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Curvelet Transform Based Image Fusion With Noise Reduction Using Gaussian Filter

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ABSTRACT

To enhance the image quality and smoothing an image are great importance issues in medical applications. Image fusion is a process in which multi modality medical images are combined together to form highly enhanced image.Main task of filter is to preserve the diagnostic information while removing noise.A new method for smoothing an image by Gaussian filtering (GF) as a preprocessing step forcurvelet transform image fusion (CTIF) is introduced. Initially, Gaussian is applied to both the medical images like Computed Tomography (CT) and Magnetic Resonance Image (MRI) to get noise free images, thencurvelet transform is applied to both denoised images to get a fine and coarse coefficients of an image. Finally inverse curvelet transform is applied to obtainenhanced fused image. Since noises and curves played most important role in medical field, this new approach was verified to be good way to enhance the curves and minimize the noises. The proposed method of fusion with Gaussian Filter proved richer information in spatial and spectral domains simultaneously as well as it had produced best fusion result.

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INTRODUCTION

The requirement for better distinguishing proof and clear understanding of the obtained images offer ascent to image fusion. The term fusion intends to join together the data procured in several domains. Image fusion has turned into an admired technique utilized inside medicinal diagnosis and treatment. Image fusion is the process of combining information from two or more images of an object into a single image. The integrated image is more useful for justification and analysis. Fused images can be created by combining information from multiple modalities such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET) and single positron emission computed tomography (SPECT).An image is regularly ruined by noise throughout its acquisition or transmission. The de-noising methodology is to uproot the noise while holding and not distorting the nature of the processed picture. The conventional method for image de-noising is filtering. As of late, a great deal of examination about non- linear techniques for image de-noising has been created. In this paper, Denoising of Medical images by Gaussian filter, Laplacian filter, Averaging filter, unsharp contrast enhancement filter is projected. Gaussian filter gives better result than other filters in terms of visually and numerically. Our Denoising algorithm performs spatial processing and preserves the image details as an advantage to other filtering techniques. Another advantage is that use of Gaussian filtering does not affect the edges or other small structures in the image. The method is more efficient for the images with very high noise ratio. After de-noising the medical image, curvelet transform is used for fusion. The fine coefficients and coarse coefficients are separated by curvelet transform, maximum selection fusion rule is applied to coarse coefficients, and finally fused image can be obtained by applying inverse curvelet transform combined with fine coefficients.

II. Related Work:

Vanithamani.R and Umamaheswari.G (2014) has introduced an algorithm by hybridizing bilateral filter with Neigh Shrink. The bilateral filter was applied before decomposition and after reconstruction of the image using discrete wavelet transform to improve the denoising efficiency and preserve the edge features effectively. The wavelet thresholding scheme Neigh Shrink is used for thresholding of wavelet coefficients.Rui Shen*et al.* (2013) has presenteda novel cross-scale fusion rule for multiscale-decomposition-basedfusion of volumetric medical images taking into account both

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intrascaleand interscale consistencies. An optimal set of coefficientsfrom the multiscale representations of the source images is determinedby effective exploitation of neighborhood information. Anefficient color fusion scheme was also proposed.

Egfin Nirmala *et al*. (2013) has presented a newregion based image fusion algorithm for combining visible and Infrared (IR) images using IndependentComponent Analysis and Support Vector Machines (SVM) was proposed. Region based joint segmentation of the source images is carried out in the spatial domain and important features of each region are computed in spatial and transform domain. A Support Vector Machine is trained to select the regions from the source images with significant features and the corresponding ICA coefficients are combined to form the fused ICA representation.Gaurav Bhatnagar *et al*. (2013) proposed a novel fusion framework for multimodalMedical images based on non-subsampled contour let transform(NSCT). The source medical images are first transformed byNSCT followed by combining low- and high-frequency components.Two different fusion rules based on phase congruency anddirective contrast are proposed and used to fuse low- and high-frequencycoefficients. Finally, the fused image is constructed by theinverse NSCT with all composite coefficients.Sudeb Das *and* Malay Kumar Kundu (2013) addressed a novel MIF method based on a hybrid neurofuzzy approach in the NSCT domain. It employs multiscale geometric analysis of the non-subsampledcontourlet transform and fuzzy-adaptive reduced pulse-coupled neural network (RPCNN). The linking strengths of the RPCNNs' neurons are adaptively set by modeling them as the fuzzy membership values, representing their significance in the corresponding source image. Use of the RPCNN with a less complex structure and having less number of parameters leads to computational efficiency—an important requirement of point-of-care health care technologies.Shutao Li *etal*. (2012) has proposed a novel dictionary learning method, called Dictionary Learning with Group Sparsity and Graph Regularization (DL-GSGR). First, the geometrical structure of atoms is modeled as the graph regularization. Then, combining group sparsity and graph regularization, the DL-GSGR was presented, which is solved by alternating the group sparse coding and dictionary updating. In this way, the group coherence of learned dictionary can be enforced small enough such that any signal can be group sparse coded effectively. Finally, group sparse representation with DL-GSGR is applied to 3-D medical image denoising and image fusion. Specifically, in 3-D medical image denoising, 3-D processing mechanisms were exploited.Al-Dahoud Ali *et al*. (2010) introduced a new denoising technique based on adaptive selection of thresholds to suppress noisy curvelet transform coefficients. Due to multi resolutional dictionary, the maxima of the curvelet transform coefficients vary and so the threshold operator is designed to produce as many local threshold values as are the scales. The proposed method efficiently adapts to noise characteristics for different scales and reduces the noise while preserving edges in the image. The thresholding function chosen are theCubic, hard and soft thresholds.Adnan Hadi M *et al*. (2009) presented a new method of image fusion based on a hybrid transform, which is an extension of Ridgelet transform. It used the slantlet transform instead of wavelet transform in the final steps of Ridgelet transform. The slantlet transform was an orthogonal discrete wavelet transform with two zero moments and withimproved time localization

III. Proposed Work:

Our proposed algorithm consists of following steps (Depicted in Fig-1):

- Two Registered images (MRI and CT) are given as input to the preprocessing stage
- In preprocessing stage, images are added with noise by using MATLAB command 'fspecial' which is also contains 'point spread function' for smoothing an image.
- Images are filtered using 'imfilter' MATLAB command.
- Filtered images are given to curvelet transform for fusion process.
- Curve let transform decomposes the images into coarse and fine coefficients.
- Coarse coefficients are combined together with efficient fusion rule called 'Maximum frequency selection rule'.
- Combined coefficients are given to inverse curvelet transform to get fused image.
- Fine coefficients are added finally to the fused image.

3.1 Advantages of Gaussian filter:

Images are corrupted by random variations in intensity values called noise due to non-perfect camera acquisition or environmental conditions.Some of the noises usually occurred in digital images, additive noise, white noise, salt and pepper noise, impulse noise (random occurrences of white intensity values). These noises should be eliminated by replacing each pixel intensity value with a new value taken over neighborhood of fixed size. Gaussian filter used to remove noise and smoothing an image.It has its basis in the human visual perception system.They also overcome the other stated drawback of moving average filters because weights decay to zero. When working with images we need to use the two dimensional Gaussian function.This is simply the product of two 1D Gaussian functions (one for each direction) and is given in equation 1,

$$w_{ij} = \frac{1}{2\pi\sigma^2} \exp\left\{\frac{-(x^2+y^2)}{2\sigma^2}\right\} \quad (1)$$

Where "$\mathbf{w_{ij}}$"is the Gaussian function, σ is the standard deviation of the distribution; 'exp' represents exponential function.The Standard deviation of the Gaussian function plays an important role in itsbehavior.In probabilistic terms, it describes 100% of the possible values of any given space when varying from negative to positive values.The idea of Gaussian smoothing is to use this 2-D distribution as a `point-spread' function, and this is achieved by convolution. Since the image is stored as a collection of discrete pixels we need to produce a discrete approximation to the Gaussian function before we can perform the convolution. In theory, the Gaussian distribution is non-zero everywhere, which would require an infinitely large convolution kernel, but in practice it is effectively zero more than about three standard deviations from the mean, and so we can truncate the kernel at this point.

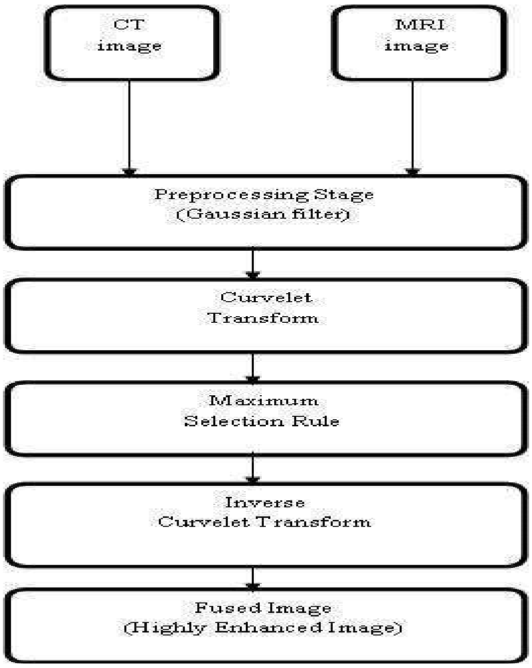

Fig. 1: Proposed block diagram

Once anappropriate kernel has been calculated, then the Gaussian smoothing can be performed using standard convolutionmethods. The convolution can in fact be performed fairly quickly since 2-D isotropic Gaussian is separable into *x* and *y* components. Thus the 2-D convolution can be performed by first convolving with a 1-D Gaussian in the *x* direction, and then convolving with another 1-D Gaussian in the *y* direction.

3.2 Curvelet TransformImage Fusion (CTIF):

Thecurvelettransformhasevolvedasa tool for the representation of curved shapes in graphicalapplications. Then,itwasextended to, the, fields ofedge detection authorshaveproposedtheapplication of the curvelet transform in imagefusion. The algorithmofthecurvelettransformofanimage Pcan be summarized inthefollowingsteps:

A)The imagePis splitup into three sub bandsΔ1, Δ2 and P3 usingtheadditivewavelets transform.

B)Tilingisperformed onthe sub bandsΔ1,Δ2

C)ThediscreteRidgelettransformisperformedon each tiles of sub bands Δ1, Δ2A schematic diagram of the curvelet transform isdepicted in Fig.2

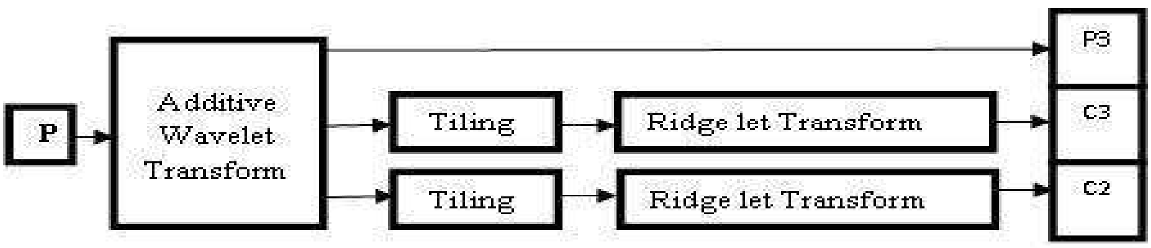

Fig. 2: Curve let transform of an image P

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3.2.1. Sub band Filtering:

The purpose of this step is to decompose the image into additive components; each of which is a Sub band of that image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform. Given an image P, it is possible to construct the sequence of approximations:f_1(P)=P_1,f_2(P)=P_2,f_3(P)=P_3....f_n (P) =P_n where n is an integer which is preferred to be equal to 3.To construct this sequence, successive convolutions with a certain low pass kernel are performed. The functions *f*1, *f*2, *f*3, and *fn*mean convolutions with this kernel. The waveletplanes are computed as the differences between two consecutive approximations P_{l-1} and P_l, i.e., $\Delta_l = P_{l-1} - P_l$. Thus, the curvelet reconstruction formula is given by:

$$P = \sum_{i=1}^{n-1} \Delta_i + P_n \tag{2}$$

3.2.2. Tilting:

Tiling is the process by which the image isdivided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the subbands Δ1 and Δ2. The tiling improves the ability of the curvelet transform to handle curved edges

3.2.3. Ridgelet Transform:

The Ridgelet transform belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool of shape detection. So, the ridgelet transform is primarily a tool of ridge detection or shape detection of the objects in an image. It is known that different imaging modalities are employed to depict different anatomical morphologies. CT images are mainly employed to visualize dense structures such as bones. So, they give the general shapes of objects and few details.On the other hand,MR images are used to depict the morphology of soft tissues. So, they are rich in details. Since these two modalities are of a complementary nature, our objective is to merge both images to obtain as muchinformation as possible. A curvelet based algorithm is introduced for this purpose.

IV. Performance Analysis;

Performance analysis consists of six parameters with reference image as MRI is taken. For analysis purpose, Computer consists of 4 GB RAM, Microsoft xp professional with service pack-2, Intel core 2 Duo processor with 500 GB hard disk and MATLAB 7.9 (2009a) software.

4.1 Peak signal to noise ratio:

Peak signal to noise ratio is defined as 'ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation

$$PSNR = 20\ log_{10}\left(\frac{L-1}{RMSE}\right) \tag{3}$$

Where 'L' is maximum intensity level possible

4.2 Standard deviation:

Standard deviation is a measure of contrast in an image. Larger the standard deviation, higher the contrast.

$$\sigma = \sqrt{\sigma^2} = \sqrt{\frac{\sum_{i=0}^{N}\sum_{j=0}^{M} x(A(i,j)-m)^2}{NM}} \tag{4}$$

4.3 Entropy:

Entropy is an important evaluation parameter to estimate the quality adherence of the fused image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the fused brain image.

$$H = -\sum_{i=1}^{g} P(d_i).\,log_2 P(d_i) \tag{5}$$

4.4Root mean square error:

Root mean squared error is the measure of differences between the reference images and fused image.

$$RMSE = \frac{1}{NM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(A(i,j) - B(i,j))^2 \tag{6}$$

4.5 Cross correlation:

Cross correlation is used to find out the similarities between fused image and registered image.

4.6 Spatial frequency:

Spatial Frequency: Activity level of an image was measured by spatial frequency. It was used tocalculate the frequency changesalong rows and columns of the image. Spatial frequency was measured using **equation (7),**

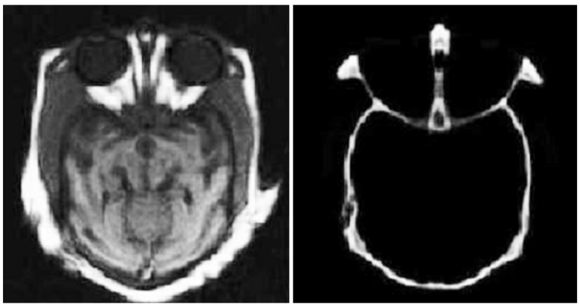
$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{7}$$

$$RF = \frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=2}^{n}[I(i,j) - I(i,j-1)]^2 \tag{8}$$

$$CF = \frac{1}{m*n}\sum_{j=1}^{n}\sum_{i=2}^{m}[I(i,j) - I(i-1,j)]^2 \tag{9}$$

Here I is the image and m*n was the image size. A large value of special frequency describes the large information level in the image and therefore it measures the clearness of the image. All six performance metrics are analyzed and compared for Gaussian filtering technique with other filtering techniques using MATLAB. Gaussian filtering technique has proved that fused image obtained by proposed method has better visual quality for Medical perception than other filteringtechnique.

Both modality images have a resolution of 256*256 with 8 bit precision is given below.Two set of input images **(**Fig3, 4**)** are used for proposed method .It has been proved that curve let transform based fusion with Gaussian filtering gives clear image than other filtering techniques visually. Fig5 and Fig6Shows the output fused images of Gaussian, Laplacian, Average, and Unsharp contrast enhancement filters. Quality measurements using six metrics are listed below in the tables. The PSNR and RMSE, Entropy, values are most important parameters when we deal with images.



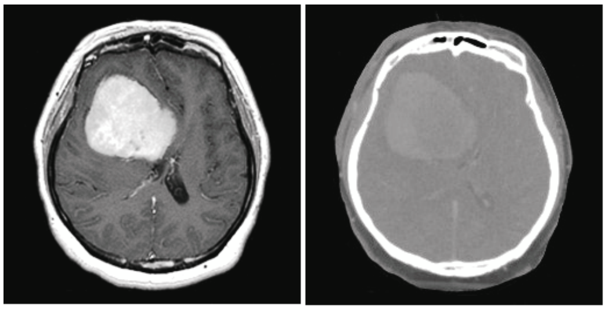
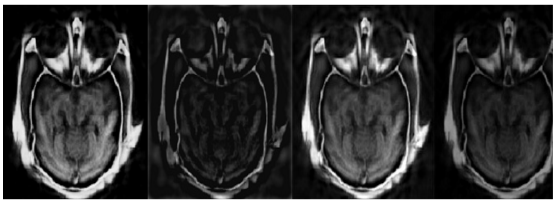


Fig. 3: Data set-1 MRI, CTFig.4: Data set-2 MRI, CT



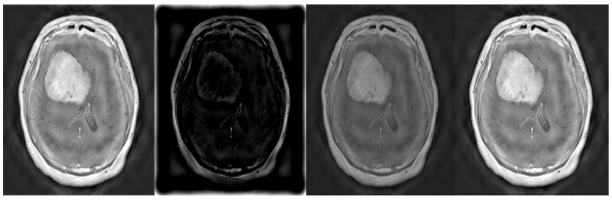


Fig. 5: Fused images for dataset-1Fig.6: fused images with four MDF for dataset-2

RESULTS AND DISCUSSION

Our proposed method is evaluated and compared in terms of subjective testing, i.e., visual quality, where recommended parameters are used. (Table1,2)shows that higher value of the Peak Signal-to-Noise Ratio (PSNR). (***28.78dB &25.0148)*** and Entropy **(7.1408 & 7.2329),** lowest value of RMSE **(0.3373&0.8036)** for data set-1and data set- 2

Table 1: Comparison of two different fusion methods for Data set -1

Fusion Method	Filtering Schemes	Quality Evaluation Metrics					
		PSNR	STD	SF	ENT	RMSE	CC
Curve let Transform	Gaussian	28.7849	22.6421	14.8724	7.1408	0.3373	0.9819
	Laplacian	24.1443	21.7628	14.7276	4.8464	0.9820	0.3303
	Averaging	28.3201	20.0488	15.0097	6.9141	0.3755	0.6739
	Unsharp	28.1972	20.9773	14.9734	7.0418	0.3862	0.9825
Wavelet Transform	Gaussian	19.4460	23.0460	16.2698	6.6958	2.8970	1.0341
	Laplacian	24.5127	21.9534	15.2016	4.2988	0.9021	0.2982
	Averaging	23.1770	21.2332	15.3892	6.4480	1.2270	0.9130
	Unsharp	19.4474	22.1551	15.3827	6.7539	2.8960	1.0347

Table 2: Comparison of two different fusion methods for Data set -2

Fusion Method	Filtering Schemes	Quality Evaluation Metrics					
		PSNR	STD	SF	ENT	RMSE	CC
Curve let Transform	Gaussian	25.0148	22.6421	14.8724	7. 2329	0.8036	1.1194
	Laplacian	23.7445	20.7743	14.8280	4.8154	1.0767	0.2194
	Averaging	23.3894	20.0488	15.0097	7.4985	1.1684	0.9365
	Unsharp	24.7675	20.9773	14.9734	7.1628	0.8507	1.1216
Wavelet Transform	Gaussian	24.8993	22.8681	15.3489	5.0597	0.8253	1.1237
	Laplacian	23.9513	21.9534	15.2016	2.9104	1.0266	0.4920
	Averaging	24.8543	21.2332	15.3892	7.1751	0.8339	1.1230
	Unsharp	24.8940	22.1551	15.3827	5.2334	0.8263	1.1257

Conclusion:

In this paper an expert image fusion system has been implemented for the grey scale images based upon curve let transform using Gaussian filtering approach. The first objective of this paper was to propose an algorithm which is effective for image fusion based upon curvelet Transformation approach. It is based on preprocessing Gaussian filter method.

The second objective of this paper was comparing the proposed method with existing state-of-art techniques. Experimental results show that Gaussian filtering method performs well than the other filtering technique in terms of quality of images. The proposed method increases the quality significantly, while preserving the important details or features. This also gives the better results in terms of visual quality.This algorithm can be used in other type of images like Remote sensing images, Ultrasound images, SAR images etc. Instead of Gaussian approach, algorithm can be modified to improve the quality of the images.

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