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Techniques for Pixel based Image Fusion of Real Image

Anand. R[1], Rahul. J. U[2], Jagadish. V. S[3], Bharath. M[4]
[1, 2, 3,4]*Students, Department of Electronics and Communication, New Horizon College of Engineering Outer ring road, Marathalli, Bengaluru- 560103*

Abstract: An Image fusion is the process of combining relevant information from two or more image of common characteristic to form a single image which acquires all the essential features of original image. Our project based on successful pixel level image fusion algorithms such as DWT and NSCT . The main aim of this is to reduce uncertainty, decrease redundancy in the output, and maximize relevant information pertaining to an function or a task using DWT and NSCT technique. Finally comparison of these two techniques is performed on the basis of some evaluation criteria and the decision has drawn that which technique is better.

I. INTRODUCTION

With the recent developments in the field of visual sensor technology, multiple imaging sensors are used in several applications in order to improve the capabilities of intelligent machines and systems. These image processing applications demand high spatial and spectral resolution in a single composite image. But the available single sensor systems are not capable of providing this sort of information convincingly due to their limited capability, the environmental conditions under which the system operates and resolution of the sensors used.

A. Image Fusion

Image fusion is the process that combines information in multiple images of the same scene. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics . The object of the image fusion is to retain the most desirable characteristics of each image. With the availability of multi-sensor data in many fields, image fusion has been receiving increasing attention in the researches for a wide spectrum of applications .

B. Classification of image techniques

Image fusion can be done in three levels: Pixel level fusion, Feature level fusion and Decision level fusion.

1) Low or pixel level: The pixel-level method works either in the spatial domain or in the transform domain. Image fusion at pixel level amounts to integration of low-level information, in most cases physical measurements such as intensity
2) Middle or feature level: Feature level fusion requires first extraction of the features, those features can be identified by characteristics such as contrast, size, shape and texture.
3) High or decision level: Decision level fusion uses the outputs of initial object detection and classification as inputs to the fusion algorithm to perform the data integration.

C. Pixel Level Fusion Methods

In recent years, many techniques for generic image fusion have been designed. Among this techniques, there are lots of methods have been proposed on pixel level image fusion. Pixel–level fusion can be used to increase the information content associated with each pixel in an image formed through a combination of multiple images, e.g., the fusion of a range image with a two dimensional intensity image adds depth information to each pixel in the intensity image that can be useful in the subsequent processing of the image. Different images to be fused can come from a single imaging sensor or a group of sensors. The fused image can be created either through the pixel-by-pixel fusion or through the fusion of associated local neighbourhoods of pixels in each of the images.

D. Proposed Methodologies

This research work concentrates on design of pixel and feature level image fusion algorithms that extracts more significant visual information from the inputs and effectively avoids the introduction of artificial information. The DWT, widely used for fusion is shift-variant and hence small shifts in the objects in the scene or camera used for acquisition results in variations in the wavelet coefficients that introduce artifacts (shadowing and rippling effects), especially around strong edges in the reconstructed image. Also as DWT has limited directionality it cannot represent 'line' and the 'curve' discontinuities in images accurately. Though different variants of DWT were introduced to overcome the shift in-variance problem, these could not capture intrinsic geometric features in images effectively. Hence this project addresses image fusion with NSCT a 'true' image transform, as it has good direction selectivity and energy convergence compared to that of wavelets and other related multi-resolution transforms. Using NSCT provides more information (due to coefficients at multiple directions) for fusion and effectively reduces the ill-effects of mis-registration on the fused results. The proposed methods in this project employ DWT and Non-Subsampled Contourlet Transform (NSCT) for multi-resolution image representation. Recent studies demonstrate NSCT as an efficient tool for image fusion, as it can effectively capture inherent geometric structures in images well. With better direction selectivity compared to that of wavelet based methods, NSCT is suitable for representing multi-sensor images bearing abundant directional information.

E. Performance Evaluation Of Image Fusion Algorithms

The quality measure approach adopted to determine the performance of the proposed fusion algorithms is discussed. There are two types of evaluation approaches, namely subjective and objective evaluations. The subjective method judges the quality of the images visually. In many imaging applications, the human perception of the fused image is of utmost significance (Wan et al 2009). Researchers seldom use subjective evaluation to assess the fused image quality as these tests are inconvenient, expensive, and time consuming. Consequently, objective performance evaluation procedures that can precisely predict human perception for a multi-sensor image fusion system is mostly used.

A number of objective fusion performance measures are available in the literature. In this thesis, for performance comparison of the fusion algorithms, five important most widely used objective metrics namely Entropy (H), Standard deviation (SD), Mutual Information (MI), Petrovic metric (ABF Q) (Petrovic & Xydeas 2000), and the Piella metric (Qpiella) (Piella & Heijmans 2003) are identified and used. These objective evaluation metrics

are actually based on the extent of the fidelity of the transfer of a feature (e.g., edges, amount of information) from the source images to the output image (Cvejic et al 2009). These five metrics do not require a ground-truth (reference) image for performance evaluation.

II. LITERATURE SURVEY

Multisensor image fusion has drawn a considerable amount of research interest in the last two decades. It has advanced rapidly in the past few years and has become a major part of any multi-sensory system. Image fusion not only provides an accurate description of the scene but also helps in reducing the memory requirement by storing fused images instead of multiple source images. Currently, image fusion approaches with considerable complexity have been proposed as processing equipment with high computational power are available. This chapter gives the overview of the state-of-the-art image fusion techniques available in the literature for the proposed research problem.

J. J. Lewis, J. Robert, O. Callaghan, S. G. Nikolov, D. R. Bull and N. Canagaraja, "Pixel- and region-based image fusion with complex wavelets," Information Fusion, Elsevier, vol. 8, pp. 119-130, 2007.

The DWT is a spatial-frequency decomposition that provides flexible multi-resolution representation of an image (Lewis et al 2007). The authors used eigen value of covariance matrix of an image block to decide the strength of edges in the block. To overcome the shift variance problem in DWT, the un-decimated DWT called Discrete Wavelet Frame Transform (DWFT) that avoids the decimation process in DWT is introduced.

Q. Zhang and B. Guo, "Multifocus image fusion using the Non-subsampled Contourlet transform," Signal Processing, Elsevier, no. 89, pp. 1334-1345, 2009.

NonSubsampled Contourlet Transform in Pixel-Level Fusion Contourlet transform with its multi-direction capabilities represent edges and other singularities along curves much more efficiently . Like the wavelet, due to the presence of downsamplers and up-samplers in its implementation the contourlet transform is not shift invariant.

Cunha A L, Zhou J, Do M N, "The nonsubsampled contourlet transform: Theory, design and application", IEEE Transactions on Image Processing, vol.15, no.10, pp.3089-3101, 2006. Hence, Cunha et al (2006) proposed an over complete, shiftinvariant representation called the Non Sub-sampled Contourlet Transform (NSCT) highly suitable for image processing applications. This image representation provides more information for fusion (due to directional filtering at different directions) and reduces the effects of mis-registration (Zhang 2009). Experiments show that NSCT based methods are better in preserving edge and texture information than wavelet transform (Li et al 2010, Wang et al 2012).

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B. Discrete wavelet transform

The DWT has been introduced as a highly efficient and flexible method for sub band decomposition of signals. The 2D-DWT is nowadays established as a key operation in image processing .It is multi-resolution analysis and it decomposes images into wavelet coefficients and scaling function. At each level of decomposition, the signal is split into high frequency and low frequency components; the low frequency components can be further decomposed until the desired resolution is reached. When multiple levels of decomposition are applied, the process is referred to as multiresloution decomposition. In practice when wavelet decomposition is used for image fusion, one level of decomposition can be sufficient, but this depends on the ratio of the spatial resolutions of the images being fused.

However, one of the main drawbacks of DWT is that the transform does not provide shift invariance due to the decimation (down sampling) process. This results a major change in the DWT coefficients of the image even for small shifts in the input. Hence wavelet based fusion tend to introduce artifacts (shadowing and rippling effects) in the fused images. In applications like medical imaging, it is important to preserve the exact location of the salient information and shift variance may lead to inaccuracies. The down sampling operation also has a negative effect on spatial features that do not have a horizontal or vertical orientation (Amolins 2007). To

C. Sub-sampled counterlet transform (nsct)

The NSCT is a shift-invariant version of the Contourlet. NSCT eliminates the down-samplers and the up-samplers in contourlet implementation during the image decomposition and reconstruction stages to achieve shift in-variance. Thus the Non-Subsampled Contourlet transform is a flexible multi-scale, multidirection, shift-invariant image representation realized using Non-Subsampled Pyramids (NSP) and Non-Subsampled Directional Filter Banks (NSDFB) (Cunha et al 2006).

III. WAVELET TRANSFORM

A. Wavelet Transform(WT)

The WT is a spatial frequency decomposition that provides a flexible multiresolution analysis of an image. In one dimension (1D) the basic idea of the WT is to represent the signal as a superposition of wavelets. Wavelet Transform are base on small waves, called wavelets.Wavelet are small waves of varying frequency and limited duration. This allows them to provide the equivalent of a musical score of an image, revealing not only what notes to play but also when to play them. Fourier transform on the other hand, provide only the notes or frequency information while temporal information is lost during transformation process.

B. Discrete Wavelet Transform

The term discrete wavelet transform (DWT) is a general term, encompassing several different methods. It must be noted that the signal itself is continuous; discrete refers to discrete sets of dilation and translation factors and discrete sampling of the signal. For simplicity, it will be assumed that the dilation and translation factors are chosen so as to have dyadic sampling, but the concepts can be extended to other choices of factors.At a given scale J, a finite number of translations are used in applying multiresolution analysis to obtain a finite number of scaling and wavelet coefficients. The signal can be represented in terms of these coefficients as

$$f(x) = \sum_{k} c_{Jk}\phi_{Jk}(x) + \sum_{j=1}\sum_{k} d_{jk}\psi_{jk}(x)$$

Figure 3.1

where cjk are the sca ling coefficients and djk are the wavelet coefficients. The first term in Eq. gives the low-resolution approximation of the signal while the second term gives the detailed information at resolutions from the original down to the current resolution J. The process of applying the DWT can be represented as a bank of filters. At each level of decomposition, the signal is split into high frequency and low frequency components; the low frequency components can be further decomposed until the desired resolution is reached. When multiple levels of decomposition are applied, the process is referred to as multiresolution decomposition. In practice when wavelet decomposition is used for image fusion, one level of decomposition can be sufficient, but this depends on the ratio of the spatial resolutions of the images being fused (for dyadic sampling, a 1:2 ratio is needed

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C. Decimated

In the decimated algorithm, the signal is down- sampled after each level of transformation. In the case of a two-dimensional image, downsampling is performed by keeping one out of every two rows and columns, making the transformed image one quarter of the original size and half the original resolution. The wavelet and scaling filters are one-dimensional, necessitating a two-stage process for each level in the multiresolution analysis: the filtering and downsampling are first applied to the rows of the image and then to its columns. This produces,four images at the lower resolution, one approximation image and three wavelet coefficient, or detail, images. A, HD, VD, and DD are the sub-images produced after one level of transformation. The A sub-image is the approximation image and results from applying the scaling or low-pass filter to both rows and columns. A subsequent level of transformation would be applied only to this subimage. The HD sub- image contains the horizontal details (from low-pass on rows, high-pass on columns), the VD sub-image contains the vertical details (from high-pass on rows, lowspass on columns) and the DD sub-image contains the diagonal details (from high-pass, or wavelet filter, on both rows and columns).

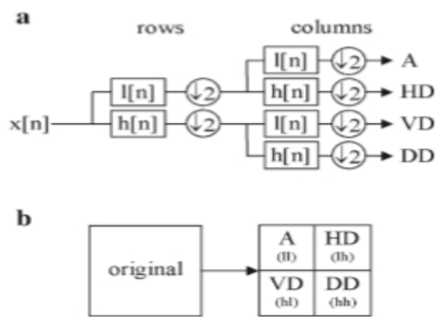

Figure 3.3 Three-Level one-dimensional discrete wavelet transform

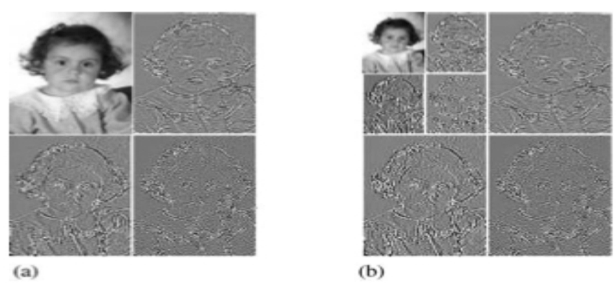

Fig.3.2. a) Image at first decomposition level b) Second Decomposition Level

The decimated algorithm is not shift-invariant, which means that it is sensitive to shifts of the input image. The decimation process also has a negative impact on the linear continuity of spatial features that do not have a horizontal or vertical orientation. These two factors tend to introduce artifacts when the algorithm is used in applications such as image fusion.

D. Undecimated

The undecimated algorithm addresses the issue of shift-invariance. It does so by suppressing the down-sampling step of the decimated algorithm and instead up-sampling the filters by inserting zeros between the filter coefficients. In this case, however, although the four images produced (one approximation and three detail images) are at half the resolution of the original, they are the same size as the original image. The approximation images from the undecimated algorithm are therefore represented as levels in a parallelepiped, with the spatial resolution becoming coarser at each higher level and the size remaining the same. The undecimated algorithm is redundant, meaning some detail information may be retained in adjacent levels of transformation. It also requires more space to store the results of each level of transformation and, although it is shift-invariant, it does not resolve the problem of feature orientation. A previous level of approximation, resolution J-1, can be reconstructed exactly by applying the inverse transform to all four images at resolution J and combining the resulting images. Essentially, the inverse transform involves the same steps as the forward transform, but they are applied in the reverse order. Reconstruction in the undecimated case is similar, except that instead of up- sampling the images, the filters are down-sampled before each application of the inverse filters. Shift-invariance is necessary in order to compare and combine wavelet coefficient images.

IV. NON SUB-SAMPLED COUNTERLET TRANSFORM

A. Nonsubsampled Contourlet Transform

NSCT is a kind of multi-scale and multi-direction computation framework of the discrete images which can be divided into two stages includes Non-Subsampled Pyramid (NSP) and Non-Subsampled Directional filter bank (NSDFB) [6]. The multiscale property using two channel filter bank, and one low-frequency image and one high-frequency image can be produced at each level of NSP decomposition. The subsequent NSP decomposition stages are carried out to decompose the low-frequency components of the image. The property of NSP is obtained by NSFB structure which is similar to that of Laplacian pyramid which is achieved by using the Non subsampled filter banks.

Non-Subsampled Pyramid NSP result in k+1 subimage, which consists of one low-frequency image and k high-frequency images having same size as the source image. Where k is number of decomposition levels [7]. The NSDFB is two-channel non-subsampled filter banks which are constructed by combining the directional filter bank. It allows the direction decomposition with l stages in high frequency from NSP at each scale and produces 2l directional sub-images as source image. The NSCT has proven to be very efficient in image denoising and image enhancement,

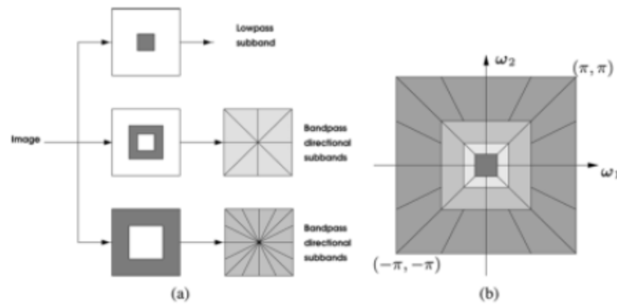

Fig. 4.1 Non-subsampled Counterlet Transform. (a) NSFB structure that implements NSCT. (b) Idealize frequency partitioning. ED

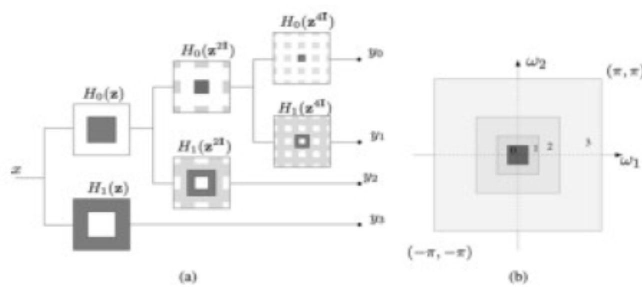

Fig.4.2 Nonsubsampled Pyramid (a) Three-stage pyramid decompostion. (b) Subband frequency plane.

The NSDFB is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. A shift-invariant directional expansion is obtained with NSDFB [9]. The NSDFB is constructed by eliminating the down samplers and up samplers in the DFB. Elimation can be done by switching off the down sampler or the up sampler in the DFB in each filter bank.

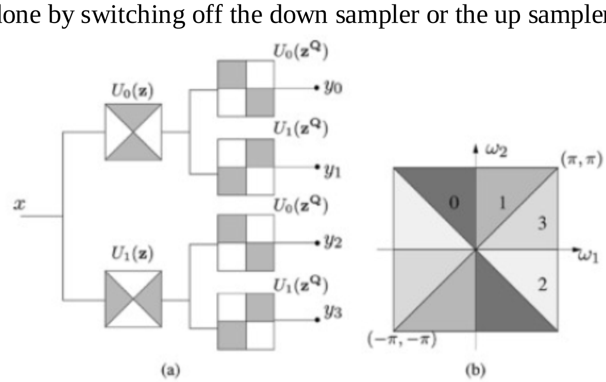

Fig. 4.3 Nonsubsampled directional filter bank constructed with two-channel fan filter banks. (a) Filtering structure. (b) Corresponding frequency decomposition.

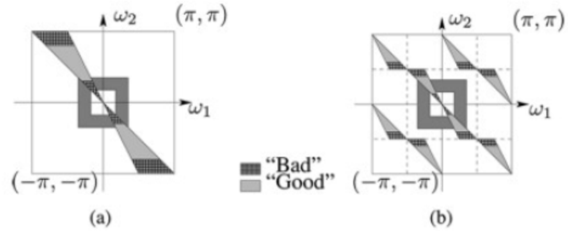

Fig.4.4 Sampling in the NSCT. (a) With no upsampling. (b) With upsampling.

the high-pass at higher scales will be filtered by the portion of the directional filter that has "bad" response. Fig (b) shows up sampling ensures that filtering is done in the "good" region. Here in image fusion of NSCT we take a pair of images to generate a composite image. The basic condition in this is that all the source images must be registered n order to align the corresponding pixels. To perform l-level NSCT on the source images to obtain one low-frequency and a series of high-frequency sub-images at each level and direction θ, i.e.,

$$A:\{C_l^A, C_l^A, \theta\} \text{ and } B:\{C_l^B, C_l^B, \theta\} \qquad (1)$$

Where C*⁎ are low-frequency sub-images and C* l represents the high-frequency sub-images at level l ϵ [1, l]
in the orientation θ. Fusion of low-frequency sub-images represents the approximation components of the source images. The easy way is to use conventional averaging method to produce the composite bands. That is first, the features are extracted from low-frequency sub-images denoted by and. Then fuse the low-frequency sub-images as

$$C_l^F(x,y) = \begin{cases} C_l^A(x,y), & if\ \mathrm{Pc}_l^A(x,y) > \mathrm{Pc}_l^B(x,y) \\ C_l^B(x,y), & if\ \mathrm{Pc}_l^A(x,y) < \mathrm{Pc}_l^B(x,y) \\ \frac{\sum_{k \epsilon A,B} C_l^k(x,y)}{2} & if\ \mathrm{Pc}_l^A(x,y) < \mathrm{Pc}_l^B(x,y) \end{cases} \qquad (2)$$

Now fusion of high-frequency sub-images, here the coefficients in the high-frequency sub-images usually include detail component of the source image. And it is also true that noise is also related to high-frequencies and it can cause miscalculation of sharpness value by affecting the fusion performance. To remove this directive contrast is done which is first applied on high-frequency sub-image of NSCT at each scale by

NSCT at each scale by $\mathrm{Dc}_{l,\theta}^A$ and $\mathrm{Dc}_{l,\theta}^B$ at each level l ϵ [1, l] in the direction θ.

$$C_{l,\theta}^F(x,y) = \begin{cases} C_{l,\theta}^A(x,y), & if\ \mathrm{Dc}_{l,\theta}^A(x,y) > \mathrm{Dc}_{l,\theta}^B(x,y) \\ C_{l,\theta}^A(x,y), & if\ \mathrm{Dc}_{l,\theta}^A(x,y) < \mathrm{Dc}_{l,\theta}^B(x,y) \end{cases}$$

VI. IMPLEMENTATION

A. Image Fusion Dwt

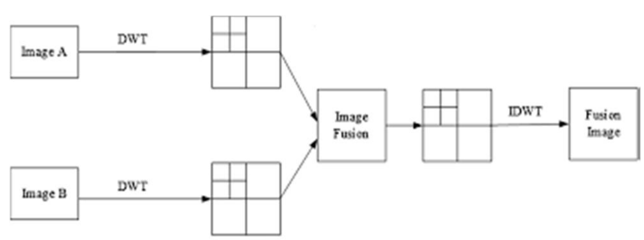

figure 6.1Block diagram of DWT image fusion.

Fusion algorithm is as follows:
We have two source images I1(x, y) and I2(x, y) respectively.
Take two source images.
Size of both image should be same.
Convert both the images into grayscale if required.
Apply 2D- DWT on both the images and obtain its four components viz: one approximation and three detail ones.

Now apply the fusion rule as per the requirement. Here we have experimented with different fusion rules viz:
Maximum pixel selection rule (all max): By selecting all maximum coefficients of both the images and fusing them.
Mean : By taking the average of the coefficients of both the images.
Now apply IDWT to obtain the fused image.

B. Image Fusion Nsct

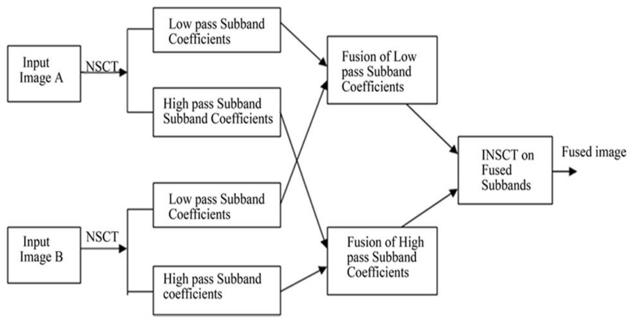

figure 6.1Block diagram of nsct.

In this project, a multimodal medical image fusion method is proposed based on Non-Subsampled Contourlet Transform (NSCT), which consists of three steps. In the first step, the medical images to be fused are decomposed into low and high frequency components by Non-Subsampled Contourlet Transform. In the second step, two different fusion rules are used for fusing the low frequency and high frequency bands which preserve more information in the fused image along with improved quality. The low frequency bands are fused by using local mean fusion rule, whereas high frequency bands are fused by using local variance fusion rule. In the last step, the fused image is reconstructed by Inverse Non-Subsampled Contourlet Transform (NSCT) with the composite coefficients.
The procedures of our method can be summarized as follows.
1) The input images to be fused must be of same size.
2) Decompose the images using NSCT to get low and high frequency subbands.
3) The coefficients of low frequency subband of NSCT are selected by averaging
4) The coefficients of high frequency subbands of NSCT are selected by maximum
5) Perform the Inverse NSCT (INSCT) with the combined coefficients obtained to get fused image.

VII. RESULT

The experimental results of fusion of a pair of multifocus images is
presented and discussed in this section. Figure 7.1 (a) and (b) shows a pair of multifocus clock source images focused on the right and left respectively.The fused image of the DWT method in Figure 7.1(c) has taken the focused clock information correctly from the source image. Figure 7.1 (d) is fused image of NSCT. Fused image of NSCT is better than DWT.Table 7.1 compare the parameter of NSCT and DWT.

Fig 7.1 (a) ClockA (b)Clock B (c) Fused Image DWT

VIII. CONCLUSION

To acquire the crucial features or attributes of the images of common features image fusion is widely used technology This chapter summarises the investigation of pixel-level fusion algorithms for fusing image information from multiple sensors. For pixel-level image fusion two approaches namely, "Non-Subsampled Contourlet Transform and DWT are proposed to produce highly informative fused images. .In this project work, attention was drawn towards the current trend of the use of multiresolution image fusion techniques, especially approaches based on discrete wavelet transforms and NSCT. The work started with the review of several image fusion algorithms and their implementation. A maximum-approximation and mean-detail fusion selection rule has been implemented. The response of image fusion is found to have higher values of Entropy, Standard deviation, Petrovic, Piella and mutual information for NSCT over DWT.

The wavelet transform is one of the most efficient approaches to extract the features by the transformation and decomposition process but this method is not efficient to retain the edge information. In future work, design such algorithm which can efficiently retain the edge information. Also NSCT with fuzzy approach can be implemented to get better fused image.

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