical Images	DCT Method	PCA Method	Proposed Method
1	34.0353	11.6584	42.8137
2	31.9206	15.3896	41.9601
3	29.1526	12.1171	38.6668
4	23.4289	11.5134	24.1895
5	20.4160	9.5062	42.9959
6	41.5874	14.0974	41.5874
7	24.7301	8.9438	31.3617
8	23.5630	7.8690	40.3199
9	29.3338	79.208596	34.4112
10	56.6791	12.4887	56.6791

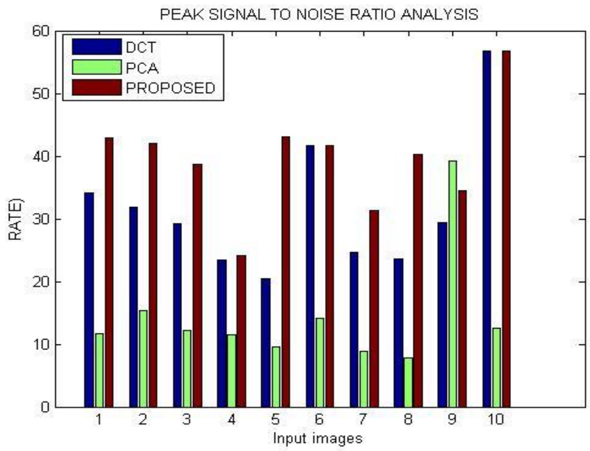

Fig 5: *PSNR Analysis*

It is very clear from the plot that there is increase in PSNR value of images with the use of proposed method over other methods. This increase represents improvement in the objective quality of the image.

6.2 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) between the fused image and original image provides error as a percentage of mean intensity of the original error. The RMSE is calculated as follows.

$$RMSE = \sqrt{\left(1 / (M * N) \right) \left[\sum * \sum y \left(I_{true}(x, y) - I_{fused}(x, y) \right)^2 \right]}$$

Where $I_{true}(x, y)$ is the original input image, $I_{fused}(x, y)$ is the fused image and M, N is the dimensions of the images. Smaller the value of RMSE, better the fusion performance.
Table 3 shows the comparison of DCT, PCA and proposed technique in terms of root mean square error. From the table it is clear that as RMSE of proposed in less as compared to DCT and PCA, therefore the proposed technique performs effectively as compared to DCT and PCA.

TABLE 3
RMSE EVALUATION

Medical Images	DCT Method	PCA Method	Proposed Method
1	5.067263	66.622204	1.844407
2	6.464162	43.356932	2.034873
3	8.890177	63.195079	2.973053
4	17.182937	67.743812	15.74222
5	24.307532	85.355217	1.806115
6	2.124088	50.311709	2.124088
7	14.792248	91.064418	6.893750
8	16.919651	103.059594	2.457786
9	8.706582	79.208596	4.852658
10	0.373755	60.548448	0.373755

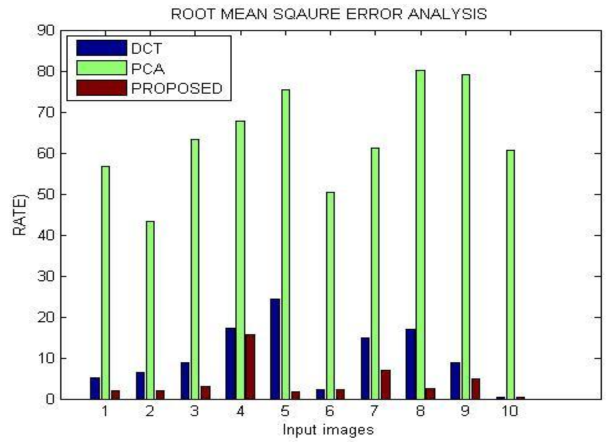

Fig 6: *RMSE Analysis*

It is very clear from the plot that there is value of RMSE lesser in every case with the use of proposed method over other methods. This represents improvement in the objective quality of the image.

6.3 Average Error (AE)

The Average maximum difference corresponds to pixel which has a value which is less than the pixel in original image and the Average minimum difference corresponds to pixel which has a value which is more than the pixel in original image. The average difference is defined as a value of the difference between maximum and minimum. It needs to be minimized.

$$AE = \frac{i}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left[A(i, j) - B(i, j) \right] \quad \ldots (6.3)$$

TABLE 4
Average Error Evaluation

Medical Images	DCT Method	PCA Method	Proposed Method
1	4.391636	58.548029	1.39418
2	2.947743	25.336414	1.096693
3	4.740129	46.916900	1.715357
4	13.806036	52.864971	12.627814
5	18.459393	66.26355	0.905507
6	1.119793	31.664414	1.119793
7	12.692843	78.484150	5.810357
8	15.961357	97.378936	2.049164
9	7.238079	65.942529	3.962864
10	0.035157	35.786350	0.035157

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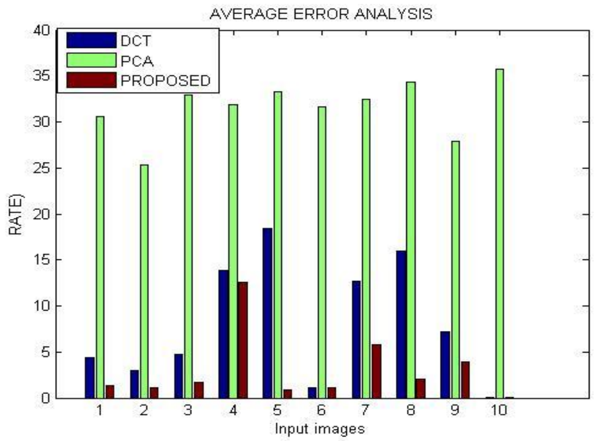

Fig 7: *Average error analysis*

It is very clear from the plot that there is decrease in AE value of images with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

7. CONCLUSION AND FUTURE SCOPE

In this paper, a comparison among image fusion techniques has been evaluated. A new technique has also been proposed which integrate the higher valued Alternating Current (AC) coefficients calculated in iterative block level principal component averaging (IBLPCA) domain base fusion with illuminate normalization and fuzzy enhancement. The proposed work has been implemented and designed in the MATLAB. From the comparison on the basis of various performance metrics, it has been concluded that proposed work performs effectively over existing DCT and PCA algorithms.

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