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AN EFFICIENT METHOD TO IMPROVE THE SPATIAL PROPERTY OF MEDICAL IMAGES

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ABSTRACT

Now a days clinical diagnosis is emerging with digital images. In this paper we have dealt with computed tomography (CT), positron emission tomography (PET) and Magnetic Resonance Image (MRI). Where CT is rich in denser tissue with less distortion. PET with border of anatomical structure are blurred. MRI image has the complementary property, which provides better information on soft tissues but with more distortion. By combining any of these two complementary images we end up with new image which contains denser tissue with lesser distortion. For this process we use Nonsubsampled Contourlet Transform to decompose the images and Pulse Coupled Neural Network is used to motivate the lower frequency pixels. Thereby the fused image's spatial property is improved. The exact edges of the fused images are found by applying it to a canny edge detection method to find tumour present in the FUSED image.

Keywords: *Computed Tomography (CT), Magnetic Resonance Image (MRI), Nonsubsampled Contourlet Transform (NSCT), Pulse Coupled Neural Network (PCNN).*

1. INTRODUCTION

Due to development in sensors and camera technology there is increase in different types of digital images from different cameras and sensors with different properties. These digital images are used for different purposes depending on the application where it is applied, for example, we have satellite images such as Panchromatic and multispectral, medical images like CT and MRI. It is not restricted with four types of images alone; there are many images from different sensors. Each image from different sensor has unique property of its own. There are also many methods to improve the property of the images like segmentation, image fusion, and edge detection. This paper discusses the image fusion and edge deduction. Image fusion becomes solution for many applications. In situation like some images requires spatial and spectral information in a single image in case of non availability of instruments for providing the above information obviously image fusion becomes the solution. In the field of medical the image fusion is used for medical diagnostics. Radiologists combine information from multiple image formats. Combined (fused) image are very much useful for diagnosing cancer. In many type of medical images this paper explains CT, MRI and PET image fusion. In the MRI image the inner contour is missing but it provides better information on soft tissues. The CT image provides the best information on denser tissue with less distortion, but it misses the soft tissue information. Hence both the technologies are fused to get an image with perfection. Edge detection is applied to the FUSED image for feature extraction and to detect the discontinuities in the surface, depth the outcome of the edge detection to an image is with a set of connected curves that clearly shows the boundaries of object. There is also a chance to reduce the amount of data by filtering out information that are irrelevant and at the same time it preserves the important structure of the image.

2. RELATED WORKS

2.1 Fusion of images

The main aim is to improve the spatial property and detect the edges of the medical images such as CT, MRI, PET images. For this purpose there are two approaches spatial domain and transform domain based methods such as Averaging method, Brovey method, Principle Compound Analysis, Intensity-hue –saturation [4].

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These methods suffer from spatial distortion in the fused image which leads to problem in classification of problemical distortion.

Now a days Modified Reconstructability Analysis (MRA) is widely used for image fusion method which contains methods like pyramid transform and multiscale Geometric Analysis (MGA) such as rigdlet, curvelet, bandlet etc.,. Pyramid based method is improper and the decomposes process is very poor for continuous function [3]. The Wavelet Transform (WT) gives good frequency division for continuous function processing and it has been widely used in medical image fusion. This method solves the problem of low contrast and blocking effects in space domain but it performs poor for curve shape, edge representation and there is also problem like directional selectivity and shift invariance. It is also expansive to represent the sharp edges [4].

This situation leads to emergence of new method which gives better information for easy diagnosis of medical images is contourlet transform [1]. Contourlet is the biggest area of MGA tool. It is best method for analysing image containing lined, curves, and edges compared to wavelet and other MGA methods. Contourlet has capability to produce different directional decomposition levels compared to the wavelet transform. While applying contourlet to the image fusion it preserves the original property of the image and gives more information in the fused image. Discrete contourlet transform (DCT), Complex Contourlet Transform (CCT), Non_subsampled contourlet transform (NSCT) are the methods of contourlet transform [5]. Discrete contourlet transform (DCT), Complex Contourlet Transform (CCT) has the problem of shift invariance and directional selectivity. Problems in the other two methods are overcome by Non_subsampled contourlet transform (NSCT) [12]. Non_subsampled contourlet transform (NSCT) is combination of Nonsubsample pyramid to produce multiscale decomposition and Nonsubsampled contourlet directional filter bank to give directional decomposition. It avoids upsampling and downsampling and gives better artifacts [4].

2.2 Edge detection of image

The edge detection is the fundamental process for low level image processing and exact edges are important requirement for high level image processing. The result of edge detection depends on the density of edges and noise in the image. Some of the edge detection methods are the Marr_Hildrath edge detector, the local threshold and Boolean edge detector, canny edge detector [8]. The basic concept behind the Marr_Hildrath edge detector method uses gradient based operator to get the second order derivative of the given image. It uses Gaussian method to smoothen the image two dimensional Laplacian is applied to the image. The applied Laplacian will be rotated due to its shape it is called as "Maxican Hat Operator". The Hildreth method gives nicely connected edges if hysteresis is used for thresolding without hysteresis there is discontinuity in the edges. In general the edges are lacking in consistency but edges are thick [8]. The threshold and Boolean function based edge detection is different from many methods. It does not use gradient or Gaussian smoothing, unlike based on the local threshold it converts pixels into binary values and masks is applied to find the existence of edges. It looks at the variance on a local level [13]. It is lacking in detecting the corner pixels and it is not guaranteed to find the thin edges also have discontinuity in the curve edges. The canny edge detector is considered to be standard and legacy method in the field of edge detection and it outperforms the many new algorithms [8]. The Marr_Hildreth edge detector is considered to be best edge operator till canny release his work. Canny edge detection was first introduced by John canny in 1983 which uses thresolding and hysterisies [14]. The canny method is still the best method due to single pixel thickness and continuous edges [8]

3. BASIC CONCEPTS

Nonsubsampled contourlet transform (NSCT) is used to decompose the images and to view the exact area of image via adaptive feature refinement method. The NSCT uses Nonsubsampled Directional filter bank (NSDFB) and Nonsubsampled Pyramid (NSP) to give multiscale and directional decomposition subbands. Whereas the traditional contourlet uses downsamplers and upsamplers [4] which makes it shift-invariant, it leads to pseudo Gibbs phenomena around singularities (i.e.) discontinuity around the reconstructed signal [2].

The proposed method uses Pulse Coupled Neural Network (PCNN) to motivate the low frequency pixels. When the PCNN transform an image, it removes "unimportant" details while improving the overall quality of the image. It also smoothen the noise present in the image without

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loss in the pattern of the image and shape of the information [16].

A PCNN is a two-dimensional neural network. They are an extension of Neural Network models. Each neuron in the processing layer has one to one correspondence between each cells , the two linking and feeding inputs are iteratively processed together to produce a pulse image with features that can be changed by varying the PCNN parameters. There is inter connection between the neurons so it can easily motivate each other. The image is reconstructed by reverse process of nonsubsampled contourlet transform. The fused image from the above process is given into canny edge detector.

The canny edge detection is optimal method it follows three main criteria 1. There should not be any missing edges and there should not any response to the non edge. 2. The edge points are well localized. 3. There should be only one response to a single edge based on the above criteria the edge detector eliminates the noise and smoothens the image [9]. Image gradient is find to get the region with high spatial values. Then the algorithm goes along the above region and suppress pixel with minimum value. It uses hysteresis to track the pixel that is not suppressed. Hysteresis uses two thresholds T1 and T2. If the magnitude value is below T1 It is made without edge. If it is high it is made with edge. Else if the value of magnitude is between T1 and T2 then set to zero, else there is path between pixels with a gradient above T2.

4. METHODOLOGIES

4.1 Nonsubsampled contourlet transform

Nonsubsampled Contourlet Transform (NSCT) is a combination of (a) Nonsubsample pyramid (NSCTP) (b) Nonsubsampled directional filter bank (NSCT_DFB).The image in figure I (a) is used to explain the above said combination.

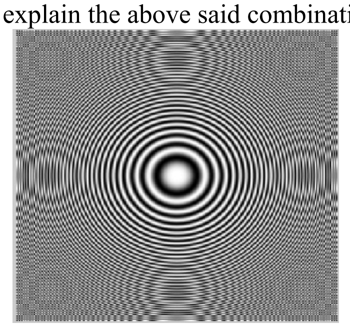

Fig.1(a) Example

4.1.1 Nonsubsample pyramid (NSCTP)

The building block of the nonsubsampled pyramid is a two-channel nonsubsampled filter bank, it avoids upsampling and downsampling to make it as shift_invarient. For the next level, we upsample all filters by 2 in both dimensions.

The fig.1 (b) shows the decomposition structure of NSCTP of the fig.1 (a)

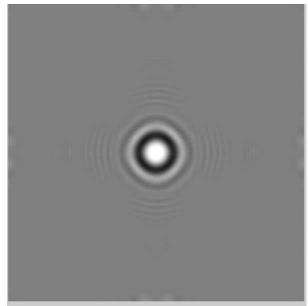

Fig.1 (b) Response of NSCTP

Fig.1 (b) shows the lowpass subbands and highpass subbands of the fig.1 (a)

4.1.2 Nonsubsampled directional filter bank (NSCT_DFB).

Nonsubsampled directional filter bank becomes the extended version of traditional DFT by adding shift invariant property to it. For further steps all filters are upsampled by a quincunx matrix [19].

$$\mathbf{Q} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The figure 1(c) shows the frequency response of NSCT_DFB for the fig.1 (a) showing decomposition of high pass subband in horizontal direction.

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Fig.1(c) Response of NSCT_DFB.

Fig.1 (d) Response of NSCT_DFB.

The figure 1(d) shows the frequency response of NSCT_DFB for the fig.1 (a) showing decomposition of high pass subband in vertical direction.

4.2 PCNN in image fusion

This is the model introduced by Eckhorn in 1989. It is a neural model developed by modeling a cat's visual contex, while most of the models are developed by human's visual contex [17]. Each neuron in the network corresponds to one pixel in an input image, it receives pixel properties such as colour of the pixel intensity as a external stimuli. Since a PCNN is a two-dimensional neural network, the local stimuli to the neurons are get from the neighbouring pixels. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output [16]. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns, etc.

4.3 Canny Edge detection

The canny edge detector is used to detect the edges of the fused image to find the tumours if present in the scan report (CT, MRI, PET) of the patient. The canny method uses Gaussian filter to filter noises which results in little blur in FUSED image. The Gaussian filter gives the better result by causing more blurring and spreading the value of the pixels in the image to a large area of image. This large blurring effect is useful in detecting larger and smooth edges. A search is done in blurred image to find if the gradient magnitude has a local maximum in the gradient direction i.e. the edges is in, the north-south direction, east-west direction, north-west direction. By this process we get a blurred image in the binary format. Canny method uses hysteresis and thresholding. It uses two threshold values low and high. Assuming the continuous curves in the image, edges are important and it leads to follow the less distinctness in the line, for this purpose we apply high threshold. At the end of these process genuine edges is obtained. Starting from the edges obtained from the previous step we again trace the edges by applying lower threshold to eliminate discontinuity in edges. This process is repeated until we reach the starting point. At the end of this process we get a binary image marked with an edge or a non_edge. Differential edge detection is applied to improve the result. By the end of this process, image with perfect edge is obtained.

5. PROPOSED METHOD

1) The images are coregistered using cubic spline interpolation.

2) The image1 and registered image 2 are decomposed to attain the high frequency and low frequency.

3) For the low frequency subbands coefficients are input to neurons. The output of each neuron is calculated by.

$$F_{IJ}^{IK}(n) = I_{IJ}^{IK} \qquad \text{Eq. (1)}$$

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$$L_{ij}^{lk}(n) = e^{-\alpha L} L_{ij}^{lk}(n-1) + V_L \sum_{pq} W_{ij,pq}^{lk} Y_{ij,pq}^{lk}(n-1)$$

Eq. (2)

$$U_{ij}^{lk}(n) = F_{ij}^{lk}(n) * (1 + \beta L_{ij}^{lk}(n))$$

Eq. (3)

$$Y_{ij}^{lk}(n) = \begin{cases} \mathbf{1}, & \text{if } U_{ij}^{lk}(n) \succ \theta lk_{ij}^{ik}(n) \\ \mathbf{0}, & \textbf{otherwise} \end{cases}$$

Eq. (5)

$$T_{ij}^{lk}(n) = T_{ij}^{lk}(n-1) + Y_{ij}^{lk}(n)$$ Eq. (6)

4) For high frequency subbands contrast is used to motivate the PCNN.

$C = (L - L_B)/L_B = L_H / L_B$ *Eq. (7)*

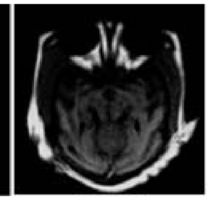
5) The image is reconstructed by reverse operation of nonsubsampled contourlet transform.

6) The reconstructed fused image is input to the canny edge detector.

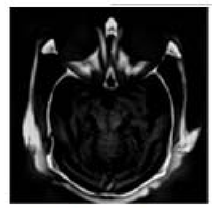
6. EXPERIMENTAL RESULTS

The proposed method is used to fuse CT and MRI image and to fuse MRI and PET images. From the experimental results of fusing CT and MRI images, it is seen that the spatial property of the image is enhanced and ending up with a image having the soft tissues and the less distortion. Where in the case of MRI and PET image the anatomical structure is clear in MRI and in the PET image the borders of these anatomical structures are blurred, in the resulting image the boarders are distinct and anatomical structure are clear.

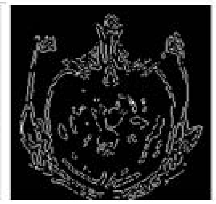
3(a) CT image



3(b) MRI image



3(c) FUSED image



3(d) Ede detected image

Fig 3(a) shows the original CT image with less soft tissues and more distortion, the fig 3(b) shows the MRI image with more soft tissue and with less distortion, the fig.3(c) shows the combined (fused) image of 3(a) and 3(b) which has less distortion and with dense tissue and 3(d) shows the edge detected image of the fused image.3(c) shows the boundary of the fused image. From the figure 3(d) if the tumour is present it can be easily indentified.

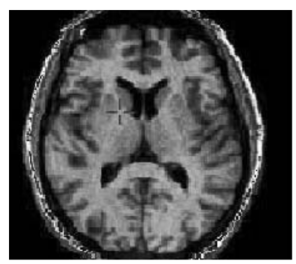


Fig.4(a) MRI image

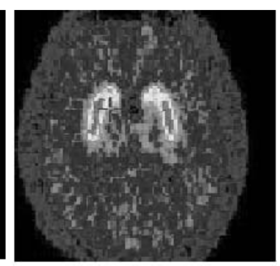


Fig.4(b) PET image

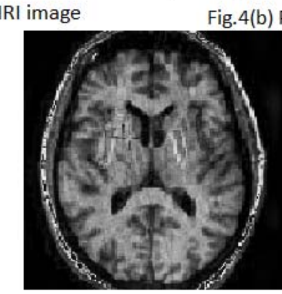


Fig.4(c) FUSED image

The fig.4 (a) shows the MRI image of 40 year old male alcoholic and fig.4 (b) shows the PET image of same patient. The MRI image clearly shows the anatomic structures of the brain. The PET image shows that both the putamen and the caudate, as indicated by the mark in the image which is not shown clearly by MRI image .The

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borders of these anatomical structures are not clear on the PET image, appear to a single structure. Combining (fusing) the MRI and PET images, an image is produced which has the identification of the borders of anatomical structures such as the putamen and the caudate.

7. OBJECTIVE CRITERIA

	CT & MRI	PET & MRI
MEANI/P	6.9192	56.9299
Mean O/P	27.2214	67.3257
BIAS	20.3022	10.3957
SD	6.1505	0.6953
MSE	0.0176	0.0351
RMS	0.0176	0.1075
CC	0.2216	0.3106

TABLE.1 Objective criteria of fused image

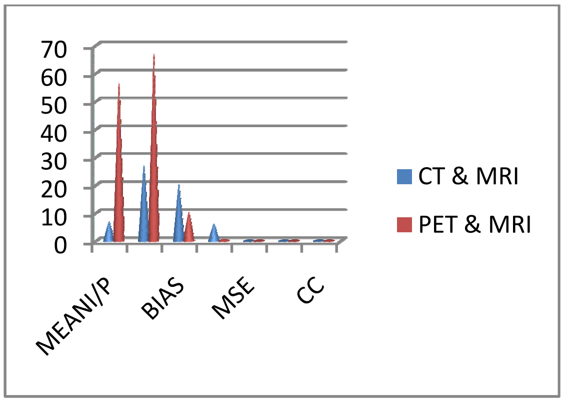

Fig. 5 Chart showing the objective criteria of fused image.

From the table.1 it is seen that, objective performance evaluation criteria of the proposed method. Particularly correlation coefficient(CC) shows that fused image is strongly correlated with the source image and low Mean Square Error(MSE),Root Mean Square Error(RMS) shows there is less error in the fusion process. All the objective criteria result shows that the proposed algorithm delivers the best fused image with the improvement in the spatial property.

8. CONCLUSION

Nonsubsampledcontourlet is used to decompose the image. Pulse coupled neural network is used to motivate the low frequency values and the image is reconstructed using inverse of nonsubsampled contourlet transform. The fig.3(c) shows the soft tissues and coronal bones and 4 (c) shows the putamen and the caudate regions clearly. From this result it is clear that because of improved directionality and better geometric representation the nonsubsampled contourlet transform can deliver good result for pixel level fusion. Hence by using Nonsubsambled contourlet transform the visual quality of the image can be improved which intern improves the spatial quality of the image. The boundary between the overlapping objects can clearly identified by canny edge detetector which is more advantageous for physicians to find out the tumours. In future researchers can use Colour edge detection using canny operator to get more detailed and dark edges. The result shows the spatial properties of the medical images have improved and it is helpful in easy clinical diagnosis. The fusion algorithm can also applied to panchromatic and multispectral images by applying hash function to the fused image to convert the resultant gray scale image into colour image.

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