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Multimodal Image Fusion in Clinical Research

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Abstract: ***With the advancement in medical imaging, far reaching changes are perceptible in clinical analysis. Most of the diagnosed medical evaluation is a resultant of imaging or it is in close synchronization with imaging techniques. This promotes the need to closely read, evaluate and collaborate images. Medical image fusion is a technique to collaborate the clinical images acquired from one or many modalities. Multimodal image analysis during fusion well capitalizes the strength of each medical modality. Incorporating the features from multimodal input images thus holds added potential to abet better-quality diagnosis. Medical image fusion is an intricate task specially when high quality fused image, possessing all relevant information and reasonable operating speed is aimed. Many efforts have been undertaken in this field resulting in diverse research approaches. Image fusion can be performed using medical images obtained from single modality or from multiple modalities. This paper has been designed collaborating the work based on multimodal medical images in multiscale image fusion domain. When the same region, organ or a tissue is captured from various different perceptions, complimentary information is maximized and diagnostic value is reinforced. The fusion framework using Mexican Hat wavelet is proposed using adaptive median filtering detailing each executable fusion block. The Fusion techniques, pre and post processing aspects and evaluation mechanisms are illustrated from literature. The drifts of researchers from single processing to multiple processing hybrid techniques are discussed. The medical modality aspects are detailed. These may provide as a valuable reference to understand the image fusion trade-offs comprehensively with future viabilities.***

Keywords : Image fusion, Spatial Domain, Transform Domain, Modality, fractional wavelets, fusion rules.

I. INTRODUCTION

With the progression in imaging technology, different procedure modalities co-exist in medical domain. An innovation in image fusion research is the availability of advanced imaging equipments to acquire images from anatomical, functional, tomography, projection modalities. Each medical imaging modality aims to deliberate and extract the precise and detailed clinical features from the domain. But due to the underlying properties, each modality has only partial ability to study the organ under observation and differentiate disease from normal.

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Therefore aiming to attain clinical diagnosis using one single modality is not realized. With limited quantifiable substance obtainable, it is hard to reveal structural tissue differences [1]. With this multidimensional focus, heterogeneous inputs are attainable to reveal vital clinical details for improved diagnosis and treatment planning.

In the process, immense amount of unprocessed data is generated. This conceptually leads to increased number of computations and higher complexities. Image fusion is a technique to extort and combine all possible information from source images. The fusion must reveal information not attainable from original images. Medical image fusion may be performed at pre or post treatment times using single or multiple modalities.

Image Fusion is widely used in various application areas. The technical areas involving analysis of images and videos descend under the fusion application category. Image fusion must be more useful for further machine processing [2]. Computer assisted diagnoses and therapy are of increasing importance in health care [3]. Medical image fusion plays a very significant role in performing accurate and early diagnosis, dosage measurement in medical dosimetry, precise tumor location and lesion identification. It includes structural analysis, bone diversity evaluation with thickness, soft tissue analysis, neuro dynamics and design identification in terms of size, shape and location. Image fusion plays an important role in radiotherapy plan, diagnosis, duties of daily treatment schedule and delineating anatomical and physiological differences amongst datasets [4]. These areas are further expanding with the introduction of new acquisition devices for scientific research. Not limiting to the listed areas image fusion techniques is fast growing with ratification.

The structure and functional information is integrated for observation and diagnosis using image fusion [5]. The possibilities and existing technical state of affairs are illustrated. The suggestions for future directions put forth. The subsections are as below: Section II gives the fusion level categorizations. The aspects pertaining to medical domain are in section III. Section IV illustrates the image fusion domains. Multiscale fusion framework is illustrated in section V. The multiscale techniques with respect to medical modalities from literature are given in section VI, Followed by discussion is enclosed in section VII, and Conclusion in section VIII.

II. LEVEL CATEGORIZATIONS

Fusion process can take place at different levels of information representation as a common categorization. This may be based on application, execution time, cost, tools, physical characteristics, into the pixel level, feature or decision level fusion [6]. Few researchers have also worked on a collaborated approach to extend fusion work on more than one level.

A. *Pixel level fusion*

The input images are temporally aligned and are radiometrically calibrated based on the application. The fused image contains original information from sources.

This is determined from the set of input pixels to help improve the performance of image processing tasks such as segmentation, and remove undesirable drawbacks such as noise, mis-registration, reduced contrast and information loss [7]. Fusion at pixel level aims to combine information from multiple sources to reduce the data volume and preserve the spatial characteristics. This technique is susceptible to suffer from dropping performance which is considerably improved using pre-processing. Pixel level fusion works on the original pixel values, in order to keep diagnostic content intact and is thus the most preferred level of computation for medical fusion domain. Further it is the simplest technique with minimum computational time.

B. *Feature level fusion*

The next level of combination is performed at feature level. This deals with the feature information and direction obtained by pre-treatment and feature extraction from input. Salient features such as size, shape, contrast grey level, or texture are extracted from different input images to create a region map using segmentation algorithms. [8]. Feature level fusion demands feature matching from the images, linking similar objects. Mapping is conducted, but unlike pixel level fusion, not all features are extracted. A segment, region or a patch is extracted and analyzed for specific features. As in literature, work in this domain involves features to be acquired from both the images and combined to obtain the fused image. Decomposition, filtering, segmentation, are used to extract features. A feature fusion mechanism was introduced with PCA based, edge based and segment based feature level fusion for panchromatic and Multispectral images [9]. Each techniques aimed to extract specific image features. In PCA based scheme features were extracted to form uncorrelated principle components for fusion. The edge based scheme proposed to extract edges using various detectors. The best results were obtained with segment based feature fusion to obtain accurate spatial and spectral information. Various schemes in multi focus domain, using sparse feature matrix, morphological filtering and multiscale transforms are proposed in literature. The extorted features are collaborated to form the feature vector. These are imposed on the formulated base image. Feature level fusion promotes reduction of data and redundancy before fusion processing. This is superior to pixel techniques but segmentation errors add up to degrade the final image quality, resulting in absence of a feature.

C. *Decision level fusion*

Decision Level fusion comprises of merging information at the highest level of abstraction. Decision level fusion integrates the information extracted in the form of features from the underlying data [10]. The Important features are extracted such as pixel intensities, edges or textures. It creates a strategy and creates the image feature identification block, and concludes a single decision from the created decision maps.

The final image is created from decision maps by means of decision rules followed by semantic equalization, combining the results from multiple algorithms into the image feature identification block. A system using the decision level fusion strategy integrates different data using feature. The system consists of a number of subsystems to make the decision independently.

There are various fusion rules and classifiers in decision level fusion widely applied in various areas as biometrics, fingerprint verification, multisensory fusion, multispectral image fusion, geosciences data fusion and object recognition [10]-[11]. The feature and decision level fusion components are illustrated in Fig. 1.

Medical image fusion technique unites multiple modalities into a single composite image. It brings about patient data to device a single fused image, rich in clinical

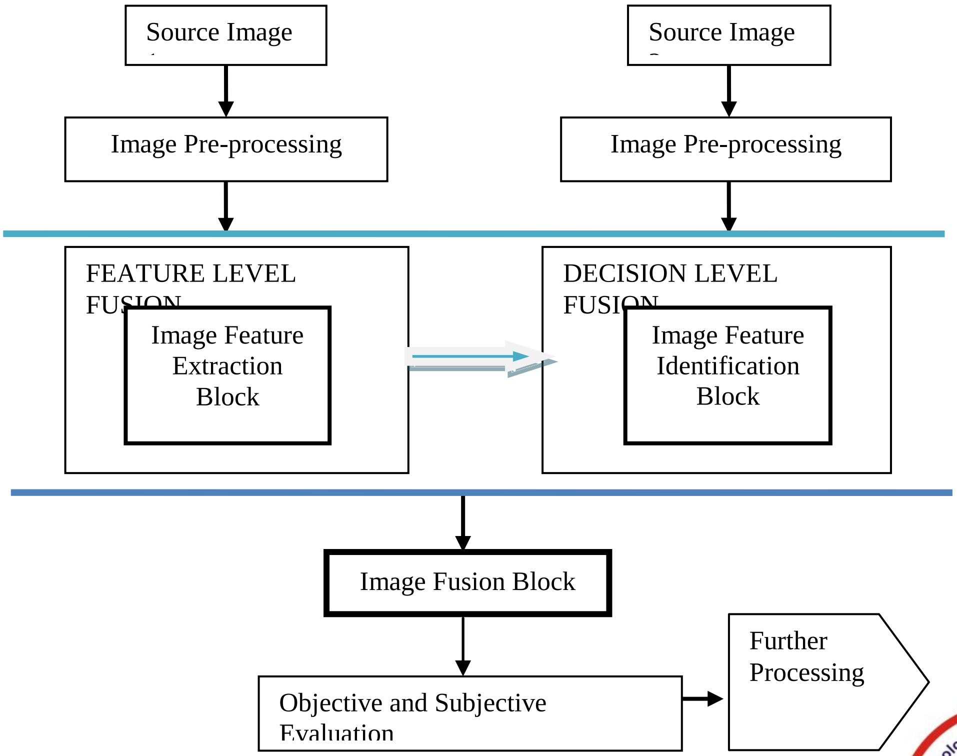

Fig. 1. Generic Structure of Feature Level and Decision Level Image Fusion

content, improvised in texture, features and anatomical details. Fusion is not as trivial as the concept illusions. It becomes even more critical in medical domain due to the involvement of heterogeneity in diagnostic content. Pictorially the components involved in medical fusion are as given in Fig. 2. Medical imaging with a set of techniques, non-invasively capture the internal body structural and functional aspects to produce referral still images or a digital video.

III. MEDICAL IMAGE FUSION ASPECTS

Modality selection is governed by the primary model of medical relevance and aimed clinical outcome. This selection of the modality is the expertise and the prerogative of medical practitioner based on his medical insight and the organ under observation. Deep domain specific knowledge is required for evaluation of nature cause of certain phenomenon and identification of a disease. Modalities function under varied formats to capture the underlying tissue. Depending on the organ and the ailment under assess, different imaging techniques are exploited [12]-[13]. These are based on different physical principles [14]-[15].

Modalities based on the processing technique are suited to a particular organ or pathology. These contribute to the diagnostic analysis independently or in correlation with another modality. The fusion level is thus governed by the diversity, unmatched and asynchronous nature of modalities. These are broadly segregated into two categories as functional and anatomical modalities [1]. Anatomical modality provides insight into anatomical morphology. The anatomical modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT) encompass the position structure and interrelationships. An external source of radiation is applied for visualization of an anatomical structure and precise localization of the abnormally [1]. Functional modality details the metabolism of underlying tissue illustrating the metabolism in pseudo color [16]. The functional modalities as Ultrasound (US), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT); radiation is emitted from within the body to reveal the chemical composition and physiology of the organs and tissues.

The nature of radiological modality determines the reference of the information captured; making even smaller details relevant with improved resolution techniques. Each modality order to assert an added confidence factor in assessment. Thus key regions need to be accessed from multiple perceptions and if needed modalities. Inspecting them together is difficult and practically not very viable for the medico.

IV. IMAGE FUSION DOMAINS

Image fusion methods broadly exercise in two domains, Spatial and Transform. In these domains, numbers of techniques are reported by researchers in literature. Each approach has a limited domain based on a particular application.

A. Spatial Domain Image Fusion

The spatial domain techniques comprise of simple combination of images in a linear or non linear manner. In spatial domain the images can be directly combined at pixel level merging the pixel intensity values by means of a combination strategy. The function at spatial locations may be given by p^i (m, n) where p^i is intensity value at pixel coordinates m, n. So for images A and B depicted by Im^A and Im^B the grouping using simple averaging technique is depicted as

$$Im_A = C_a \, p_i(m,n) \, . \, Im_A \tag{1}$$

$$Im_B = C_b \, p_i(m,n) \, . \, Im_B \tag{2}$$

$$a = C_b p_i(m,n) \tag{3}$$

$$b = C_b p_i(m,n) \tag{4}$$

$$Im_F(A,B) = (a.Im_A + b.Im_B)/2 \tag{5}$$

where C_a and C_b are constants defining the fusion mechanism. The combination based on selection of the maximum pixel value at each spatial position to obtain the fused image given by

$$Im_F = \max[\, p_i \, (m,n) \, . \, Im_A \, , p_i \, (m,n) \, . \, Im_B \,] \tag{6}$$

In spatial domain, the fusion rule is very sensitive to random noise. During combination of images from different modalities, minute changes of pixel values sway away the fusion results from actual. Furthermore the variations in the original images lead to spatial inconsistencies [17].

The spatial alignments of features from complementary images suffer from registration errors and posses a limitation in obtaining accurate fusion results. Certain vital details from the fused image are smoothened due to combination resulting from overlap of the images.

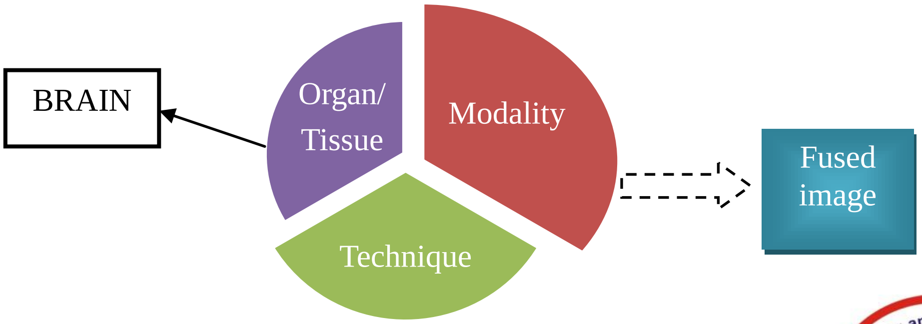

Fig. 2. Image Fusion Component

B. Transform Domain Image Fusion

In medical imaging methods different imaging equipment is used to capture clinical information from anatomical or functional perspective. In transform domain it is better accustomed to attain precision. Prior to fusion the intensity pixel values are altered into the transform domain. These techniques are governed by multiscale principle. Transform domain techniques are broadly classified into Color Space Transform, Karhunen Loeve transform and Multiscale Transforms.

The color space transforms are important when dealing with functional images from medical domain. The chemical compositions of functional modality represents the psychology of the organs and tissues with metabolic changes in pseudo color. Various techniques have been proposed in fusion based on color space models as in Red-Green-Blue (RGB) color space, Intensity hue saturation (IHS) color space, The CIELAB color space, Hue saturation value and (HSV) color space [18]-[19]. In many fusion models the input image is inserted into one color channel of a color space. These are associated with precise description of how the components are to be interpreted based on the application for further processing. The color information is not well depicted clinically in RGB color space. Higher contrast and correlation among colors help exploit the color opponency and better visualize the functional content [20]. Statistical transforms like the Independent component analysis (ICA) or Principal Component Analysis (PCA) produce statistically independent images. These work on correlation among elements to PCA with arbitrary no of bands, PCA permits decomposition of input image based on tailored set function to produce uncorrelated principal components, keeping the highest value of variance foremost. Eigen vectors and eigan values are formed in the directions of eigan vector to preserve disparity and aid dimension reduction. These uncorrelated vectors are sorted as per significance well revealing the internal structures and aid superior diagnosis [21]-[22].

The multi scale transforms are broadly segregated into pyramid transforms, basic wavelet transforms and advance wavelet transforms. Filter subtract decimate pyramid, Laplacian pyramid, morphological pyramid, ratio to low pass pyramid, contrast pyramid and gradient pyramid technique comprise the techniques in pyramid multiscale domain [23]-[25]. The basic wavelets transforms include Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Lifting Wavelet transform (LWT) , Discrete Dyadic Wavelet Transform (DDWT), Dual Tree Complex Wavelet Transform (DTCWT) and Discrete Fractional Wavelet transform. (DFRWT) extended to complex wavelets as Ripplet Transform (RT), Shearlet Transform (ST), Curvelet Transform (CVT), the Contourlet Transform (ConT), Non-subsampled Contourlet Transform (NSCT) [7],[26] and Discrete Fractional Wavelet Transform [27]. The multiscale techniques in transform domain are enlisted in Fig. 3.

Multiscale transforms represents localization of features at proper scale. Image Fusion occurs independently at different orientations and scales with more detailed information being captured at higher scales. It exhibits similarity with Human visual system (HSV) gaining similar neuron response to different spatial frequencies. These transforms better represent the edges, boundaries and discontinuities analogous to human visual system. In provisos of techniques, pyramid transforms comprises of series of original image. With gradually decreasing resolution at each higher level in pyramid structure filtering of the original image is done. The size and resolution are reduced to half from the predecessor in both spatial directions. This difference is maintained to permit perfect reconstruction. During this phase the image is rebuild by up sampling. Pyramids suffer from blocking effects and do not represent the heterogeneous aspects from medical data adequately. The complex wavelets better preserve the image details and attain stability with added phase information. But these advance wavelets further increase the complexity and processing cost for multimodal input images.

The mathematical base for wavelets is fourier transform. Fourier transform has base functions locally oscillating, which are replaced by wavelets. These sinusoidal functions are shifted and scaled version of band pass filters. These are capable of capturing both frequency and time location. These transforms ably represent the input in fractional domain. On translation of mother wavelet, a new fractional wavelet transform (FRWT) is devised, inheriting benefits of wavelets and FRFT [27]

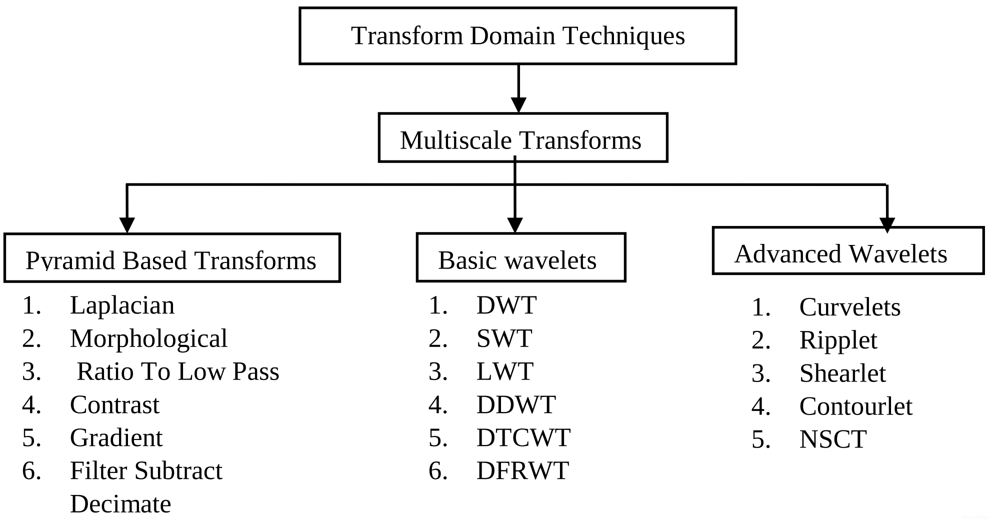

Fig. 3. Multiresolution Transform Domain Image Fusion Techniques

V. MULTISCALE FUSION FRAMEWORK

Multiresolution techniques formulate sequence of bands from decomposition of original image in order to separate information at different resolutions [28]. A categorization of image fusion methods was presented with multi scale decomposition in [2]. Researchers worked on pixel level multi-resolution techniques for extraction of information content at various scales [5]. Comparison of different multi-resolution techniques was performed in literature [29].

The multiscale fusion mechanism in transform domain has two parts the analysis block and the synthesis block. The Multiscale transforms are applied to decompose the image into low and high band coefficients. The decomposition is a combination of up-sampling and down-sampling operations. For perfect reconstruction, the analysis and synthesis filters need to satisfy the perfect reconstruction and anti-aliasing. conditions [8]. The decomposed image coefficients are combined using devised fusion rules. The processing is fed to synthesis block for inverse transform to obtain the final fused image.

There are various fusion rules based on certain permutations defined in literature. The obtained decomposed components can be combined based on certain permutations.

The evaluation of the fusion mechanism includes objective and subjective metrics. Metrics are selected appropriately based on problem definition. Each metric is capable of reading only partials diagnostics aspects as malignant and beguine structural or functional content, pseudo aspects etc. The Subjective assessment is based on the visual image assessment evaluation and validation by a clinical specialist by a group of random evaluators. It depicts the visual quality of the fused image, the content, contrast, and diagnostic perception. The interpretational details from subjective metrics are elaborate and time consuming. These metrics are influenced by individual perception. The objective assessment is labeled into two classes of "with reference" and "without reference". Reference indicates existence of gold standard image for comparison. The reference metrics can well grab content or its relative contribution. The image feature based metric lies under the with reference category. The objective metrics under without reference category includes Information Theory Based metrics and Local feature Based metrics. Most used metrics used in literature for evaluation of image fusion performance are Peak signal to noise ratio, Mean square error, Shannon's Entropy, Structural Similarity Index, Mutual information, Average Gradient and Standard Deviation[30]-[33].

A. Proposed Fusion Method

Neuro medical images are acquired from multiple modalities for the clinical case of Alzheimer's from a online benchmark database of Med Harvard [34]. The medical images are pre processed using adaptive median filter and processed using Mexican hat wavelet. The median filter is a non linear filter to well preserves the edges during processing. It is robust in nature and well removes the large magnitude noise. The algorithm for the proposed mechanism is as devised below

Algorithm for Proposed Fusion

1. Images from anatomical modality IM^1 and functional modality IM^2 are acquired from online Benchmark dataset.
2. The anatomical MRI T2 and functional SPECT are pre-processed using adaptive median filter.
3. The source images are decomposed using multiscale Mexican Hat wavelets.
4. The images are decomposed into approximation band A^b and detail bands D^b coefficients. The Detail D^b has horizontal {h}, vertical {v} and diagonal {d} orientations.
5. Fusion rule for both the bands are adopted as average energy rule (E^A_R) for approximation band and maximum selection rule (M^S_R) for detailed band coefficients.
6. Inverse transform is applied for obtaining the final fused image.
7. Subjective evaluation is performed to validate he findings.

The Mexican hat wavelets is a multiscale transform used to decompose the images into various coefficients at multiple scales. Mother wavelet Mexican hat is selected possessing fitting properties. The mathematical representation is given by

$$\Psi (t) = 2\,\boldsymbol{\pi} 1/4\sqrt{3}\boldsymbol{\sigma}\,(t2\ \sigma 2 - 1)\exp(-t2\ \sigma 2) \qquad (7)$$

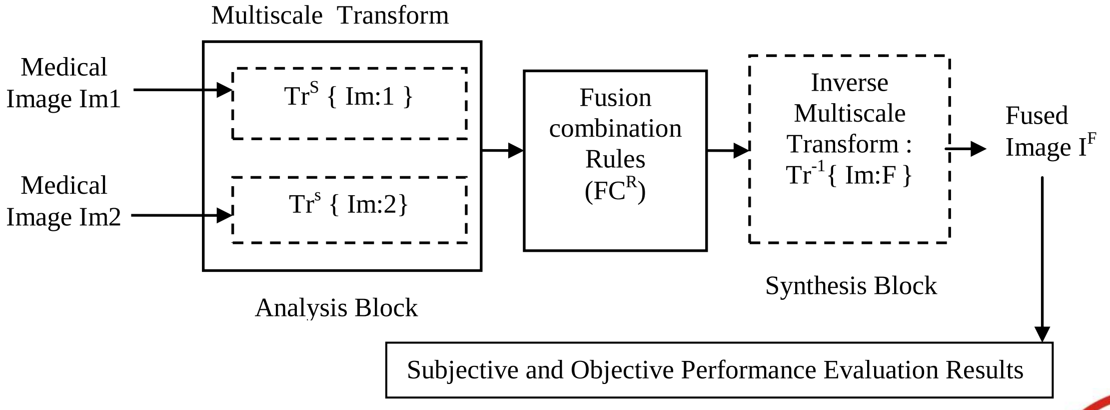

Fig. 4. Multiscale Medical Fusion Method

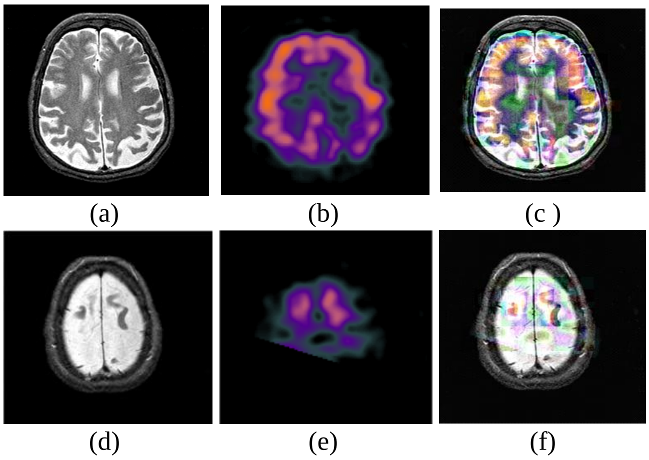

Fig. 5. Results (a) MRI T2 Set 1(b) SPECT Set 1 (c) Set 1 Fused Image (d) MRI T2 Set 2 (e) SPECT Set 2 (f) Set 2 Fused Image.

Mexican-hat wavelet is resultant of the fast decompose of Gaussian function. It provides with horizontal, diagonal and vertical orientations at 0°, 45° and 90°, it provides localization and critical sampling in the fused image. As the mother wavelet is dilated and translated, the low and the detailed component features are precisely located with properties of scarcity and multiresolution structure [35]. The new image coefficients are obtained by combining the coefficients of different decomposed while taking care to retain the source image information. Then the inverse wavelets transform is applied on the merged coefficients to get the resultant fused image using mean fusion rule for low band coefficients and max rule for high band coefficients. The multiscale medical fusion method is as depicted in Fig. 4.

Subjective evaluations propose to validate the proposal. The sample input images and the resultant fused image is depicted in Fig. 5. Each medical modality functions in its own preview to provide precise insight into the tumor, organ, lesions, structural details. When complementary medical images are fused, they provide superior diagnostic information. Higher spatial resolution is achieved, for improved diagnosis.

VI. MODALITY ASPECTS IN IMAGE FUSION

The fusion techniques are devised on various principles in medical domain. The literature is presented with respect to the fusion aspects pertaining to medical modalities as below:

A. Anatomical - Anatomical Modality Fusion

The image scans for fusion of the underlying organ or tissue obtained from different anatomical modalities illustrating the structural aspects are given below.

Reference [36] proposed multiresolution fusion for CT-MR morphological brain images. The hierarchical scheme was used to preserve clinical details irrespective of their scale. Results of the patients undergoing radiotherapy and skull based surgery, claimed to preserve entire illustration of anatomical structures and pathological values. Morphological filters well preserved the local contrast and edges without blurring.

Medical brain images using CT and MRI modality are fused and compared using different wavelet schemes of DWT, Dual Tree Complex Wavelet Transform and Discrete Dyadic Wavelet Transform (DDWT) [37]. Fusion rules with weight coefficients were processed to enhance micro-calcifications, circumscribed masses and lesions. DT-CWT preserved regions better, but micro-ringing artifacts appeared due to discontinuities in edge magnitude. Experiments results indicate improved outputs in comparison to average pixel fusion, PCA and shift invariant DWT.

A combined multispectral approach using MRI T1, T2 and proton density brain images from web database using RDWT technique was proposed [38]. Experiments were conducted to incorporate properties of decomposition technique based on mutual information over non linear registration. The performance value attained higher entropy by preserving spectral content and edges devoid of spatial misrepresentation in comparison to DWT schemes.

A wavelet, to combine MRI, CT brain image coefficients exploiting human visual system (HVS) characteristics was proposed [39]. Visibility and variance fusion rules were adopted for low and high bands respectively. Series of comparisons and experiments were performed on real and simulated medical images. For validation of the fusion results, the process was subjected to window-based consistency verification process.

Ripplet transform type-I was proposed to fuse CT/MRI and T1-MR/MRA multimodal images [40]. Combinations of four different fusion rules were used for each sub band. The performance was evaluated both visually and quantitatively using mutual information, spatial frequency, entropy and standard deviation. The technique performs better and resolved two dimension singularities with more efficient representation.

A method using sub sampled Contourlet transform with pulse coupled neural network was proposed to fuse CT/MRI, T1-MR/ MRA, CT/ T1-MR images [41]. Pulse coupled technique and max fusion rule was used for high and low sub-bands. Evaluation using spatial frequency, mutual information, standard deviation entropy with manual evaluation by a radiologist was done. Discrete wavelet preserved spectral information but spatial characteristics were not well expressed. It is difficult to preserve salient features from loss of fine image details. Improved fusion results were achieved with less distortion.

A 3D medical image denoising mechanism on synthetic brain MR images was proposed. Gaussian noise and rician noise was added using dictionary learning with group sparsity and graph regularization (DL-GSGR) method [42]. The scheme was code effective by incorporating cluster structure into sparsity. The group graph sparsity and graph regularization was combined. In addition a fusion method called GSLDF was proposed to extract salient feature effectively on groups of multimodal images of CT, PD-MR, T2-MR. The performance was evaluated using NSCT, DWT based methods giving superior results.

A combined fusion approach with multiscale transform and sparse representation to overcome the inherent limitations of each of the techniques was proposed [43]. A sliding window mechanism was adopted to divide image into patches and arrange into column vectors. The sparse coefficient is computed based on orthogonal matching pursuit algorithm.

The high pass fusion adopted max-absolute rule and consistency verification. The proposal in medical domain was tested on CT with MRI and Gd-DTPA-MR with MR-T2 pairs. Results were compared with state of art techniques as LP, RP, DWT, DTCWT, CVT, and NSCT.

Hybrid technique with Curvelets and Wavelet was proposed for medical diagnosis based on fusion of CT and MRI [44]. These were broken down into straight lines and curves. The overlapped tiles, profiles and corners fuse well using Curvelets. The authors achieved a high quality fused image with least local errors, testing the proposal in terms of PSNR, MI, entropy, CC and edge association.

A multimodal image fusion techniques using NSCT with activity measure of Shannon entropy for low frequency and directive contrast was proposed in [45]. The author claim that NSCT is unable to attain high quality results in medical domain due to the complicated image structures and do not reveal the coefficient well. The Directive contrast well exemplify the clinical value and help attain more, textures, spatial features and functional content. The evaluation was based on two clinical image sets and four sets of CT, MRI and MR T1, MR T2 brain images.

A Multimodal Image Fusion model was proposed to fuse MRI and CT cerebral infraction suffered patients [46]. The authors fused T1 and DWI sequences using wavelet weighted fusion , pseudo code fusion and alpha channel fusion. Objective evaluation was performed using entropy, mutual information, mean grad and spatial frequency metrics with visible highlights of lesions in cerebral infraction patients. Wavelet weighted fusion attained better entropy, mean grad and spatial frequency. The metric mutual information gave better results with respect to CT images using pseudo color fusion. With respect to MRI alpha channel fusion resulted in superior result.

The image fusion techniques have been discussed from literature pertaining to fusion of anatomical image sets.

B. Functional - Anatomical Modality Fusion

Multiple proposals were devised in multimodal domain with images acquired from anatomical MRI, CT and functional PET, SPECT.

Reference [47] proposed multi-sensor image fusion for MRI and PET images using DWT technique. The activity measure was area based maximum selection fusion rule. A window of 3x3 or 5x5 was devised to construct the decision map. The centre pixel represented the maximum absolute value, indicating presence of dominant features. The decision map was validated by consistency verification process. Anatomic landmarks and their positioning with respect to the functional information were displayed. Standard deviation values validated superiority over Laplacian pyramid. Directional selectivity, compactness and orthogonality reinforced the superior performance even when tested for satellite imaging.

Data fusion using PROCUR system for prostate brancytherapy was implemented [48]. The method involves bi-modality transrectal ultrasound images (TRUS) and MRI. Radioactive seeds were permanently implanted in the gland for localized prostate cancer, treatment based on the intensive use of TRUS imaging. TRUS stage segmentation was improved with a significant impact on treatment planning.

A image fusion tutorial for multiresolution pixel level wavelet decomposition was presented in [49]. Functional PET and MRI brain images were fused, with PET. The spatial resolution of PET is lower than of MRI. The spectral information from multispectral data is distorted. Performed comparative analysis with classical strategies obtains the best results, with filters of size 6, finding a handicap in decomposition level for multiresolution approach.

Reference [50] proposed multiscale variable weight fusion method for MR and SPECT brain images grouping to locate functional changes. The weight matrix is estimated under generalized intensity-hue-saturation framework for preservation of detail features and minimizing the cost function. The manifested variation with global transparency changes from 0 to 1. Clinical cases revealed brain structures and hyper-fusion and quantitative assessment was performed using IHS, PCNN etc to achieve superior results, which can be applied to grey structural and color functional images.

The idea to reduce the tremendous increase in volume of data was advanced to achieve superior results for further processing using multiple modalities[51]. For each decomposition level optimal coefficient set using intra, inter scale consistencies and neighborhood information was selected. A cross scale fusion rule for multiscale decomposition using Laplacian pyramid and alternatively using wavelets for volumetric medical images was proposed. Results reported enhance contrast preservation and demonstrated improved results achieved using cross scale fusion rules.

A multi level local extrema based image fusion technique was proposed using energy and contrast based fusion rules for guided surgery and radiotherapy [52]. Superposition of selected coefficients was performed to obtain the final image in coarse and detail layers. Measures using cumulative MI, spatial frequency and a blind quality index were adopted for evaluation, further indicating that noise effected the detailed layers.

Twelve sets of coronal, normal axial and Alzheimer brain PET and MRI images were fused using IHS and Log Gabor wavelet transform [53]. Maximum fusion rule is used for high band and visibility rule was used for low bands to better preserve the anatomical structures and color changes. The technique outperformed Framelet transform using spectral discrepancy, average gradient, average standard deviation, $Q^{AB/F}$.

A multiscale image fusion approach using multiple medical modalities was proposed [54]. The scheme combined pyramid coefficients using union laplacian pyramid for extracting multiple features. The outline features map is obtained using affine transform and contrast feature map is achieved using kirch scheme and PCA at each scale. The tests were conducted on multiple modalities of MRI-CT, MRI-PET and MRI-SPECT images, The proposal was evaluated using SSIM, PSNR, STD, TMQI metrics.

The multimodal anatomical and functional based fusion techniques in literature are discussed.

VII. DISCUSSION

The organ under study, acquired modalities and the processing technique formulate the clinical fusion analysis aspects and the level of processing complexity. The limitations and future directions in medical fusion domain are hence put forth.

A. Technique Based Fusion Analysis

Various models and aspects in medical image fusion are presented. Pixel level fusion keeps investigative information intact and is the simplest technique. The salient image features are better depicted in transform domain with clarity. Each transform is limited in its ability to rationalize the fusion based in neuro imaging.

The color space models in literature result in compromised output and lack in interactive consideration dealing with multimodal images [55]. The color processing help better quarry the diagnostic information when transformations from one color space to another is plied.

The multiscale transforms are extensively presented from literature. It decomposes the image in various scales where information may coexist at different levels pertaining to its relevance. The pyramid transforms do not provide any directional information and fail to represent the structures efficiently [56]. The segment information is difficult to remain preserved with wavelets, with missing edges [57]. Pre-processing help enhance the performance using wavelets. Wavelets have been used extensively in research with various application areas [27].

Complex wavelets are proposed to offer better results with a higher cost and complexity. Curvelet, Contourlet and NSCT possess anisotropic basis elements. CVT is limited in its ability to represent discontinuities with boundary issues and along the square of the continuously differentiable function. The contourlet transform uses fan filter banks to combine and form a two channel Laplacian pyramid and DFB with multi-direction property. The Laplacian pyramid doesn't signify the contrast and outline well. These fail to provide any directional information [54]. NSCT comprises of two components, the multiscale non subsampled pyramid transform and non subsampled directional filter bank. Suppressing the down sampling from Laplacian pyramid results into a redundant transform. It has high complexity with long fusion time and is a surplus transform.

Fourier transforms do not endure the problems associated with wavelets and complex transforms. An extension to these, the fractional wavelet transform has important properties being a global localized transform. It proficiently provides the representation in time-fractional-frequency domain along with constituting the filter bank as per multiresolution analysis theory. Lot of recent image fusion attempts have been in fractional wavelets.

The studies in literature have moved from single transform processing towards aspects of hybrid techniques and fusion using multiple medical image types in order to exploit the underlying variation amongst modalities and to better captivate the diagnostic value.

In addition to the technique to implement image fusion, there are various other factors affecting fusion results. The fusion is guided by activity measure and match measure. The properties such as filter banks, localization, directionality, shift invariance, anisotropy and sparsity contribute towards the final outcome of the fused image.

B. Medical Modality Based Fusion Analysis

The fusion results are primarily governed by medical aspects of organ and capturing modalities. The multimodal images may be obtained of the same anatomical structure but using varied capturing mechanisms. As per the discussion from literature when anatomical modality is fused with another anatomical modality the complexity level remain controlled with registration errors not prevalently reported in literature. The anatomical structures are well illustrated. The spectral content is preserved but the spatial information is misrepresented with loss of spatial features.

Fusion of images acquired from anatomical and functional modality result in a more complex model. The acquisition principal, interdependencies and diagnostic contents obtained from both the modalities differ. Higher clinical content is visible in the fused images, but these tend to be limited by registration errors due to high levels of inherent variation. The inputs differ in content and resolution due to low similarity. The anatomical landmarks with respect to functional information are better displayed. Higher contrast and better color perception is reported in work when dealing with anatomical and functional modality medical images.

VIII. CONCLUSION

Extensive research has been done in the domain of image fusion. Vital algorithms have been proposed for reinforcing basic diagnostics in the domain of medical image fusion. It is difficult to identify and extract the most relevant clinical aspects and associated features from medical images. These evaluations tend to get limited due to the intricate nature of medical images. The transformations, the modalities under observation , the organ, tissue or lesion and the affecting attributes together formulate the complexity and the intrinsic worth of the fused image.

The work from literature is put forth from multimodal image fusion using multiscale techniques. Mexican hat are good in extracting information from dented signal portions. Accordingly these well suit to fuse the multimodal medical images. It is proposed to implement Mexican Hat wavelets to fuse brain MRI-T2 and SPECT images. These images are from clinical case of Alzheimer's are obtained from a benchmark dataset. The source images are enhanced using adaptive median filtering and decomposed using Mexican hat wavelets. This well exemplifies the performance using visual subjective assessment.

Due to the acclaimed heterogeneity in anatomical and functional modalities, better diagnostic value is attained from fusion results in literature. Fractional wavelet transforms characterize in time-fractional-frequency domain with lot of recent attempt in medical fusion. These aspects need to be further explored. With the identified limitations discussed in literature in terms of diversity in the image modalities, it is learnt that existing techniques and affecting attributes, in neuro imaging have a greater potential of progression.

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