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Robust multimodal fusion network employing novel Empirical Riglit Wavelet Transform for brain images☆

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ABSTRACT

Machine learning is useful for pattern recognition, if allowed access to patient data, it can notice patterns that would be missed by human doctors, which could be used to predict if a person is at risk for a disease that would not have been anticipated by a doctor. In this paper, the authors have proposed an Empirical Riglit Wavelet Transform algorithm. In this algorithm, the authors have fused the filter banks of CT and MR images obtained from Ridgelet and Little wood Empirical Wavelet Transform. Four possible combinations were used for the fusion. Image boundaries were evaluated as performance parameters. With that parameters helps in understanding the small elements and details from given CT and MR images. The objective of this paper is to classify and extract specific patterns in the images using different combinations of CT and MR by fusing them. The proposed algorithm is validated via filter banks obtained for fused CT-MT images using the same techniques.

1. Introduction

Medical image fusion refers to a group of techniques that integrate the information, and complimentary features of two or more imaging modalities to enhance visualization and perception enabling the extraction and classification of vital features that may not be noticeable within each modality [1]. Brain anomalies are categorized depending on the position and form of tissues, which aids in the diagnosis of cancerous or non-cancerous abnormalities [2]. Infections, bleeding, hemorrhage, epilepsy, and cancers are a few examples of brain defects. Anatomical imageries like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET) can aid with this [3]. MRI and CT are among the most widely used radiology modalities for detecting neurodegenerative problems and diagnosing hemorrhage, acute stroke, and inflammation, with the assistance of image data processing. SPECT is also beneficial when there is a need to examine the activity of a few human body parts. A PET scan diagnoses certain health problems like cancer, neurology, and cardiology treatments and assesses the efficacy of a treatment by representing the appearance of an organ and how it functions [4,5]. MRI provides significant soft tissue visibility, contrast, and spatial resolution while avoiding the use of toxic ionized radiation. Because of these properties, MRI has become a valuable method in clinical and surgical settings for diagnosing tumors. Whereas, CT scans are most often used to distinguish between hemorrhage due to profuse bleeding and stroke when blood supply gets blocked in the brain. The CT scans enable vital details with faster scanning, making them more useful for detecting hemorrhage and stroke. Note that in other modalities, for example, MR, a single series can contain multiple planes of reconstruction (e.g., multiplanar localizers) but this is not the case in CT. The four commonly used modalities are T1-weighted (T1), T2-weighted (T2), T1-weighted with contrast enhancement (T1-ce), and Fluid Attenuated Inversion Recovery (FLAIR) [6] as shown in Fig. 1.

T1 and T2 are known as relaxation times measured in milliseconds, and explain how the brain reacts to electromagnetic energy. When having an MRI, the scanner sends radiofrequency waves to the brain. The energy of this signal is absorbed by brain tissue increasing its "magnetic momentum". Then when the radio frequency signal stops, the scan measures how long it takes for the tissue to give back this energy, or to "relax" which explains T1. In contrast, T2 relaxation measures the time it takes for the magnetic momentum to lose coherence, after the RF signal has ceased, in a plane that is transversal to the main magnetic field of the scanner (which is head to toe) [5]. The time to give back energy (T1) and the time to lose coherence (T2) are biomarkers that

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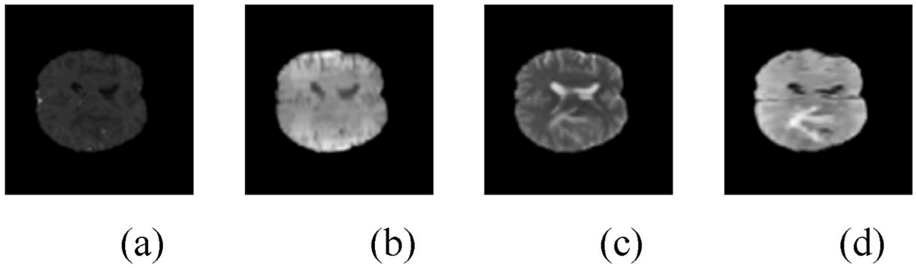


Fig. 1. MR images with different slices (a) T1ce (b) T1 (c) T2 (d) Flair.

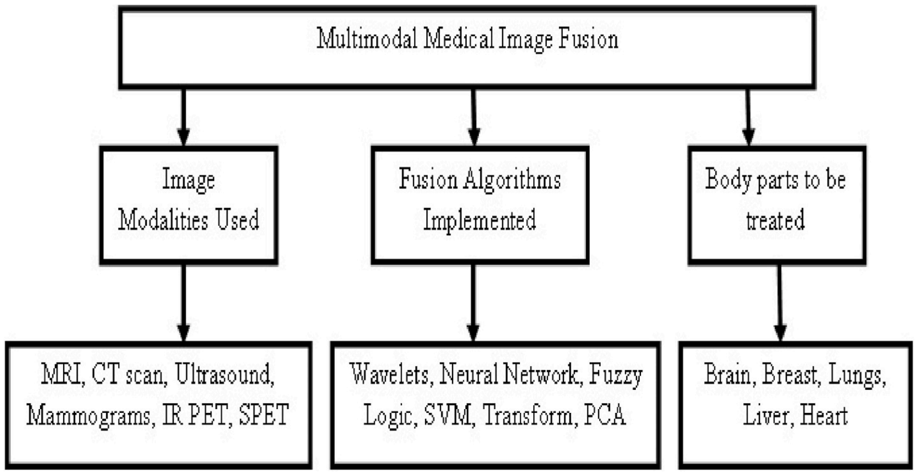


Fig. 2. Multi-modal Medical Image fusion.

characterize healthy tissue. Therefore any abnormal values can be either identified by visual inspection by a radiologist) or calculated using computer analysis. FLAIR is a particular type of medical image that is used to eliminate cerebrospinal fluid from the image.

Image processing is used for analyzing and manipulating images to improve their quality. Image processing explains the exact quality of the image in form of pixels and its co-ordinate. Medical image fusion is the most common way of blending various pictures from numerous imaging modalities to acquire an intertwined picture with a lot of data for expanding the clinical materialness of clinical pictures. Henceforth, fusion algorithms rely upon 3 principal factors: imaging methodology, various parts of the body, and fusion algorithm as shown in Fig. 2.

Image Fusion methods can be classified as spatial-based and frequency-based strategies as explained in Table 1. The spatial strategy manages pixel operations of the information pictures where pixels values are controlled to accomplish a reasonable result.

1.1. Literature review

A few exploration works have been started and done over the most recent twenty years in the field of clinical picture combination. Different logical diaries have been distributed in such a manner. We audit a couple concerning their huge commitments. In Ref. [1] synopsis of the much comprehensively used pixel-level picture combination techniques and comments about the general characteristics and downside sare presented. Explicit pressure was set on multiscale-based strategies. Barely any executions gauge functional for pixel-level picture blends was also tended to. Singh and Khare [2] proposed a Repetitive Wavelet change (RWT and R-DWT) for the picture combination technique in the multimodal clinical pictures. In their technique, they found that the shift-invariance of the R-DWT produces quality picture combinations on CT, MRI, and PET clinical pictures, and the outcomes were drawn utilizing shared data and strength measurements [3]. An upgraded multi-modality clinical picture combination was proposed by Bhateja et al. [4], that additionally involved a multiscale joint disintegration system (MJDF) and shearing channel (SF). The last combination results were acquired by directional coefficients and the union of the intertwined low-pass layers, showing further developed picture combinations in the clinical space. As indicated by Bhatnagar et al. [5], strategies for picture combination are for the most part dependent on a multi-goal examination (MRA) that is fit for decaying pictures into different areas at assorted measures. In their paper, they presented a combination framework because of wavelet change that melded clinical CT and MRI pictures as per the MRA norms, utilizing difference and modulus maxima as two quality significant parts. Their tests were generally uplifting and created outcomes for picture combinations that were quantitatively and quantitatively gotten to the next level. In Ref. [6] uniform-based picture combination calculation was introduced where the information pictures were partitioned into blocks. The perfection of each square is registered using the difference between the squares. Also, unique pixel-based calculations were tried and Peak Signal to Noise Ratio (PSNR) is used as an evaluation parameter. Nirmala et al. [7] executed the isolated highlights in ICA and DT-CWT space. Likewise, spatial spaces were used to improve the exhibition of the mixed methodology. Desale et al. [8] enlightened that picture combination is a technique that joins the basic information from different pictures in light of their separate class, into an individual melded picture, wherein the resultant result picture will be more educational and sheer than any of the

Table 1
Different fusion techniques.

Spatial Based Techniques		Frequency Domain	
Simple Average	A combination is used to consolidate images by averaging pixels [4].	Laplacian Pyramid Fusion Technique	It utilizes the arrangement & Gaussian pyramid for multi-goal investigation for picture combination.
Minimum Technique	It chooses the most reduced power worth of the pixels from pictures and produced a fused image [2]. It is utilized for hazier pictures [5].	Discrete Transform Fusion	Discrete change-based combinations take composite pictures. RGB parts of the pictures are isolated along these lines, discrete change on pictures is applied and later the normal of various pictures is registered an opposite charge is applied to get the fused image.
Maximum Technique	It chooses the pixel's upside of focused energy from the image resulting inan intertwined picture [6].	Discrete Cosine Transform (DCT)	In picture combination, DCT has different types namelyDCT magnitude (DCTma), DCT energy (DCTe), DCT contrast highest (DCTch), DCT contrast measure (DCTcm), and DCT normal (DCTav) [7]. This method doesn't give a superior outcome with the size of the square under 8×8. In the DCT area, DCTav is a direct &essential technique for picture combination. DCTe and DCTma techniques performed well in picture combination. This procedure is direct and utilized in verifiable time applications.
Max–Min Technique	It chooses the averaging of the pixels' littlest and biggest from the image that results in a fused image.	Discrete Wavelet Transform (DWT)	DWT technique divides pictures into different high and low-recurrence groups. This technique limited the ghostly bending in the resultant intertwined pictures by creating the great sign to clamor proportion with a less spatial goal when contrasted with the pixel-based strategy. Wavelet combination performed better than the spatial area combination strategy concerning limiting the shading mutilations [3].
Simple Block Replace Technique	It adds all pictures of pixel values and takes the square of it. It depends on pixel adjoining block pictures.	Stationary Wavelet Transform (SWT) Method	DWT technique has an impediment to interpretation invariance and SWT conquers this issue [8]. It gives an improved investigation of picture realities.
Weighted Averaging Technique	It allocated the loads to each pixel in the source pictures. The resultant picture is delivered by the weighted amount of each pixel esteem in source pictures. This technique further develops the location unwavering quality of the resulting picture.	Curvelet Transform Method	SWT has a superior trademark in time-recurrence. It can accomplish well outcome for concocting smoothly. The second-era Curvelet is a new multi-scale change.
Hue Intensity Saturation (HIS)	An essential combination shading procedure changed over the Red-Green-Blue picture into HIS parts and later power levels are separated with a panchromatic (PAN) picture.		
Brovey Transform Method	It is a direct method for consolidating information from more than one sensor. It defeats the three band issues. It normalized the three multispectral groups utilized for RGB to affix the power and splendor into the picture [9].		
Principal Component Analysis (PCA)	It is a factual technique based on symmetrical change for changing over a bunch of perceptions of a conceivably related variable into head parts that are set of directly uncorrelated factors. The principal downside of PCA is otherworldly debasement and shading contortion.		

information pictures. Their paper explains the ideas, and assessments of DCT, PCA, and DWT-based picture combination schedules. In Ref. [9] the specialists suggested a staggered combination of clinical pictures using wavelet change. In his proposition, the locales are fragmented and utilized as essential highlights for the portrayal and recovery of information amid pictures and a district contest-based level set division as opposed to wavelet change. Kusuma and Murthy [10] utilized coordinated various information sources including multimodal clinical pictures, presuming that picture combination sturdily further develops the data content and unwavering quality. Practically intertwined multimodal pictures ought to be liberated from any antiquities. In addition, it should not wipe out any relevant data from the first information. In their paper, another method called Shearlet Transform (ST) is utilized on pictures by utilizing the Singular Value Decomposition (SVD) for the improvement of picture data substance. In Ref. [11] the multimodal pictures can be intertwined to various levels prompting various mixes conceivable to be examined. They made sense of the strategies that are associated with clinical picture combination connected with cardiovascular pictures using discrete wavelet change, showing the possibilities of utilization of multimodal strategies in the useable investigation, pre-careful preparation, and conclusion processes. In Ref. [12], a combination of elements like edges and limits of information pictures has been done which is excerpted using maxima basis in wavelet change. The portrayed technique gives better outcomes for picture combination, as data subtleties, picture difference, and normal data content of intertwined pictures are gotten to the next level. In Ref. [13],a multimodal combination of clinical pictures using the Redundant DWT has been examined. Cui et al. [14] utilized both ICA and wavelets change for the combination of CT pictures. In this technique, discrete wavelet change was utilized to break down each picture. A short time later, ICA was utilized to investigate the wavelet coefficients in different degrees of ICA. Finally, the combination of CT pictures is done that gives more point-by-point data about delicate tissues like veins and muscles. In Ref. [15], input clinical pictures are intertwined because of the curvelet and wavelet Transforms using different combination strategies talked about in the review. The MR& CT input pictures are enrolled and curvelet& wavelet changes are applied to them. The results are figured using particular combination estimating strategies. Abhinav Krishn et al. [16] did a clinical picture combination to blend correlative indicative substance with the assistance of a wavelet change and PCA technique. Nonetheless, in clinical angles, the clinical pictures have phenomenal properties that fluctuate from one picture to another. These characteristics are the heterogeneity of pictures. Different investigations have attempted to execute various calculations with the end goal of their particular strategies and accomplishments in clinical picture combination. Fajaryati et al., 2020, explained multi-focus picture mix infers merging an absolutely clear picture with a lot of photos of a comparable arena and under comparative imaging circumstances along with varied focus centers. To attain a sensible picture which contains entire relevant things around there, the multi-focus picture blend computation is proposed subject to wavelet change. First thing, the multi-centered pictures had been crumbled because of wavelet change. Likewise, these wavelet coefficients of an approximant as well as comprehensive sub-pictures have been merged independently subject to the blend policy.

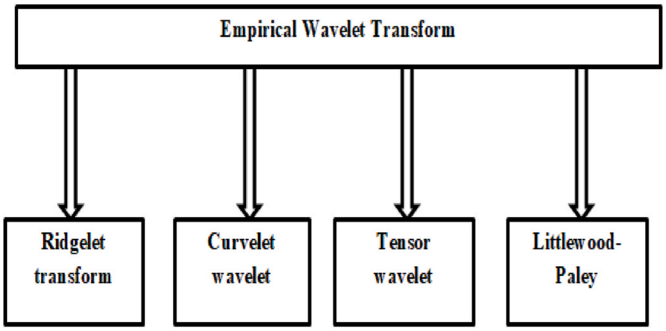


Fig. 3. Types of EWT techniques.

Ultimately, the interlaced picture had been gotten by utilizing the contrary wavelet change. Among these, for the low-repeat as well as high-repeat coefficients, we introduce a blend rule subject to the weighted extents and these weighted points with the enriched edge disclosure chairman. These preliminary outcomes address that proposed computation has been amazing to hold the ordered pictures [17].

Vidhya et al., 2019, studied the combination of pictures is the way toward consolidating at least two pictures into a solitary picture holding significant highlights from each. Combination is a significant procedure inside numerous dissimilar fields like far off detecting, advanced mechanics and clinical applications. Wavelet based combination procedures have been sensibly powerful in joining perceptually significant picture highlights. Shift invariance of the wavelet change is significant in guaranteeing vigorous sub-band combination. In this manner, the unusual use of the shift invariant as well as directionally particular Dual Tree Complex Wavelet Transform (DT-CWT) to picture combination has been presently presented [18].

Mahyoub et al., 2019, reported about the image blend subject to the wavelet change and examination of picture mix major head, methodology and benefit. The essential objective of the picture blend is to solidify information received from various images of a comparable picture reliant upon a particular estimation; the delayed consequence of picture mix is another consequent that can be more appropriate for human as well as machine. This present day's image blend advancement has been for the most part applied in various fields including distant distinguishing, automata affirmation, PC vision, clinical picture dealing with. This report designs and comprehends the strategy for picture computation which relies upon wavelet change [19].

D. Hemasree et al., 2019, An Image blend is the headway of amalgamating in any event two image of essential brand name to outline a lone picture which secures all of the crucial features of interesting picture. Currently lot of work will be executed on the area of picture mix and moreover used in numerous applications like clinical imaging, multi spectra sensor picture entwining, etc. For interweaving the image, a variety of systems have been proposed by distinct makers, for instance, the wavelet change, IHS and PCA put together methods thus with respect to in this paper composing of an image blend with the wavelet change has been inspected with advantages and blames [10].

In this paper, the author proposed the Empirical Riglit Wavelet Transform algorithm. In this algorithm, the fusion technique is used where filter banks of EWT little wood and Ridgelet were fused for the CT and MR images of the brain. The novelty of the paper is the fusion of filter banks of two types of EWT techniques. Four possible filter banks were fused (a) CT and MR ridgelet, (b) CT and MR Little wood, (c) CT little wood and MR ridgelet, and (d) CT ridgelet and MR little wood. Image boundaries were evaluated and the results are validated on the fused CT-MR images. All these have one single goal to help medical image processing be a better diagnostic tool.

The paper comprises section 2 explains the methodology of how 2D EWT filter banks were fused, and section 3 shows results and discussion of different fused filter banks & classification using machine learning techniques. Section 4 explains the concluding remarks followed by future work.

2. Methodology

EWT breaks down a signal or a picture on wavelet tight approaches which are constructed adaptively. The vital benefit of this experimental methodology is to hold together some data that ought to be spitted on account of dyadic channels [17,18]. In 2D, tensor wavelet, a 2D Littlewood-Paley, Ridgelet, and Curveletare different types as shown in Fig. 3. In EWT, a bunch of wavelets is worked by adaption from the handled sign.

In this paper, the authors have proposed the Empirical Riglit Wavelet Transform algorithm (ELRWT) a fusion technique using EWT little wood Paley and Ridgelet as shown in Fig. 4.

Input MR and CT Brain images are considered which were pre-processed and the detection method is applied [19–22]. Initially, MR & CT images were pre-processed. Filter banks of Littlewood-Paley and Ridgelet are fused of the same patient for(a) CT and MRridgelet, (b) CT and MR Little wood, c) CT little wood and MR ridgelet and d) CTridgelet and MR little wood. The filter banks are fused [23–26] using the discrete wavelet transform (DWT) techniques as explained in Algorithm 1. Image boundaries were evaluated. Algorithm2 explains the proposed Empirical Riglit Wavelet Transform algorithm. Later the results were validated on the fused CT-MR images.

Algorithm 1. Algorithm of image fusion for two different multimodal images.

Input: Two different image modalities

Outputs: Fused image

Start

Step 1 Read two different image modalities.

Step 2 Resizingthe input images

Step 3 Computation of two dimensions using WT.

Step 4 Applying the Fusion rule.

Step 5 Inverse discrete wavelet transforms

Algorithm 2. Empirical Riglit Wavelet Transform algorithm

Input : Images $f(x)$, Number of filters : N

Outputs: Reconstructed Signals

Start

Step 1 Select the input image (CT image and MR image of same patient or CT-MR fused))

Step 2 Apply preprocessing technique

Step 3 Selection of the regularization to prevent statistical overfitting in a predictive model

Step 4 Selection of the detection method (detection on the log spectrum)

Step 5 Apply Littlewood-Paley and RidgeletEWT on each image.

Step 6 Computation of the Pseudo-Polar FFT$F_P(h)(\theta_i, |\omega|)$ and take the average concerningθ_i:

$$\widetilde{F_P(|\omega|)} = \frac{1}{N_\theta}\sum_{i=0}^{N_\theta-1} |F_P(h)(\theta_i, |\omega|)|$$

whereθ_i is i_{th}Fourier boundary angle ϵ [0,π] and N is the number of filter segments.$\widetilde{F_P(|\omega|)}$is the average Pseudo-Polar FFT.

Step 7 Fourier boundary detection $\widetilde{F_P(|\omega|)}$is done to build Filter bank B(little wood)

$$B_{little} = \{\phi_1(x), \{\psi_n(x)\}_{n=1}^{N-1}\}$$

where $\phi_1(x)$and$\psi_n(x)$are filter bank parameters.

Step 8 Fourier boundary detection $\widetilde{F_P(|\omega|)}$is done to build Filter bank B(ridgelet)

$$B_{ridge} = \{\phi_1(x), \{\rho_n(x)\}_{n=1}^{N-1}\}$$

where $\phi_1(x)$and$\rho_n(x)$are filter bank parameters.

Step 9 Apply fusion on different filter banks

Step 10 Pass extracted channel image $h(x)$from the designed filter bank B to obtain the sub-band images $W_g^{eLP}(n, x)$ where $W_g^{eLP}(n, x)$ is n^{th} EWT Littlewood Paley component and $W_g^{er}(n, \theta, x)$.where$W_g^{er}(n, \theta, x)$is n^{th} EWT Ridgelet component.

Step 11 Evaluation of image boundaries.

Step 12 Validation of results on fused CT-MR image.

END

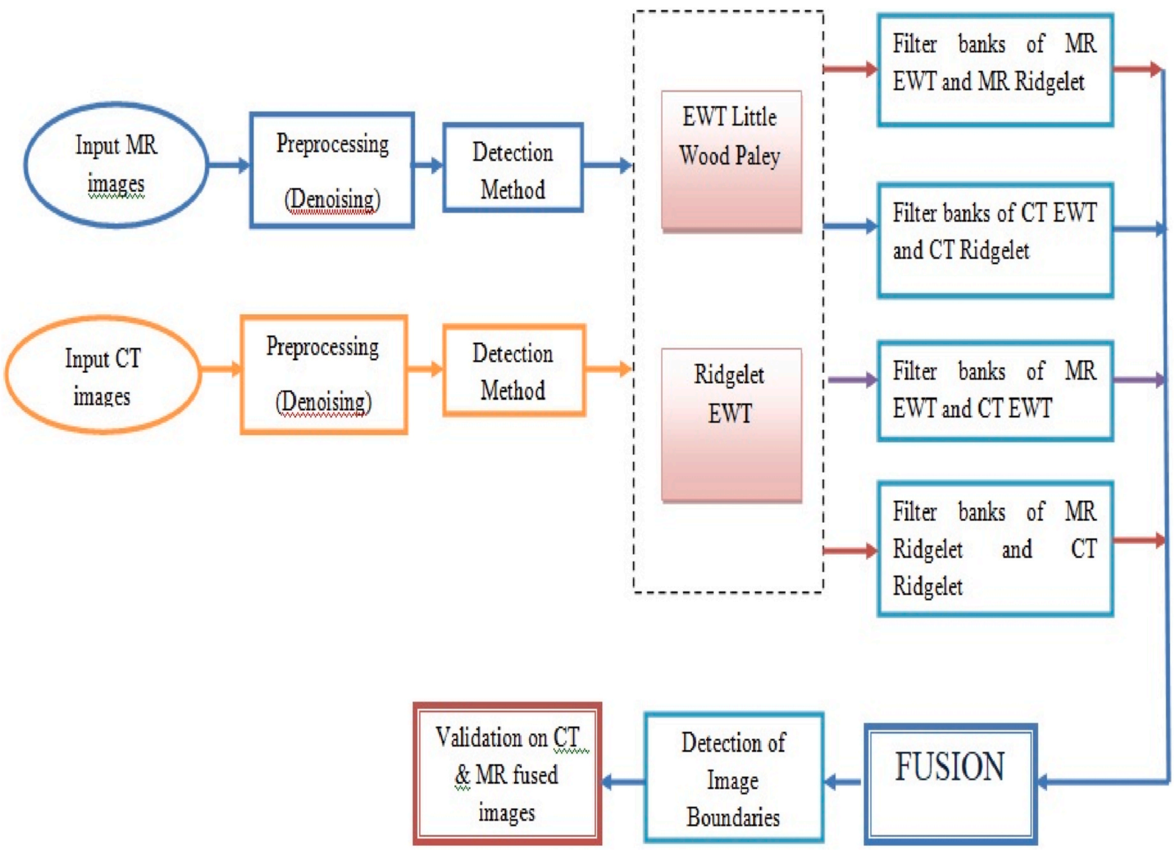


Fig. 4. Empirical Riglit Wavelet Transform algorithm.

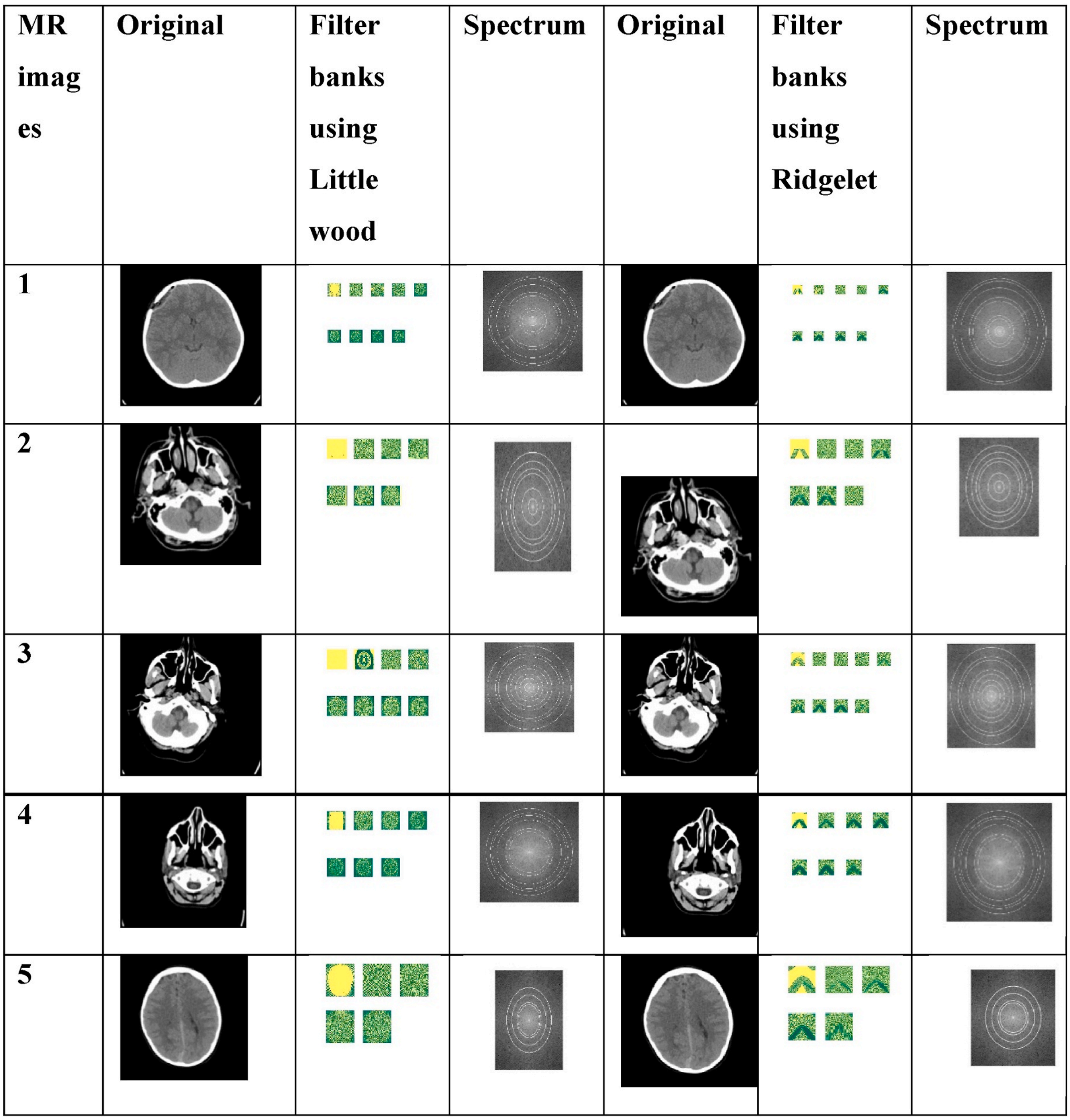


Fig. 5. Filter banks of MR images using Little wood and Ridgelet.

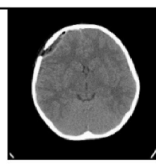
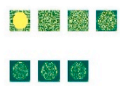
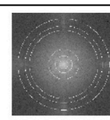
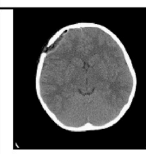
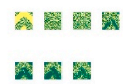
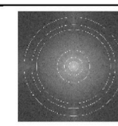
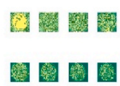
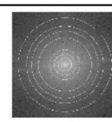
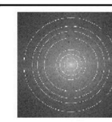
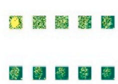
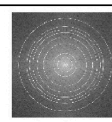
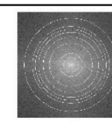
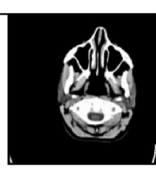
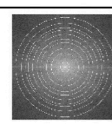
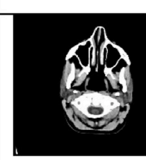
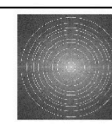
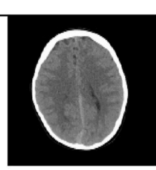
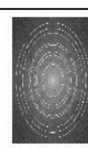
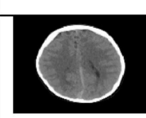
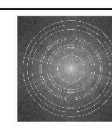
CT images	Original	Filter banks using Little wood	Spectrum	Original	Filter banks using Ridgelet	Spectrum
1						
2						
3						
4						
5						

Fig. 6. Filter banks of CT images using Little wood and Ridgelet.

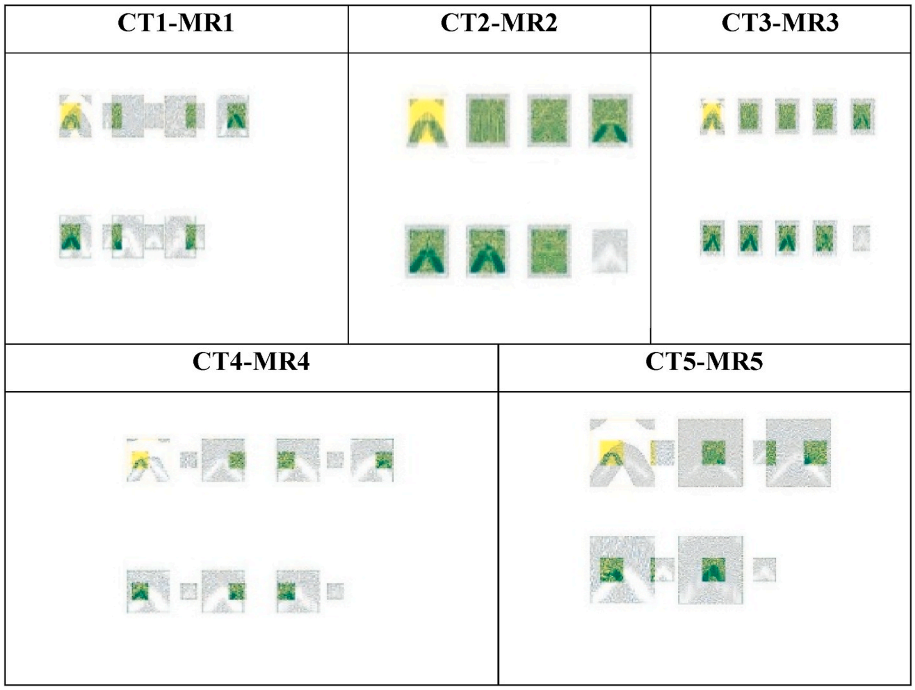


Fig. 7. Fused Filter bank of CT & MR image using Ridgelet.

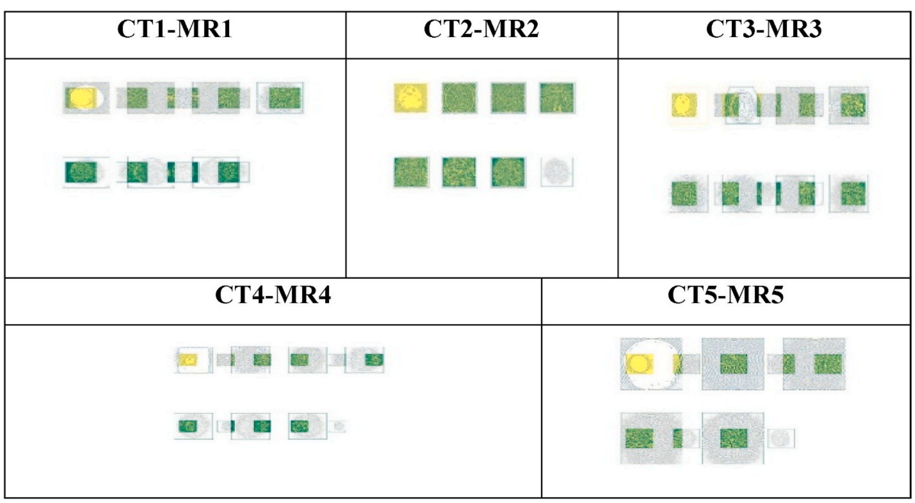


Fig. 8. Fused Filter bank of CT & MR image using Little wood.

3. Results and discussion

In this paper, the authors have fused the filter bank of various CT and MR images [27–30] using little wood and Ridgelet techniques. The pre-processing is done using Top-hat transform. All the simulations were performed MATLAB 2019b software. Figs. 5 and 6 show the Filter banks of MR and CT images using the little wood and Ridgelet technique respectively.

The filter banks were fused for the four different combinations i.e. (a) CT and MR ridgelet, (b) CT and MR Little wood, (c) CT little wood and MR ridgelet, and (d) CT ridgelet and MR little wood. Fig. 7 shows the fused [31–34] filter-bank result of CT and MR ridgelet, Fig. 8 shows the fused results of CT and MR Little wood, Fig. 9 shows the result of CT little wood and MR ridgelet and Fig. 10 shows the results of CT ridgelet and MR little wood. The image boundaries of all five possible combinations of fused filter banks are evaluated and tabulated in Table 2.

Table 2 tabulated the image boundaries of CT Ridgelet, MR Ridgelet, CT Little wood, MR little wood, CT and MR using Little-wood, CT and MR using ridgelet, CT Little wood, and MR ridgelet, CT ridgelet, and MR Little Wood. It has been observed that the image boundaries are almost similar for every case using different techniques. The results are validated on the fused CT-MR image. Fig. 11 shows the fused CT-MR images and their filter banks using the little wood and Ridgelet technique Image boundaries are evaluated and tabulated in Table 3.Table 3 tabulates the image boundaries for fused CT-MR images.

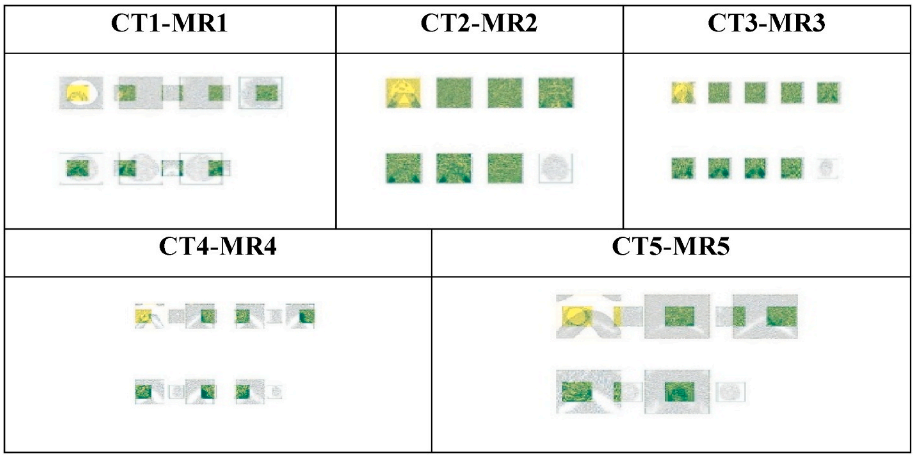


Fig. 9. Fused Filter bank of CT little wood and MR ridgelet.

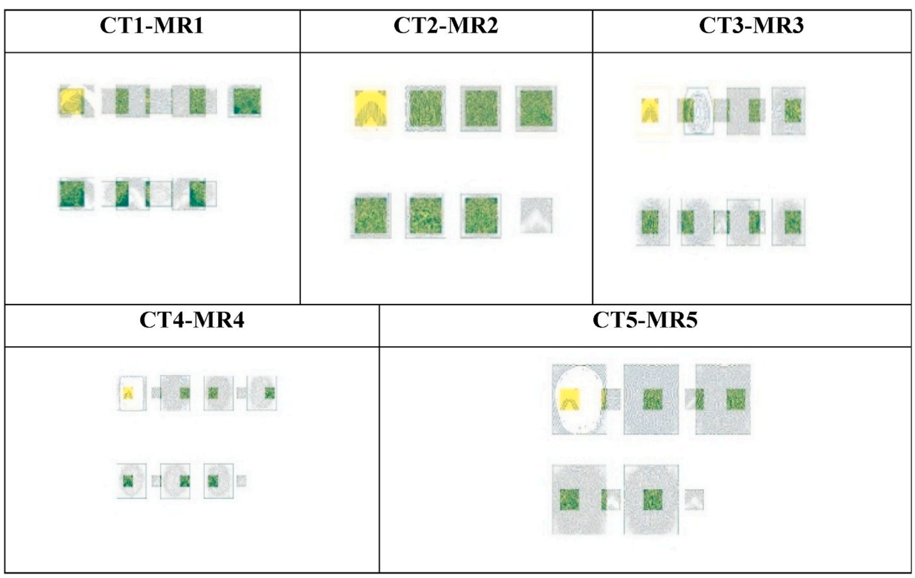


Fig. 10. Fused Filter bank of CTridgelet and MR little wood.

4. Conclusion and future work

Image processing is used for analyzing and manipulating images to improve their quality. Image processing let us know about exact quality of the image just by giving some important data that is pixel and co-ordinate of the image. Medical image fusion is the most common way of blending various pictures from numerous imaging modalities to acquire an intertwined picture with a lot of data for expanding the clinical materialness of clinical pictures. In this paper, the authors have used CT & MR images of the brain considered from the online dataset considering EWT. Tophat technique is used for preprocessing while little wood and Ridgelet techniques are used for the processing. In this paper the author have used the combination of CT-MR with two types of ewt techniques but with less dataset of images. In this algorithm, the fusion technique is used where filter banks of EWT little wood and Ridgelet were fused for the CT and MR images considering four possible combinations (a) CT and MR ridgelet, (b) CT and MR Little wood, (c) CT little wood and MR ridgelet and (d) CT ridgelet and MR little wood. Image boundaries were evaluated and the results are validated on the fused CT-MR images. In the future author will try to classify the data. And for future purposes, the author will use different preprocessing and denoising techniques for better results and also conclude a comparative study.

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Availability of data and material

Not applicable.

Code availability

Not applicable.

Table 2
Image boundaries of CT-MR images.

CT					MR					CT					MR				
Ridgelet										Little wood									
0.265	0.404	0.141	0.288	0.803	0.263	0.389	0.323	1.288	0.995	0.265	0.404	0.141	0.288	0.803	0.263	0.389	0.323	1.288	0.995
0.517	0.644	0.441	0.816	1.264	0.668	0.903	0.664	1.497	1.150	0.517	0.644	0.441	0.816	1.264	0.668	0.903	0.664	1.497	1.150
0.923	0.895	0.687	1.122	1.417	0.846	1.640	0.960	2.030	1.633	0.923	0.895	0.687	1.122	1.417	0.846	1.640	0.960	2.030	1.633
2.097	1.601	1.288	1.472	1.754	1.607	1.876	1.328	2.325	2.115	2.097	1.601	1.288	1.472	1.754	1.607	1.876	1.328	2.325	2.115
2.373	2.006	1.656	1.681	1.859	1.816	2.251	1.606	2.466		2.373	2.006	1.656	1.681	1.859	1.816	2.251	1.606	2.466	
2.808	2.313	1.938	1.957	2.350	2.319	2.696	2.190	2.748		2.808	2.313	1.938	1.957	2.350	2.319	2.696	2.190	2.748	
	2.816	2.123	2.221	2.595	2.681		2.405				2.816	2.123	2.221	2.595	2.681		2.405		
		2.294	2.362	2.871	2.816		2.962					2.294	2.362	2.871	2.816		2.962		
		2.785	2.632									2.785	2.632						
			2.982										**2.982**						
CT and MR using Little-wood					**CT and MR using ridgelet**					**CT Little wood and MR ridgelet**					**CT ridgelet and MR Little Wood**				
0.65	0.90	0.74	0.61	1.20	1.55	0.75	1.00	1.36	1.22	1.32	0.78	0.61	0.72	1.06	0.70	0.87	1.26	1.09	0.74
0.93	1.14	1.04	1.09	1.58	1.77	1.17	1.40	1.55	1.55	1.63	1.22	0.96	1.31	1.44	1.00	1.15	1.59	1.38	1.20
1.12	1.55	1.22	1.44	1.88	2.08	1.45	1.70	1.86	1.68	2.07	1.94	1.17	1.59	1.72	1.50	1.63	1.95	1.59	1.58
1.27	1.80	1.81	1.90	2.25	2.69	2.00	2.03	2.28	1.90	2.23	2.35	1.44	1.76	2.18	1.90	1.77	2.26	1.88	1.87
1.46	1.90	2.07	2.21	2.57	2.88	2.18	2.30	2.88	2.13	2.55	2.51	1.68	1.91	2.65	2.31	2.01	2.59	1.99	2.36
1.59	2.06	2.19	2.49	2.77		2.70	2.77		2.84	2.75	2.69	2.09	2.17	2.86	2.52	2.38	2.92	2.26	2.51
1.80	2.38	2.45	2.85	2.88		2.96					2.93	2.27	2.53		2.69	2.83		2.47	2.94
2.08	2.78	2.93	2.89									2.50	2.77					2.63	
2.41												2.54						2.86	
2.54												2.84						2.97	
2.93																			

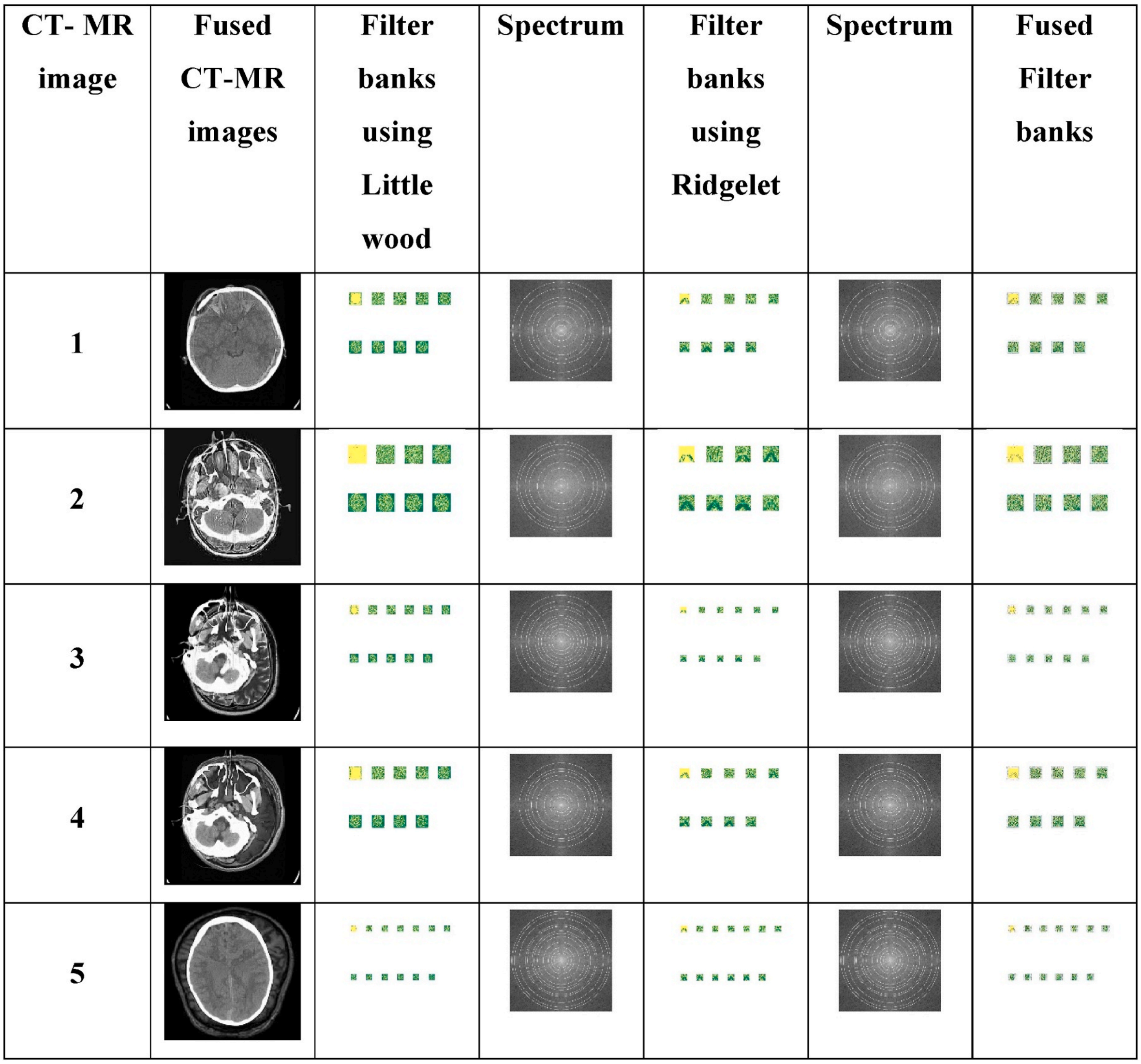

Fig. 11. Filter bank and spectrum of CT-MR fused image.

Table 3
Image boundaries of fused CT-MR images.

Fused Image Boundaries				
Filter bank 1	Filter bank 2	Filter bank 3	Filter bank 4	Filter bank 5
1.19	1.37	0.79	0.74	0.84
1.53	1.81	1.23	1.05	1.23
2.30	2.25	1.46	1.18	1.43
2.42	2.40	1.85	1.32	1.91
2.78	2.66	2.21	1.57	2.13
	2.84	2.45	1.79	2.34
		2.59	1.89	2.76
		2.75	2.27	2.96
		2.99	2.44	
			2.75	

CRediT authorship contribution statement

Anupama Jamwal: Idea, Conceptualization, and Implementation. **Shruti Jain:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Not applicable.

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