AN EFFICIENT WRAPPING FASTDISCRETE CURVELET TRANSFORM WITH SPARSE REPRESENTATION BASED FUSION FOR SONAR IMAGES

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Abstract: To realize earth surfaces with focus on underwater applications like depth sounding, sea-bed imaging and fish echolocationthe SOund Navigation And Ranging (SONAR) technology is used. Various factors are affected the captured sonar images such as low contrast, disturbance of lightening, the transmission of limited range of light, limited range of light and blurring of image, colour diminishing for the period of shooting and noise. The above disturbances affected the quality of image which often leads to incorrect analysis and has to be handled cautiously. To efficiently analyze an image, the quality of the image must be high typical and consequently, enhancement of image excellent has emerge as principal in image evaluation programs. To improve the sonar image quality, wrappingFast Discrete Curvelet Transform (FDCT) with Sparse Representation (SR) is proposed in this paper. The proposed system consists of four phases like pre-processing, feature selection, pixel quality improvement and image fusion. Initially, the input sonar image is pre-processed to remove noise using FDCT with warping the image. Secondly, the features or pixels are selected from sonar image using Novel Principal Component Analysis (PCA) method. Then, the image quality is increased by using super resolution and K-SVD algorithm. Finally, image fusion is obtained using Enhanced Multi-Scale Transform (MST) with SR structure. The experimental results show that the proposed method has attained good performance for image fusion comparison with state-of-the-art methods.

Keywords:image fusion,sonar image, fast discrete curvelet transform, sparse representation, multi-scale transform, super resolution, PCA.

1. INTRODUCTION

With the development in the field of sensing technology, attain images in more viable techniques, and the image fusion categories are presented like the multi-spectral image fusion of single sensor, image fusion of same sensor, the image fusion of the sensors with different categories and the fusion of image and non-image. They find application in different fields like remote sensing, military applications and medical imaging. Relying upon the variety of fusion it's categorized as feature-level fusion, pixel-level fusion and resolution level fusion. They use various fusion algorithms and find application in different fields. There are few classical fusion algorithms like Laplacian pyramid, the pixel-pixel average gray level value of the source images, Ratio pyramid, Contrast pyramid, and Discrete Wavelet change into (DWT). Nevertheless, computing the usual pixel-pixel level value of the source images has undesirable facet results corresponding to contrast reduction.

Wavelet based image fusion approach provides high spectral quality of the fused images however they lack spatial knowledge as it's an essential aspect so far as the spectral knowledge. In certain, it improves the effectiveness of the image fusion application. As a consequence, it is crucial to advance developed image fusion process so that the fused images have the same spatial resolution and the same spectral resolution with minimum artifacts. The principle behind DWT is to perform decompositions on each and every source image, and then combine all these decompositions to receive composite representation, and then inverse transform is used to receive the ultimate fused image which is determined to be effectual. Nevertheless, one of the vital important properties of wavelets transform to can only reflect via edge characteristics, however are not able to categorical along edge characteristics. Whilst, the wavelet transforms cannot precisely show the edge direction as it adopts isotropy. Image fusion integrates the multisensory knowledge to create a fused image containing spectral, high spatial and radiometric resolutions. In remote sensing, image fusion is most useful process for utilization of multisensor, multispectral at different resolutions of earth observation satellites [1]. Spatial resolution plays a primary function to delineate the objects within the remote sensing image. It is easy to interpret the features with excessive spatial decision [2] image with multispectral data than the single excessive decision Pan image. Image fusion increase the spatial, spectral and radiometric [3] resolutions of graphics. There are a couple of satellite image fusion techniques however spatial and spectral details retention concurrently is a trade off.

Nencini et al., [4] proposed a fusion scheme based on Inter Band Structure Model (IBSM) in first generation curvelet transform domain. The process uses Quick-bird and Ikonos multispectral and Pan Images. The experimental results proven that, the method reasonably higher than the Atrous Wavelet Transform (ATWT) and outperform Grams-Schmidt spectral sharpening process. Ying Li et al., [5] proposed a Fast Discrete Curvelet Transform (FDCT) based remote sensing image fusion. The procedure makes use of Synthetic Aperture Radar (SAR) and Thematic Mapper (TM) images for fusion. It concluded that FDCT established fusion method preserve good spatial important points and concurrently preserve the rich spectral content material when compared with Discrete Wavelet Transform (DWT) and Intensity-Hue-saturation (IHS).

ArashGolibag et al. [6] focuses on region based image fusion making use of linear dependency decision rule situated on Wronskian determinant. The system uses multispectral Landsat and IRS Pan Images for fusion. Shutao Li et al. [7] have carried out multifocus image fusion via combining curvelet and wavelet transform. Cai Xi [8] proposed FDCT established image fusion with the aid of making use of Support Vector Machines (SVM) and Pulse Coupled Neural Network (PCNN) to narrate the high sensitivity to boundaries of objects, concluded that the system has higher performance than FDCT. Fast Fourier and wavelet transform based image fusion ways maintain better spectral characteristics but signify terrible spatial small print in fused pix. Objective of this paper is to improve a process, which retains better characteristics of both spatial and spectral characteristics of source image. Wavelet transforms don't signify the curved objects as in HR Pan Images. To conquer such problems of wavelet the curevlet transform is introduced. Over an interval, curvelet transforms are evolved in two generations, comparable to first iteration curvelet transforms and 2nd new release curvelet transforms named as FDCT. To compute the curvelet coefficients [4], First generation curvelet transforms has high computational complexity. To conquer these difficulties Emmanuel J.Candes [9] developed FDCT. It represents linear-edges and curves accurately than another mathematical transforms.

In this work, wrappingFDCT with SR based image fusion is proposed for sonar images. First, the input image is pre-processed to remove the noise and improve the image accuracy. Second, the obtained pixels are selected and image quality improved by using K-SVD. Finally, Enhanced MIT with SR structure. The performance of proposed system is evaluated and compared with existing image fusion methods such as DWT-SR, DTCWT-SR, CVT-SR and NSCT-SR.This article consists of five sections. The review of some image fusion relevant background material is given in section2. Section 3 describes a brief overview of proposed system followed by pre-processing, feature selection and image fusion. The results are presented in Section 4, followed by conclusions in Section 5.

2. BACKGROUND

In this section,the existing image fusion methods are discussed.Wan et al., [10] proposed a Robust Principal Component Analysis (RPCA) based image fusion method. First, the input matrix of data is split into a principal matrix of low rank and a sparse matrix. Then the principal elements in sparse matrix signify dissimilar data. This procedure is used to form an effective fusion method to differentiate focused and defocused areas. The extracted features from sparse matrix symbolize the salient expertise from supply portraits. These regional sparse aspects are combined to form the consequent image. For reducing blockading artifacts, method of sliding window can be used for computation of the frequency matrix by searching entire image and choose pixels in line with sharper areas. This method outperforms wavelet based fusion ways and presents higher visual notion. Cost of computation of this manner is excessive. The efficiency evaluation of this method is completed making use of three metrics like mutual expertise, petrovic’s metric and Structural Similarity Index (SSIM).

Li and B.Yang [11] proposed a region based multi-focus image fusion approach. It's processed in the spatial domain. It includes of three steps: segmentation of image, measuring region based readability and formation of fused image. First, input images are fused by averaging. Segmentation of fused image is done using normalization based cuts. Measure of normalized criterion can measure total similarity as well as dissimilarity within different collections. Using this segmentation influence, partitioning of source images is prepared. At last, based on the measure of spatial frequency, the fusion of corresponding regions of source images is done. Objective nice index is developed for evaluation of fusion based on spatial frequency. Based on mutual information and Petrovic’s metric the performance is evaluated. This method more reliable and reduces complexity.

Liu et al. [12] proposed a fusion procedure based on dense Scale Invariant Feature Transform (SIFT)for multi-focus images. The SIFT image is calculated from each and every source image. Accretion of all elements of unnormalised SIFT descriptor is done to form an activity level map, including focal data. Normalisation rule is utilized to get a normalized SIFT image. After that, the initial decision map is shaped with the aid of combining focus data in two undertaking stage maps. Feature matching is finished for the further refinement of decision map. This sophisticated fusion map is used to form a fused image. Excessive memory is required. This

process outperforms different procedures in recognize of function founded efficiency evaluation and visible perception.

Ziang and Guo [13] proposed a Non-Subsampled Contourlet Transform (NSCT) based fusion method for multifocus images. It's a contourlet transform based on shift invariance property. It is established on the ideas of picking out low pass and bandpass directional subband coefficients. Used for the low subband coefficients, selecting scheme is combined with the averaging scheme based on the common directional vector. For the bandpass directional coefficients, precept of selection is established on ordinary deviation of directional vector and directional bandlimited contrast. For the shift invariance property, elimination of downsamplers and upsamplers is finished during decomposition and image reconstruction. It depends on non-subsampled pyramid filter and directional filter banks. This approach is better in of both objective based performance assessment and visual quality compared to other wavelet based approaches.

Miao et al. [14] proposed a shearlets based image fusion method. By shearlets the features like directionality, localization, multi-scalability and anisotropy are possessed. Using shearlet transform, image decomposition will also be executed in any path and any extent.The multidirection decomposition of image is done by Shear matrix. Wavelet packets decomposition is used to decompose each direction based on multiscale. Typical of coefficients of low frequency of two source images replaces low frequency coefficients of fused snapshot. Then coefficients of high frequency are chosen selectively. The resulting decision map is focused to the region based consistency check.

Wu et al. [15] proposed a Hidden Markov Model (HMM) based image fusion. The input images are split to form patches. The clarity is calculated Blurred image A and Blurred image B Fusion approach Computation of max count on AC coefficients choose image block with better value of max depend Fusion of DCT coefficients and Inverse DCT to get a fused image of every patch. The compatibility is computed for each and every of two neighbouring patches. The fused photograph is modeled established on clarity and fidelity of every patch utilizing HMM. Additionally it is based on compatibility of neighbouring patches and the patches obtained from input images. The algorithm of perception propagation is utilized to kind the fused patches. The fused patches are then integrated to form an output fused image. It provides better visual perception compared to multiscale transform methods.

Singh and A.Khare [16] proposed a Daubechies Complex Wavelet Transform (DCWT) based image fusion approach.It has properties of shift invariance, segment information and multi-scale edge data. It's established on multi-decision precept and used to decompose source images at various stages. After that, wavelet coefficients are formed. Rule of maximum determination is utilized to fuse these wavelet coefficients. Inverse DCWT is applied to form a fused image. It has no redundancy and is symmetric. This method outperforms other wavelet based and spatial domain methods.

Bai et al. [17] proposed a multi-scale toggle solid operator based an edge preserving image fusion method. This approach extracts the multi-scale dilation and erosion features. These features are used to represent the edge information for source images. These extracted features are used for the development of ultimate dilation and erosion fusion features. These constructed features are finally combined to form a fused image.This method is effective for preserving edge information.

Bai et al. [18] proposed a quadtreebased fusion method for multi-focus images using a weighted focus measure. Decomposition of input images is done into blocks of best sizes established on the constitution of quadtree. Based on a weight based measure, the detection of focused blocks is done, known as sum of the weighted modified laplacian. In this method, noise intrusion is suppressed using modified laplcaian.These detected regions are combined to form focused blocks. For consistency verification, focused regions are reconstructed utilizing sequential filters. The morphological filter is used which eliminates small lines or blurrs and connect nearby regions. Next, a filter based on small region is utilized which eliminates remoted blocks of small dimension. Finally, these regions are fused to get a resultant image. It outperforms compared than other transform domain methods.

Zin et al. [19] proposed a compressive sensing based fusion technique. Decomposition of source images is completed using non-subsampled contourlet transform. The subbands of low pass are combined making use of dual layer Pulse Coupled Neural network model. The high pass subbands are mixed utilising edge-retention based fusion rule. Gaussian matrix is used to combine the sparse coefficients. Subsequently, reconstruction of fused photograph is finished using Compressive Sampling Matched Persuit algorithm. Probably the most significant feature can also be extracted from source images by means of directly fusing sparse coefficients. The reconstruction error is diminished via using related size matrix for measuring the fused coefficients.It performs better than other traditional based methods in respect of visual quality.

Li et al. [20] proposed a sparse matrix and morphological filtering based image fusion technique for multi-focus images using decomposition. The source images are decomposed

after the extraction of sparse feature matrices. These sparse matrices include salient aspects of source images. A temporary matrix is formed through weighting these sparse matrices. Morphological filtering is applied to this temporary matrix for the extraction of brilliant and dark areas. These extracted features are developed into base image and combined to form a fused image. Decomposition technique used on this procedure extracts extra salient information than RPCA. Pixel wise fusion used in this system takes comparatively less jogging time and type fused images with higher contrast.

Vijayarajan and Muttan [21] proposed a DWT based on averaging of principal components based image fusion technique.The input images are decomposed using DWT. PCA is is done for detailed and approximate coefficients of input images. Evaluation of PCA is finished for multiscale coefficients. Averaging of those principal coefficients is completed, which constitutes weights for the fusion rule to be applied.It outperforms compared than other existing state-of-art methods.

Liu and Yu [22] proposed an automated image fusion algorithm for multi-focus images. The input images are aligned making use of image registration. Based on entropy idea, one image is chosen as a reference picture for image registration system. For feature matching, Binary Robust Invariant Scalable Keypoints (BRISK) with Speeded up Robust Features (SURF) feature descriptor is used. To reject improper matches, extended technique of Random sample Consensus (RANSAC) is utilized followed by means of transformation and resampling of image. Then Stationary WaveletTransform (SWT) is used to decompose the registered and reference images. Inverse SWT is used to reconstruct the focused image.

3. PROPOSED METHODOLOGY

In this section,FDCT with SR based image fusion has been discussed.

3.1. System overview

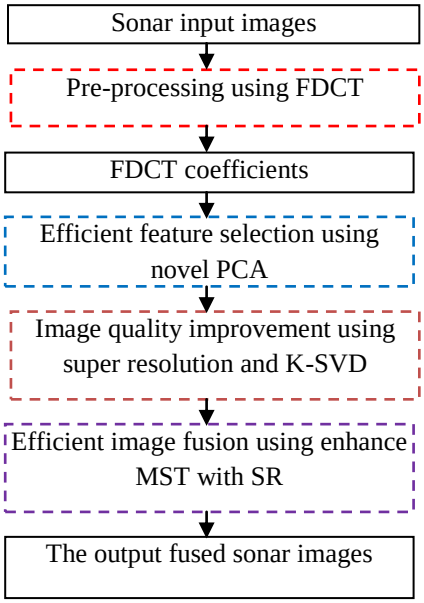


Fig 1: overall architecture diagram

The overall process of proposed system is illustrated in fig 1.It shows the wrapping FDCT with SR based image fusion is proposed for sonar images. First, the input image is pre-processed to remove the noise. In FDCT, initially, the Fourier sample of the image is obtained by Fast Fourier transform (FFT). Then in windowing, the input image is divided into collection of digital corona tiles, and then translated to the origin. After that, the parallelogram shaped support of the tile is wrapped in the region of a rectangle centered at the source. Finally, Inverse FFT of the wrapped support is determined and the resulting curvelet array is stored to the collection of curvelet coefficients on which the two non-linear techniques are applied to remove noise from input image. Second, the obtained pixels are selected and image quality improved by using K-SVD. Finally, Enhanced MIT with SR structure.

3.2. Image Pre-processing

The image is pre-processed to remove noise using FDCT. The curvelet transforms is classified as first generation [23] and second generation [24], provide a near-optimal sparse representation for images having discontinuities along twice differentiable ($C2$) curves. In second generation curvelets, two separate digital implementations were proposed in [25] and the two implementations are such as Unequi Spaced Fast Fourier Transform (USFFT) and frequency domain wrapping. The two implementations are conceptually the same. Proposed FDCT common steps involved in both the implementations are outlined in Fig 2. The computation of 2-D (two-dimensional)Discrete Fourier transform (DFT)of the image using the FFT, and curvelet frequency windows at various scales and angles are implemented.With computing the 2-D inverse DFT (IDFT) of each windowed output, and then curvelet coefficients are attained. The pre-

processed output image canbe recovered without error from the curvelet coefficients through inverting each step involved. Evaluated to the first generation curvelets, the FDCT is conceptually simple and attained less redundant. The pre-processed image has better computational complexity. Similarly, when compared to the NSCT, the FDCT has efficient frequency resolution and improved directionality properties[25].The second algorithm of wrapping transform uses a series of translation and a wrap around techniques. The wrapping FDCT is more intuitive and has less computation time.

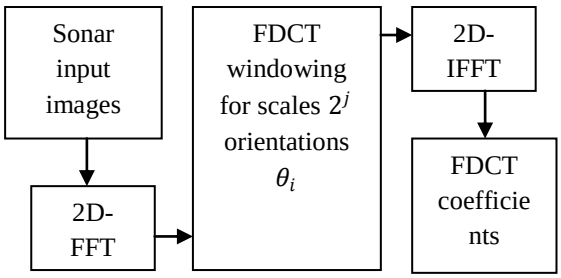


Fig 2:FDCT based pre-processing

Wrapping FDCT Algorithm

1. First, the input image is considered, and then take FFT of the image
2. FFT image is divided in to collection of Digital Corona Tiles
3. For each Corona Tile
   a. The tile is Translate to the origin
   b. The parallelogram shaped support of the tile Wrapped around a rectangle centered at the origin
   c. Inverse FFT takes for wrapped support
   d. The curvelet array is added to the collection of curvelet coefficients.

Inverse Wrapping FDCT Algorithm

1. for each curvelet coefficient array
   a. Considered the FFT of the array.
   b. The rectangular support unwrapped to the original orientation shape.
   c. Converted to the original position
   d. Finally, the translated array is stored.
2. All the translated curvelet arrays are added.
3. the inverse FFT taken to reconstruct the image

The FDCT coefficients are used for best Feature selection. Efficient FDCT coefficient selection is discussed given below.

Fast Discrete Curvelet transform (FDCT)

FDCT gives dissimilar frequency components locally for analysis and synthesis of digital image in multi-resolution analysis. Fast Discrete Curvelet transform (FDCT) is multi-scale geometric transform, which is a multi-scale pyramid with many directions and positions at each length scale. FDCT is fundamentally 2D anisotropic extension to classical wavelet transform that has main direction connected with it. Analogous to wavelet, FDCT can be converted and dilated. The dilation is given by a scale index, The scale index controls the frequency content of the curvelet using the indexed position and direction can be changed through a rotation. An angular index is used to index these rotations. anisotropic scaling relation is used to satisfy Curvelet, which is generally referred as parabolic scaling.This anisotropic scaling relation related with curvelet is a main ingredient to the proof. These curvelet provides sparse representation of the C2 function away from edges through piece wise smooth curves.FDCT is built by a radial window W and angular window V. The radial window W is expressed as

$$\widehat{W}_j(w) = \sqrt{(\phi_{j+1}^2(w)} - \phi_j^2(w), j \quad (1)$$

Where, $\phi \rightarrow$ the product of low-pass one dimensional window. The angular window V is defined as

$$V_j(w) = V\,(2^{\frac{j}{2}} w_2/w_1) \quad (2)$$

Where, w_2 and $w_1 \rightarrow$ low pass one dimensional windows. The Cartesian window$\widehat{U}_{j,l}(w)$ is constructed as

$$\widehat{U}_{j,l}(w) = W_j(w) V_j(S_\theta w) \quad (3)$$

Where, $S_\theta \rightarrow$ shear matrix, $S_\theta = \begin{bmatrix} 1 & \phi \\ \tan\phi & 1 \end{bmatrix}$

Shear matrix S_θ is used to maintain the symmetry around the origin and rotation $\pm\pi/2$ radiance. The frequency domain definition of digital curvelet is,

$$\varphi_{j,l,k}^{\bar{D}}[t_1, t_2] = \widehat{U_{j[t_1,t_2]}} e^{-t_2\pi[k_1 t_1 + k_2 t_2]} \quad (4)$$

Where $\varphi_{j,l,k} \rightarrow$a Cartesian window. The Discrete Curvelet transform is expressed as

$$C^D(j,l,k) = \sum_{0 \le t_1, t_2 < n} f[t_1, t_2]\, \varphi_{j,l,k}^{\bar{D}}[t_1, t_2] \quad (5)$$

Where,$C^D(j,l,k) \rightarrow$a curvelet coefficient with j is scale parameter, $l \rightarrow$ orientation parameter and $k \rightarrow$position parameter. $f[t_1, t_2] \rightarrow$an input of Cartesian arrays. This transform is also invertible. The image features captures only in horizontal, diagonal, and vertical directions with isotropic scaling in classical wavelet transform. Wavelets do

well for point singularities but don't for singularities along curves.Because of isotropic scaling wavelets are not well adapted to edges. FDCT is applied to a rotated and up sampled high-resolution grid.In curvelet domain the high- resolution grid is decomposed at three levels. The missing pixels locations need to determine in each sub band due to interpolate the missing pixels. In curvelet domain missing pixels depends to missing coefficients of each sub band. At finest scale the missing coefficients are interpolated. Original high resolution grid is rebuilt using the Inverse curvelet transform. It will enhance the image quality.

3.3. Novel PCA based feature selection

Pre-processing is done, after that, a novel PCA method is applied to obtain the brightness information of the original two images. It is implemented by pixel by pixel calculation of source image. For instance, let us consider that original image size is 250×250, then first apply the PCA method for pixel 1×1, after finding the eigen vector of 1×1 pixel, then apply PCA method to 2×2 Pixel. This process is continued until 250×250 pixel.

PCA[26] is standard method used for statistical pattern recognition and data reduction of signal processing and feature extraction is discussed [27].First step of the PCA algorithm is to find average for original image is calculated using below equation

$$x_k = \frac{1}{N}\sum_{m=1}^{N} F_m, k = 1,2 \quad (6)$$

Where $m \rightarrow$the sum of pixels in an image

For source image a data matrix is formed is given in below equation

$$X = (x_1, x_2)^N = \begin{pmatrix} x_{11} & \dots & x_{1m} \\ x_{21} & \dots & x_{2m} \end{pmatrix} \quad (7)$$

The covariance matrix C for obtained data matrix X is calculated using below equation

$$C = \frac{1}{m}\sum_{i=0}^{m-1}(x_{i,j} - \bar{x}_i)(x_{j,j} - \bar{x}_i) \quad (8)$$

In the above equation, $\bar{x}_i$ defines the average gray value of ith image.

Let us consider eigen vector e_i of $(x_{i,j} - \bar{x}_i)(x_{j,j} - \bar{x}_i)$ such that

$$(x_{i,j} - \bar{x}_i)(x_{j,j} - \bar{x}_i)e_i = \mu_i e_i \quad (9)$$

The above equation is multiplied by $(x_{i,j} - \bar{x}_i)$ is given in below

$$(x_{i,j} - \bar{x}_i)(x_{i,j} - \bar{x}_i)(x_{j,j} - \bar{x}_i)e_i = \mu_i e_i \quad (10)$$

In the above equation $(x_{j,j} - \bar{x}_i)e_i$ defiens the eigen vector and μ_i defines the eigen value.

3.4. SR and K-SVD based image quality improvement

Super Resolution (SR) is the method of obtaining High Resolution (HR) images from a collection of blurred and noisy low resolution observations. SR image reconstruction can also be executed by utilizing either a single image or a set of multiple images. The SR single image techniques require a large amount of training data for the learning approaches, where as the SR multiple image methods deal with the inverse problem [28]. In multiple SR reconstruction system, the Low Resolution (LR) images are attained with a low resolution camera or sensor operated from different viewpoints, at various times or with the usage of cameras having specific resolution. The low decision observations will also be formulated as

$$A_{c,i} = DHF_{c,i}X_c + N_{c,i}, c = R, G, B \text{ and } i = 1,2,3, \dots N \quad (11)$$

Where $N \rightarrow$ the number of low resolution observations made, $X_c \rightarrow$ the cth colourcomponent of unknown High resolution image, $A_{c,i} \rightarrow$the ith Low resolution image of the X_c,$D \rightarrow$ the down sampling matrix, $H \rightarrow$ the point spread function of the blur operator, $F_{c,i} \rightarrow$ the warping matrix and is the additive noise.After that, to improve the Peak Signal Noise Ratio(PSNR) of proposed system the K-SVDalgorithm is used. K-SVD is generalizing the K-Means clustering process,for adapting dictionaries in order to achieve sparse signal representations.

According to Elad et al. [29], the sparse decomposition problem is formulated as

$$\min_{D, x_i} \|y - Dx_i\|_2 \text{ subject to } \|y_i - Dx_i\|_2 < \varepsilon \quad (12)$$

Where, $x_i \rightarrow$ a vector containing the linear combination of atoms from the redundant dictionary, $D \rightarrow$dictionary, $\varepsilon \rightarrow$ the tolerable limit of the error,$\|.\|_0 \rightarrow$denotes the l_0 norm representing the number of non-zero-elements of the vector. The problem of sparse representation can be defined by Eq. 12. This work assume problem formulation presented in eq.12 and extend it to include the entire set of observed signals denoted by the set $Y = \{y_i \in [1, K], y_i \in R^n\}$ as

$$\min_{D, x_i} \|y - Dx_i\|_F \text{ subject to } \|x_i\|_2 < \varepsilon \quad (13)$$

Where $x \rightarrow$ formed by column stacking all vectors $x_i$and$\|y - Dx_i\|_F$ denotes the Frobenius norm

square which represents the square of every elements in the matrix.

The K-SVD algorithm attempts to minimize the cost function iteratively, by first finding x using the OMP algorithm (using an initial estimate of D). This coding is highly effective because it minimizes the error in representation and at the same time maintains a sparsity constraint as defined in Eq. 13. After completion of sparse coding stage, the algorithm proceeds to update the atoms of the dictionary, one atom at a time, such that the error term is further reduced [30, 31]. The K-SVD algorithm is highly efficient for training dictionaries to achieve sparse signal representations.

Here, the application of the K-SVD algorithm to denoising of images has been discussed. In KSVD, the noisy image is divided into patches and the vectorised version of each patch is treated as signals, thereby restricting the dimensionality of each atom in the dictionary [29]. However, the size of the patch has to be chosen such that it encodes enough details of the underlying signal. Dealing with patches as signals, the K-SVD algorithm can be effectively scaled to de-noise large images [31, 32].

For a given image, the denoising method can be used to find a set of patches Z which are related by

$$Y = Z + \eta \qquad (14)$$

Where $\eta \rightarrow$ the noise which corrupts the patches. The noise over the entire image is assumed to be zero mean gaussian noise. In order to find the denoised image patches$Z$.

3.5. Enhanced Multi-Scale Transform with SR

In this proposed work, enhanced MST with Sparse representation framework is introduced. It consists of four popular MST algorithms are DWT, DTCWT, CVT and NSCT. Here, combination of MST and SR based fusion methods are evolved. The fused image is obtained by each MST methods, i.e. first obtain the low pass and high pass coefficients using DWT algorithm and obtained decomposition result is given to next algorithm of DTCWT, it provide low pass and high pass coefficients it given to input of CVT algorithm. Like DTCWT, CVT algorithm provides coefficients of low pass and high pass and it given as an input to NSCT algorithm. Finally NSCT algorithm provides low pass and high pass coefficients, and the low-pass bands are merged with a SR-based fusion approach while the high-pass bands are fused using the total values of coefficients as activity level measurement. The Multilevel wavelet decomposition from DWT, DTCWT, CVT and NST provides the information about frequency components present and enhances the information about the signal or image for further processing also preserve the contrast of the image.

Step 1: Obtain low pass band $\{L_A, L_B\}$ and high pass band H_A, H_B from last level of decomposition from NSCT algorithm on two source images$\{I_A, I_B\}$.

Step 2: Divide the low pass band into image patches of size $\sqrt{N} \times \sqrt{N}$ using sliding window technique from upper left to lower right with a step length of s pixels. If there are T patches in L_A, L_B and it is represented as $\{p_A^i\}_{i=1}^T$and$\{p_B^i\}_{i=1}^T$.

Step 3: For each position$i$, rearrange $\{p_A^i, p_B^i\}$ into column vectors $\{V_A^i, V_B^i\}$ and then normalize each vector's mean value to obtain $\{\hat{V}_A^i, \hat{V}_B^i\}$ using below equation

$$\hat{V}_A^i = V_A^i - \bar{v}_A^i.1 \qquad (15)$$
$$\hat{V}_B^i = V_B^i - \bar{v}_B^i.1 \qquad (16)$$

In the above equation, value 1 represents the all-one valued $n \times 1$ vector, mean value of all elements are denoted as $\bar{v}_A^i$ and $\bar{v}_B^i$.

Step 4: Sparse coefficient vectors are calculated using the Orthogonal Matching Pursuit (OMP) algorithm [33] and it is defined in below equation

$$\alpha_A^i = arg\min_{\alpha} \|\alpha\|_o s.t \left\|\hat{V}_A^i - D\alpha\right\|_2 < \varepsilon \qquad (17)$$
$$\alpha_B^i = arg\min_{\alpha} \|\alpha\|_o s.t \left\|\hat{V}_B^i - D\alpha\right\|_2 < \varepsilon \qquad (18)$$

In this above equation D represents the learned dictionary

Step 5: Merge the obtained two sparse coefficients vectors using max-L1 rule to obtain the fused sparse vector.

$$\alpha_F^i = \begin{cases} \alpha_A^i if \left\|\alpha_A^i\right\|_1 > \left\|\alpha_B^i\right\|_1 \\ \alpha_B^i otherwise \end{cases} \qquad (19)$$

Finally the fused result of V_A^i and V_B^i is calculated using below equation

$$V_F^i = D\alpha_F^i + \hat{v}_F^i.1 \qquad (20)$$

In the above equation, $\hat{v}_F^i$ is obtained using below equation

$$\hat{v}_F^i = \begin{cases} \hat{v}_A^1 if \alpha_F^i = \alpha_A^i \\ \hat{v}_B^1 otherwise \end{cases} \qquad (21)$$

Step 6: The above process is continued for all source image patches to obtain the fused vectors.

Step 7: Max-Absolute rule is used to merge the H_A andH_B to obtain fused high-pass bandH_F.

4. RESULTS AND DISCUSSION

In this section, the performance of proposed FDCT-SR is evaluated. The image datasets are collected and implemented using MATLAB. The image processing steps are completed, then the

performance of proposed is compared with existing systems. The existing image fusion methods such as DWT-SR, DTCWT-SR, CVT-SR and NSCT-SR are compared with proposed image fusion.

Performance evaluation

The performance of image fusion is analyzed with the following parameters.

Standard deviation (SD):

$$SD = \sqrt{\frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}(F(x,y)-\mu)^2} \quad (22)$$

In the above equation, μ represents the mean value of the fused image, M and N defines the size of the two source image. SD is used to measure the overall contrast of the fused image.

Entropy (EN):

$$EN = -\sum_{i=0}^{L-1} p_F(l) log_2 p_F(l) \quad (23)$$

In the above equation, $L \rightarrow$ represents the number of grey level, histogram of fused image is denoted as$p_F(l)$. L is the size and is set as 256. EN is used to measure the amount of information in the fused image.

Peak Signal-To-Noise Ratio (PSNR):

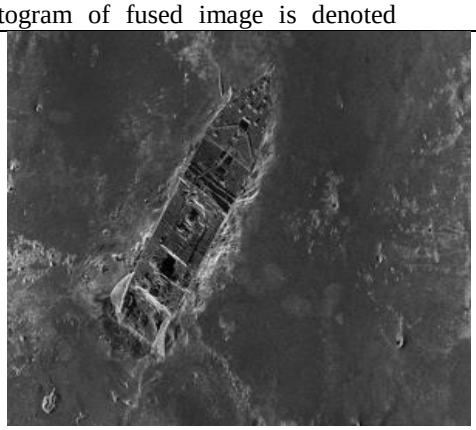
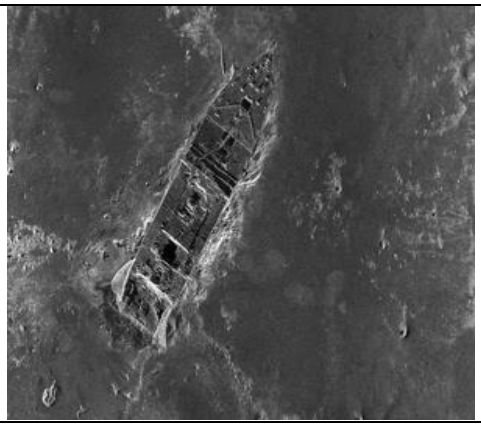
The ratio between the maximum possible powers to the power of corrupting noise is known as PSNR. It affects the fidelity of its representation. Also PSNR defined as the logarithmic function of peak value of image and Mean Square Error (MSE).

$$PSNR = 10\, log_{10}(MAX_i^2/MSE) \quad (24)$$

Where MSE ismean square error of an estimator is to quantify the difference between an estimator and the true value of the quantity being estimated.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-K(i,j)]^2 \quad (25)$$

Fig 3 illustrates the step by step process of proposed system.It gives the denoised image and super resolution images. After that image quality increased by K-SVD, finally, the output fusion image is shown in fig 3.

Input images		
FDCT image		

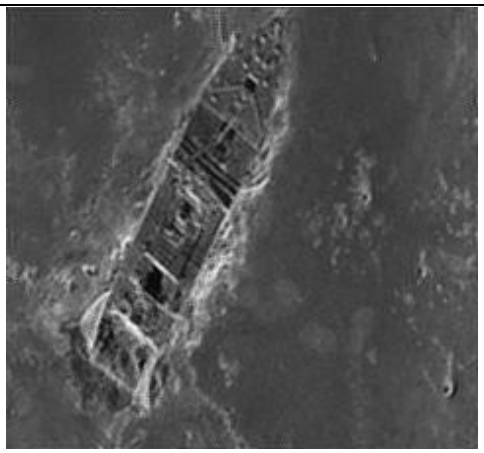
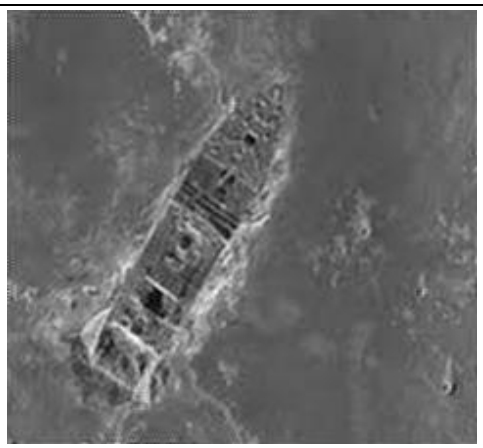
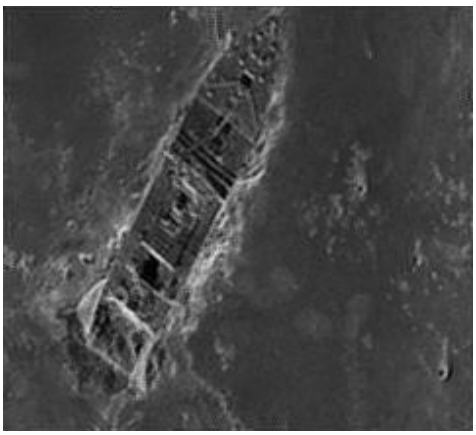
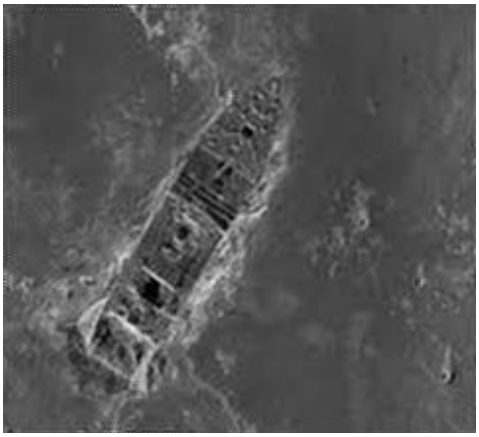
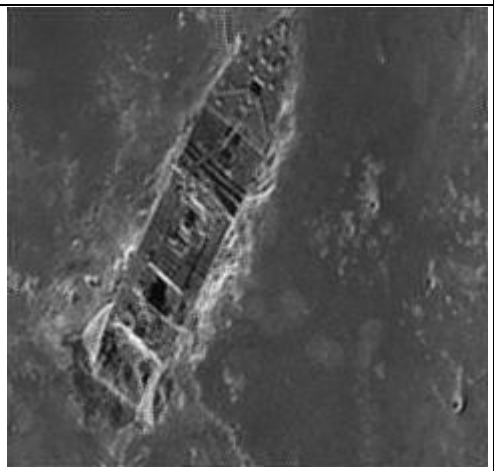
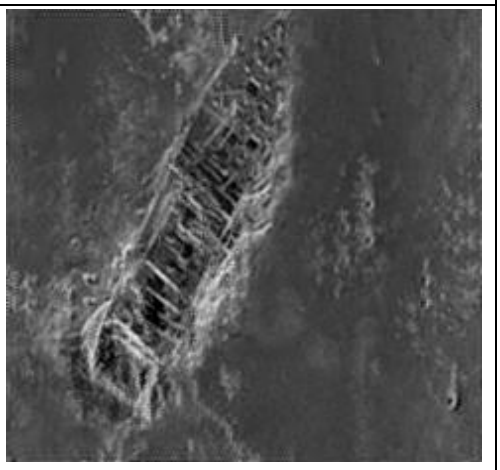
Super resolution image		
K-SVD based recovered image		
Fusion image		

Fig 3: step by step process of proposed system evaluation

Standard Deviation (SD)

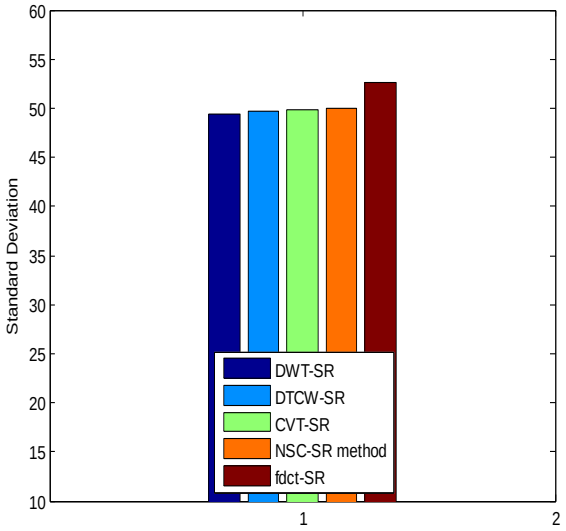


Fig 4: standard deviation comparison

Fig 4 shows the standard deviation comparison of proposed FDCT-SR and existing image fusion methods. It illustrate the proposed system has higher SD compared than existing algorithms, because the K-SVD improves the quality in proposed method.

Entropy comparison

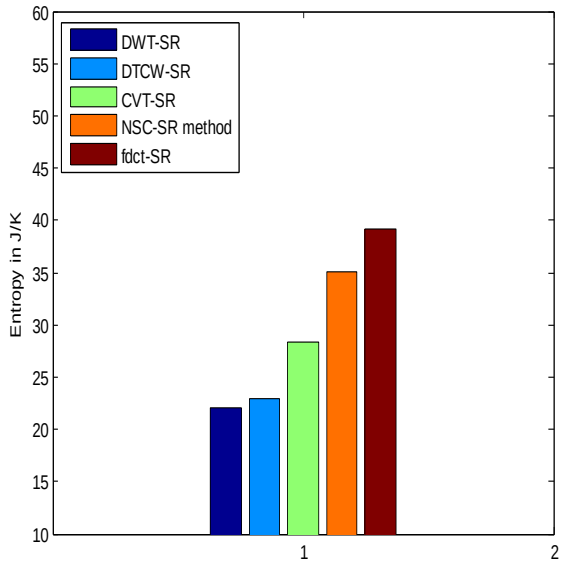


Fig 5: Entropy comparison

Fig 5 shows the entropy comparison of proposed FDCT-SR and existing image fusion methods. It shows that the proposed method attained high entropy compared than existing image fusion methods. The high image quality improved the entropy measure in proposed method.

PSNR comparison

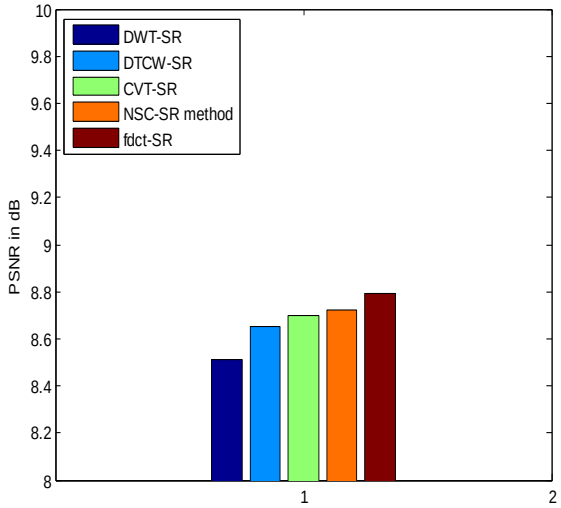


Fig 6: PSNR comparison

To measure the perceptual quality, after the noises are added to sonar images and then calculate the PSNR that is used to estimate the quality of the pre-processing sonar images in comparison with the original ones. The performance of the proposed FDCT-SR iscompared with the existing methods. The PSNR result of the proposed is higher when compare to existing method is shown in Fig.6.

5. CONCLUSION

This research paper presented a wrapping FDCT with SR based image fusion for sonar images. First, the input image is pre-processed to remove the noise. Second, the obtained pixels are selected and image quality improved by using K-SVD. Finally, Enhanced MIT with SR structure. Enhanced MST method with SR technique improved the fusion image contrast. Compared to conventional method of MSTs with SR technique, proposed enhanced MSTs with SR techniques provides better results in terms of standard deviation, entropy and PSNR from sonar images. The final output fused image has better visual effect with high contrast. The proposed method is robust in sonar-image fusion and it has better fusion quality than some existing methods. The proposed method can be applied to other applications and other multi resolution transforms will attract more future work.

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