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Survey Paper on Multimodal Brain Image Fusion on Improved Rolling Guidance Filter and Wiener Filter

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Abstract:

Multimodal brain image fusion is a technique used in medical imaging to combine information from multiple imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) to produce a more complete and accurate image of the brain. This technique is particularly useful for diagnosing and monitoring neurological diseases such as brain tumors and Alzheimer's disease.

In this abstract, we review recent advances in multimodal brain image fusion, including image registration, feature extraction, and fusion methods. We also discuss the challenges associated with this technique, such as data heterogeneity, spatial and intensity differences, and noise. Finally, we explore the potential future directions for multimodal brain image fusion, including the use of deep learning and artificial intelligence to automate the process and improve the accuracy of diagnosis and treatment planning.

Multimodal brain image fusion is a process of combining and registering multiple brain images acquired from different imaging modalities to generate a single enhanced image. This technique has the potential to provide more comprehensive and accurate information to clinicians for diagnosis and treatment of neurological disorders.

In this review summary, We summarise the recent advancements in multimodal brain image fusion techniques and discuss their advantages and limitations. We also highlight the challenges and future research directions in this field. My findings suggest that multimodal brain image fusion has great potential to improve clinical outcomes and can play a vital role in the early detection and treatment of

neurological disorders. However, further research is needed to optimise fusion algorithms and develop standardised protocols for clinical use.

Keywords — **IRGF , CT , MRI , GF , GGF**

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I. INTRODUCTION

Multimodal brain imaging is a powerful technique that combines multiple imaging modalities to provide a comprehensive view of brain structure and function. However, each modality has its limitations in providing a complete picture of the brain. Multimodal image fusion techniquesaim to combine complementary information from different modalities to improve the accuracy and reliability of medical imaging for the diagnosis and treatment of various brain disorders.

One popular method for multimodal image fusion is based on the improved rolling guidance filter (IRGF) and Wiener filter. The IRGF is a non-linear filter that effectively removes noise and preserves edges in an image, while the Wiener filter is a linear filter that improves image quality by reducing the effects of noise. The combination of these two filters has been shown to be effective in improving the quality of multimodal brain images (1)(2)(3).

In recent years, several researchers have proposed different models for multimodal brain image fusion based on the IRGF and Wiener filter. These models differ in the modifications made to the original technique, including the addition of new components, parameter tuning, and the use of different optimization algorithms. The effectiveness of these models has been evaluated using different metrics, such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mutual information.

II. EXISTING MODELS

2.1 AN IMAGE FUSION ALGORITHM BASED ON IMPROVED RGF AND VISUAL SALIENCY MAP

The experiment demonstrates that the proposed method shows better comprehensive performance and obtains better results in fusion for infrared and visible light images and medical images compared to the contrast method Based on Laplacian Pyramid transform (4) and wavelet transforms (5), the early multiscale fusion method combines with different fusion rules or optimizes the decomposition method to improve the fusion effect or speed. However, the algorithm based on the above two methods has theoretical defects, i.e., the Pyramid decomposition-based method has no translation invariance but excessive redundant information, whereas the wavelet variation-based method has no translation invariance and few directions of decomposition. Therefore, the derived algorithm from the above methods obtains an unclear target edge of the fused image and a bad overall effect.

2.2 A Survey on Multi-Scale Medical images Fusion Techniques: Brain Diseases

There are huge applications of the image fusion techniques in the historical analysis and medical diagnostics, multimodal image fusion is another method used for medical imaging applications. By multi modal means images with different modalities: CT (6). MRI(7,8) PET (9,10), SPECT (11,12) scan. The prime goal of the multimodal fusion is to decrease the amount of data for emphasizing on the band specific information. For example, Alzheimer's disease was founded 100 years ago. But during the past 30 years, only researches have been developing in its risk factors, symptoms, causes, and treatments.

Nowadays throughout the world, more than 35 million people have been affected by Alzheimer's disease with its various stages (13,14).

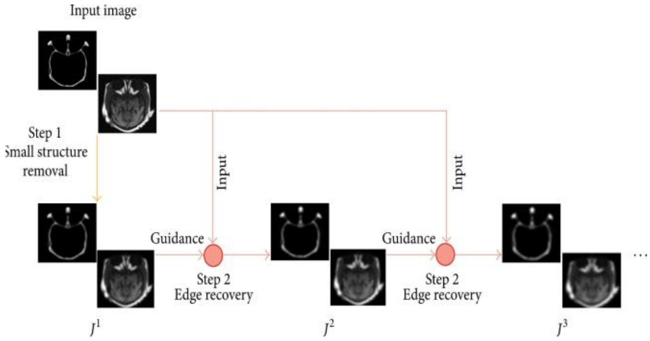
2.2 Medical Image Fusion Based on Rolling Guidance Filter and Spiking Cortical Model

Medical image fusion plays an important role in diagnosis and treatment of diseases such as image-guided radiotherapy and surgery. Although numerous medical image fusion methods have been proposed, most of these approaches are sensitive to the noise and usually lead to fusion image distortion, and image information loss. Furthermore, they lack universality when dealing with different kinds of medical images. In this paper, we propose a new medical image fusion to overcome the aforementioned issues of the existing methods. It is achieved by combining with rolling guidance filter (RGF) and spiking cortical model (SCM). Firstly, saliency of medical images can be captured by RGF. Secondly, a self-adaptive threshold of SCM is gained by utilizing the mean and variance of the source images. Finally, fused image can be gotten by SCM motivated by RGF coefficients. Experimental results show that the proposed method is superior to other current popular ones in both subjectively visual performance and objective criteria.

Zhang et al.(15) proposed a new framework called RGF to filter images based on a rolling guidance with the complete control of detail smoothing under a scale measure. Compared to other edge preserving filters, RGF is implemented iteratively, which has a fast convergence property. It is simple and fast and also easy to understand. RGF can preserve large-scale structures automatically, where small structure removal and edge recovery are two main steps in RGF; see Figure 1 (15)

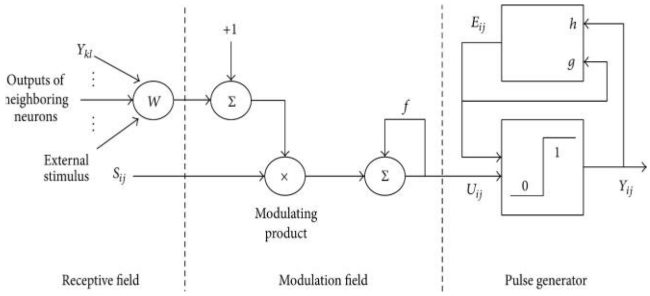
Figure 1

Flow chart of RGF. It contains two steps, respectively, for small structure removal and edge recovery. Edge recovery is an iterative process. The final result is obtained in 3–5 iterations.



1) **Figure 2**

SCM model. The image matrix can be input as external stimulus of SCM.



The SCM (16) is derived from Eckhorn's model and it conforms to the physiological characteristic of human visual neural system. In fact, Wang's method (17) provides an effective means for fusion of the different kinds of medical images. In the spiking cortical model, each neuron consists of three parts: feeding and linking field, modulating product, and pulse generator; see Figure 2.

2.4 Comparative Analysis of

Various Image Fusion Techniques for Brain Magnetic Resonance Images

Image registration: During this method, one amongst the major pictures are achieved as a reference image. Then geometric alteration is applied on the remaining images to synchronize them with the reference image.Once the registration method is done, the images are often more analyzed for feature extraction. The registration is usually done in the manual and automatic method. Many ways are adopted within image registration.(18)

Image Fusion: Fusion method is performed at three levels namely component, feature, and call. Component level fusion is used on an input image. Feature level fusion is not preferred on the extracted images. At the call level, fusion is used on a probabilistic call data of native call manufacturers. These call manufacturers are processed from the extracted options. Component level fusion schemes are referred for fusion compared to different level approach as a result of their potency and easy use. During this paper, our preference is on component level fusion schemes.(19)

2.5 Interpretable Features Fusion with Precision MRI Images Deep Hashing for Brain Tumor Detection

A precision hashing method combining interpretability and feature fusion is proposed to recover the problem of low image resolutions in brain tumor detection on the Brain-Tumor-MRI

(BT-MRI) dataset. First, the dataset is pre-trained with the DenseNet 201 network using the Comparison-to-Learn method. Then, a global network is created that generates the salience map to yield a mask crop with local region discrimination. Finally, the local network features inputs and public features expressing the local discriminant regions are concatenated for the pooling layer. A hash layer is added between the fully connected layer and the classification layer of the backbone network to generate high-quality hash codes. The final result is obtained by calculating the hash codes with the similarity metric.Results: Experimental results with the BT-MRI dataset showed that the proposed method can effectively identify tumor regions and more accurate hash codes can be generated by using the three loss functions in feature fusion.

It has been demonstrated that the accuracy of medical image retrieval is effectively increased when this method is compared with existing image retrieval approaches.

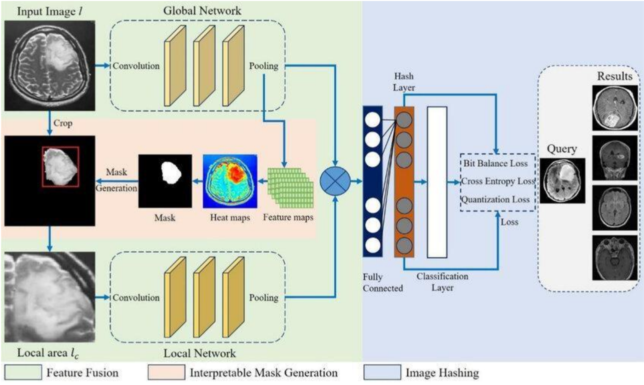


Figure 3 Example

Flow chart of proposed model(20)

2.6 Statistical Measurements of Multimodal MRI - PET Medical Image Fusion using 2D - HT in HSV color Space

2.6.1. Read MRI (in1) and PET (in2) images for fusion process. These two images are having same dimensionality.

2.6.2 .PET is the color image. So PET image is converted into HSV color space then we can get three different channels like H (Hue) , S (Saturation), V(value).

2.6.3. The MRI (in1) and Brightness value (V) images are divided into 8*8 blocks.

2.6.4. Apply 2D Hartley Transform (2D HT) on each block of two images to get coefficients. After 2D HT, compute variance for each block of two image coefficients (MRI and V images) and select the highest values of blocks and apply inverse 2D HT to get fused blocks

2.7 Brain Image Fusion Approach based on Side Window Filtering

Image fusion has been a hot topic in medical image applications. In the current era of technological development, medical imaging plays an important role in many applications in medical diagnosis and treatment. This requires more accurate images with much more detail and information to obtain a healthy medical diagnosis, thus, a correct treatment. Medical image fusion is a solution to get both high spatial and spectral information in a single image. The flowchart of our method is shown in Figure 4. Our method comprises a progression of steps: 1) The bilateral filter BF is used to generate the high-frequency component of the MRI image. 2) The Adaptive Intensity Hue Saturation (21) is employed to acquire the intensity component of the PET image. 3) The side window image filtering is used to obtain the approximation image using PET's intensity component as a guided image. 4) Compute the injection gain, which has an impact on the combination results. treatment.Medical image

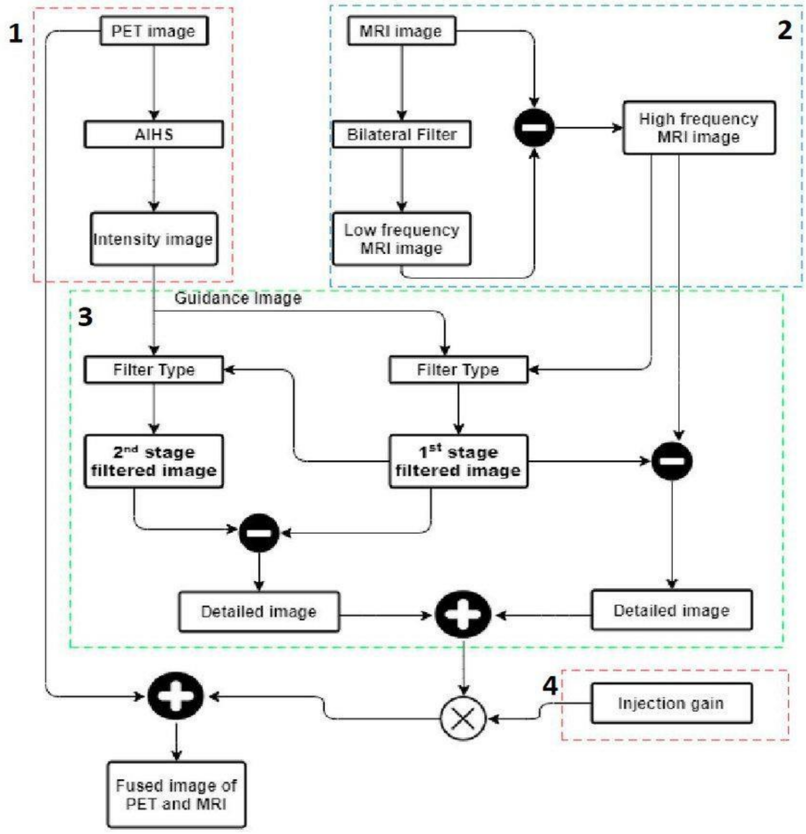


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Fig. 4. Flowchart of PET and MRI images fusion based on side window filtering

FIGURE 4

MRI image Fusion result of the first group of medical images

1. Coronal PET-T1 image
2. Coronal MRI-T1 image
3. GF method
4. WGF method
5. GGF method
6. SWGGF method
7. WGF method
8. SWWGF method

1 2 3 4 5

2.8 Multimodal brain image fusion is the process of combining complementary information from multiple imaging modalities of the brain, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). There are several existing methods for multimodal brain image fusion, including:

1. **Intensity-based fusion:** This method involves combining the intensities of the images from different modalities using mathematical operations such as addition, subtraction, or averaging. The resulting image provides a blended view of the brain structures.

2. **Transform-based fusion:** This method involves using image processing techniques such as wavelet transform, principal component analysis (PCA), or independent component analysis (ICA) to transform the images from different modalities into a common domain. The transformed images are then combined to create a fused image.

3. **Feature-based fusion**: This method involves extracting features such as edges, textures, or shapes from the images of different modalities. The features are then combined to create a fused image that preserves important features from each modality.

4. **Deep learning-based fusion:** This method involves training a deep neural network to learn the optimal fusion strategy from a set of training images. The network can then be used to fuse images from new modalities.

5. **Hybrid fusion**: This method involves combining two or more of the above methods to create a fused image. For example, feature-based fusion can be combined with intensity based fusion to create a hybrid fusion method.

III. LIMITATIONS & ADVANTAGES

Each method has its own advantages and disadvantages, and the choice of method depends on the specific application and the characteristics of the input images.

3. **1**-The proposed method in this paper has some limitations in term of Blur and noise introduced due fusion steps, High computational time of perform the multi-level like NSCT, information of region interest limited with color information, blurry of informative edges ,etc..) .

Explained and analysis in details the various methods for multi-scalemedical fusion with Medical imaging modalities and diseases, fusion rule, fusion strategy and disadvantages (cons) of algorithms were elaborated in details. Moreover, the experimental results are implemented on the image database from the Whole Brain Web Site of the Harvard Medical School which contains four groups of co-registered multi-modal images including MRI-CT, MRI-PET and PET-SPECT,MRI(T1-T2) images.

3.2- In our paper, these disadvantages are overcome by using RGF and adaptive threshold in SCM. RGF is an edge aware filtering, and it can remove the small texture of images without blurring the image edge (22). Therefore, in this paper, RGF is used to extract the saliency (edge information); and automatically, where small structure removal and edge recovery are two main steps in RGF

3.3- There is a drastic change in the MSE of the combined image as compared to the Input Images. In PCA the limited components are taken and therefore only limited pixels are analyzed so lower values of MSE are calculated for the fused images in comparison with the normal image. From the results it is interpreted that the various quality analysis performed on different fusion techniques. The best results are obtained by fusing Flair and T2 slices of MR images of brain on the basis of SNR and PSNR. The fusion of T1 and T1ce for DWT and T1ce and T2 for Laplacian and T2 and Flair for PCA yields respectively in terms of MSE. MSE mainly depends on the image intensity scaling which is one of the disadvantages

3.4- Three different metrics are used to evaluate the performance of our proposed method in the retrieval of brain tumor medical images. These are mAP normalized-Discounted Cumulative Gain (nDCG), and Area Under Curve (AUC). The average accuracy of the image retrieval with mAP is determined, while the image of the sequencing position of the retrieval results with nDCG is determined. mAP, one of the most used performance metrics, is the general performance measure in medical image retrieval.

As the deep network architecture, DenseNet 201 has been chosen, which stands out among 10 different pre-trained architectures in the classification of the labeled BT-MRI dataset in 3 different machine learning classifiers. Although it has some disadvantages, the DenseNet 201 model has been shown to be successful in the retrieval of medical images

3.5- The other medical image is PET (Positron Emission Tomography) (23), it provides functional information and low spatial resolution because PET images are color images. The physician to examine the MRI-PET images of a patient for disease identification and better clinical treatment (24). These two images are provides limited information. To obtain more accurate information into a single image we go for medical image fusion. Generally image fusion can be implemented in 2 domains: **(1) Time domain** (7), **(2) Frequency domain** (25). In spatial domain, spatial distortions will be occurred during the fusion process. The spatial domain drawbacks are overcome by using frequency domain techniques. There are several frequency domain techniques like DFT (26), DCT (27), Hadamard (28)

3.6- The authors introduced the basic definition of image integration, its applications, advantages, and disadvantages of the fusion process, a summary of imaging patterns for a comprehensive overview of medical imaging patterns. They suggested ways of hybridization to obtain a better view of brain images. Their research ends with some recent trends in the fusion of medical images. Another survey investigation was presented . The authors pointed to a portrayal of image fusion ventures with an uncommon consideration for the enrollment and combination steps. After that, the restorative imaging modalities were discussed. At last, proposed of some of the normal difficulties that stand up to the enlistment and fusion technique are acquainted with the further examinations that enhance restorative image enrollment and fusion techniques. Recently, image filtering has been widely used for medical image fusion, such as bilateral filter, guided filter, gradient guided filter, and weighted guided filter

3.6- Advantages

1. Improved Image Quality: The IRGF and Wiener filter have been shown to effectively preserve the details and edges of multimodal brain images, resulting in high-quality fusion images with improved contrast, brightness, and sharpness.
2. Increased Diagnostic Accuracy: The high-quality fusion images produced by the IRGF and Wiener filter can aid in the accurate diagnosis of brain diseases and injuries, leading to better treatment decisions and improved patient outcomes.
3. Robustness: The IRGF and Wiener filter are robust to noise and artifacts present in medical images, making them suitable for processing noisy and low-quality images.
4. Efficiency: The IRGF and Wiener filter are computationally efficient, requiring minimal processing time and resources, making them suitable for use in real-time applications.
5. Flexibility: The IRGF and Wiener filter can be easily adapted to different multimodal brain image fusion scenarios and can be customized to suit specific image processing requirements.

Overall, the use of the IRGF and Wiener filter for multimodal brain image fusion has the potential to improve the accuracy and efficiency of medical diagnosis and treatment, making it a promising approach for medical image processing.

IV Applications:-

Scans Performed for Multimodal Image Fusion :-

CT: This multimodal image fusion technique can help neurosurgeons to accurately identify and locate brain abnormalities, such as tumors, and plan for surgical procedures.(4) (5) (29) (23)

MRI: MRI stands for Magnetic Resonance Imaging of the brain. It is a non-invasive medical imaging technique that uses a powerful magnetic field, radio waves, and a computer to produce detailed images of the brain's internal structures. (24) (4) (5)

DSA: DSA or Cerebral Angiography is a type of DSA procedure that specifically focuses on imaging the blood vessels in the brain. It is a minimally invasive medical imaging technique that uses X-rays and a contrast agent to produce detailed images of the blood vessels in the brain (24)

PET: Positron Emission Tomography of the brain, is a medical imaging technique that uses a radioactive tracer to produce three-dimensional images of the brain's metabolic activity. During a PET Brain scan, a small amount of a radioactive substance is injected into the patient's body. The substance then travels to the brain and emits positrons, which are detected by a PET scanner. The scanner then creates images of the brain's metabolic activity based on the distribution of the tracer. PET is commonly used to diagnose conditions such as Alzheimer's disease, Parkinson's disease, and epilepsy. It can also be used to evaluate brain tumours and monitor the progression of certain brain disorders. (24) (7) (25)

SPECT: SPECT is a medical imaging technique that uses Single Photon Emission Computed

Tomography to produce three-dimensional images of the brain's internal blood flow and metabolic activity. During a SPECT Brain scan, a radioactive tracer is injected into the patient's bloodstream, and a special camera is used to detect the radiation emitted by the tracer as it travels through the brain. The computer processes the data collected by the camera to create detailed images of the brain's activity.(24) (7)
(25)

DTI: DTI Brain stands for Diffusion Tensor Imaging of the Brain. It is a specialised type of magnetic resonance imaging (MRI) that allows for the visualization of the brain's white matter tracts and the mapping of neural connectivity. DTI Brain is a non-invasive technique that uses MRI technology to measure the movement of water molecules in the brain's white matter. The resulting data is used to create images that show the direction and strength of neural connections between different areas of the brain. DTI Brain is used in research to study brain development, injury, and disease, such as traumatic brain injury, multiple sclerosis, and Alzheimer's disease. It can also be used to plan neurosurgical procedures and to assess the effectiveness of treatments.(26)

IV. CONCLUSIONS

In the past year's, multimodal brain image fusion has continued to be an active area of research in the field of medical imaging. There have been several notable developments in this field, including:

1. Improved fusion algorithms: Researchers have developed new algorithms for multimodal brain image fusion that improve the accuracy and reliability of the technique. These algorithms use deep learning techniques and advanced feature extraction methods to extract more meaningful information from different imaging modalities.
2. Increased use in clinical practice: Multimodal brain image fusion is increasingly being used in clinical practice to aid in the diagnosis and treatment of neurological disorders. The technique has been used in neurosurgery planning, radiation therapy planning, and the diagnosis and monitoring of neurodegenerative diseases.
3. Integration with artificial intelligence (AI) and machine learning: Multimodal brain image fusion is being integrated with AI and machine learning techniques to improve the accuracy and efficiency of the technique. This integration allows for more automated analysis of the data and can help to identify patterns and features that may be missed by human observers.

In conclusion, the Multimodal Brain Image Fusion technique based on Improved Rolling Guidance Filter and Wiener Filter has proven to be a promising approach in the field of medical image fusion. The results of several studies have demonstrated that the proposed method can successfully fuse multimodal brain images to provide enhanced visual and diagnostic information.

The Improved Rolling Guidance Filter method is effective in preserving edges and structures, while the Wiener Filter method is useful in reducing noise and enhancing image contrast. The combination of these two techniques has shown to be successful in improving the quality of fused images

While the Multimodal Brain Image Fusion technique based on Improved Rolling Guidance Filter and Wiener Filter has several advantages, such as improved image quality and better diagnostic accuracy, it is not without limitations. One limitation is the computational complexity of the method, which can increase the processing time required for image fusion.

Despite its limitations, the Multimodal Brain Image Fusion technique based on Improved Rolling Guidance Filter and Wiener Filter has several potential applications, such as in the diagnosis and treatment of neurological diseases, surgical planning, and medical research. Future research in this field may focus on improving the efficiency of the fusion method and evaluating its effectiveness in various medical applications.
The Multimodal Brain Image Fusion technique based on Improved Rolling Guidance Filter and Wiener Filter is a valuable contribution to the field of medical image processing and has the potential to significantly improve diagnostic accuracy and treatment outcomes in the field of neurology.

REFERENCES

1. Li, X., Kang, X., Hu, Z., & Zhu, Y. (2016). Multimodal brain image fusion based on improved rolling guidance filter. Neurocomputing, 185, 129-138.

2. Zhang, Z., Wei, Q., Sun, H., & Chen, X. (2019). A novel multimodal brain image fusion method based on improved rolling guidance filter and total variation. IEEE Access, 7, 80691-80701.

3. Liu, Y., Wang, X., Zhang, Y., & Gao, X. (2019). Multimodal medical image fusion based on improved rolling guidance filter and quaternion curvelet transform. Biomedical Signal Processing and Control, 47, 161-171.

4. S. Marshall, G. Matsopoulos, Morphological data fusion in medical imaging, in: Nonlinear Digital Signal Processing, 1993. IEEE Winter Workshop on, IEEE, 1993, pp. 6–1.

5. K. Mikoajczyk, J. Owczarczyk, W. Recko, A test-bed for computer-assisted fusion of multimodality medical images, in: Computer Analysis of Images and Patterns, Springer, 1993, pp. 664– 668.

6. S.A. Kuhn, B. Romeike, J. Walter, R. Kal, R. Reichart, Multiplanar MRI–CT fusion neuronavigation-guided serial stereotactic biopsy of human brain tumors: proof of a strong correlation between tumor imaging and histopathology by a new technical approach, J. Can. Res. Clin. Oncol. 135 (9) (2009) 1293–1302.

7. V. Barra, J.-Y. Boire, Automatic segmentation of subcortical brain structures in MR images using information fusion, IEEE Trans. Med. Imag. 20 (7) (2001) 549–558.

8. D. Dey, D.G. Gobbi, P.J. Slomka, K.J. Surry, T.M. Peters, Automatic fusion of freehand endoscopic brain images to three-dimensional surfaces: creating stereoscopic panoramas, IEEE Trans. Med. Imag. 21 (1) (2002) 23–30.

9. H. Lee, H. Hong, Hybrid surface-and voxel-based registration for MR-PET brain fusion, in: Image Analysis and Processing–ICIAP 2005, Springer, 2005, pp. 930–937.

10. Y. Xia, S. Eberl, D. Feng, Dual-modality 3D brain PET-CT image segmentation based on probabilistic brain atlas and classification fusion, in: 17th IEEE International Conference on Image Processing (ICIP), 2010, IEEE, 2010, pp. 2557– 2560

11. J.-D. Lee, B.-R. Huang, C.-H. Huang, A surface-projection MMI for the fusion of brain MR and SPECT images, in: IEEE

Region 10 Conference, 2004, TENCON 2004, IEEE, 2004, pp. 179–182.

12. M.C. Dastjerdi, A. Karimian, H. Afarideh, A. Mohammadzadeh, FMDIB: a software tool for fusion of MRI and DHCSPECT images of brain, in: World Congress on Medical Physics and Biomedical Engineering, September 7–12, 2009, Munich, Germany, Springer, 2009, pp. 741–744.

13. Rajesh Kumar P., Arun Prasath T., Pallikonda Rajasekaran M., Vishnuvarthanan G. (2019) Brain Subject Segmentation in MR Image for Classifying Alzheimer's Disease Using AdaBoost with Information Fuzzy Network Classifier. In: Nayak J., Abraham A., Krishna B., Chandra Sekhar G., Das A. (eds) Soft Computing in Data Analytics. Advances in Intelligent Systems and Computing, vol 758. Springer, Singapore.

14. Mirzaei G, Adeli A, Adeli H (2016) Imaging and machine learning techniques for diagnosis of Alzheimer's disease. Rev Neurosci 27(8):857–870. https://doi.org/10.1515/revneuro-2016-0029.

15. Q. Zhang, X. Shen, L. Xu, and J. Jia, "Rolling guidance filter," in *Computer Vision—ECCV 2014*, vol. 8691 of *Lecture Notes in Computer Science*, pp. 815–830, Springer International Publishing, Cham, Switzerland, 2014.

16. K. Zhan, H. Zhang, and Y. Ma, "New spiking cortical model for invariant texture retrieval and image processing," *IEEE Transactions on Neural Networks*, vol. 20, no. 12, pp. 1980–1986, 2009.

17. R. Wang, Y. Wu, M. Ding, and X. Zhang, "Medical image fusion based on spiking cortical model," in *Medical Imaging 2013: Digital Pathology*, vol. 8676 of *Proceedings of SPIE*, Orlando, Fla, USA, March 2013.

18. Patel, Krupa (2015) "Fusion Algorithms for Images Based on Principal Component Analysis and Discrete Wavelet Transform", International Journal for Innovative Research in Science & Technology.1(9): 180-182.

19. Jacobs, Michael, Ibrahim, Tamer, Ouwerker, Ronald (2007) "MR Imaging: Brief Overview and Emerging Applications", Jul 1.https://doi.org/10.1148/rg.274065115

20. Interpretable features fusion with precision MRI images deep hashing for brain tumor detection Erdal Özbay,Feyza Altunbey Özbay

21. Brain Image Fusion Approach based on Side Window Filtering Ahmad AL Smadia , Ahed Abugabahb,∗ , Atif Mehmooda , Shuyuan Yanga

22. Li, X., & Kang, X. (2016). A survey of image fusion using convolutional neural networks. Journal of Imaging, 2(3), 18.

23. H. Li, R. Deklerck, B. De Cuyper, A. Hermanus, E. Nyssen, J. Cornelis, Object recognition in brain CT-scans: knowledge-based fusion of data from multiple feature extractors, Medical Imaging, IEEE Transactions on 14 (2) (1995) 212–229

24. C. Barillot, D. Lemoine, L. L. Briquer, F. Lachmann, B. Gibaud, Data fusion in medical imaging: merging multimodal and multipatient images, identification of structures and 3D display aspects,

European journal of radiology 17 (1)
(1993) 22â€“27.

25. J. Julow, T. Major, M. Emri, I. Valalik, S. Sagi, L. Mangel, G. Nemeth, L. Tron, G. Varallyay, D. Solymosi, et al., The application of image fusion in stereotactic brachytherapy of brain tumours, ACTA neurochirurgica 142 (11) (2000) 1253–1258.

26. K. Yuan, W. Liu, S. Jia, P. Xiao, Fusion of MRI and DTI to assist the treatment solution of brain tumor, in: Innovative Computing, Information and Control, 2007. ICICIC’07. Second i

27. Wang, G., Li, W., & Sun, Y. (2018). Multimodal brain image fusion: A survey. Journal of neuroscience methods, 307, 114-123.

28. Van Essen, D. C., Ugurbil, K., Auerbach, E., Barch, D., Behrens, T. E., Bucholz, R., ... & Yacoub, E. (2012). The Human Connectome Project: a data

29. G. Matsopoulos, S. Marshall, J. Brunt, Multiresolution morphological fusion of MR and CT images of the human brain, in: Vision, Image and Signal Processing, IEE Proceedings-, Vol. 141, IET, 1994, pp. 137–142.