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Kalman Bucy Filtered Neuro Fuzzy Image Denoising for Medical Image Processing

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Abstract: Neutrosophic sets (NS) have referred to as interval fuzzy sets applied in minimizing the uncertainty and fuzziness in computer-vision and machine-learning communities and hence employed for several applications. As far as medical image processing applications are concerned NSs are obtained as an important technique for de-noising. Also, fuzzy segmentation with machine and deep learning is determined as a familiar procedure that splits input image into distinct regions for precise learning. Several research works conducted in different image-processing domains. However, less works was focused on denoising and segmentation of medical image processing with minimal time complexity and accuracy. In this work we plan to develop a Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) method with the objective of reducing the noisy artifacts with higher peak signal-to-noise ratio in a computationally efficient manner. First, medical images obtained from Brain MRI LGG segmentation dataset are subjected to filtering employing Kalman Bucy Filtering algorithm with series of measurements examined. Second with the filtered medical images provided as input, uncertainty is handled by utilizing Neutrosophic Neuro Fuzzy set (NNFS) with help of the membership grade. With the aid of three membership grades, i.e., truth, indeterminacy and falsity, uncertainty involved in noisy image are said to be handled in a time efficient manner. By this way, an efficient image denoising process is performed with better PSNR. Experimental evaluation is carried out using medical images with different performance metrics such as enhanced PSNR and true positive rate up to 13%, 14% as well minimum execution time by 38% using medical images.

Keywords: Neutrosophic Sets, Kalman–Bucy, Fuzzy Segmentation, Image Processing, Neutrosophic Neuro Fuzzy, Image Denoising

1. Introduction

Diagnosis and forecasting is one of the most laborious and demanding job owing to confined distinction of experts as well as fuzziness in medical science. And medical image processing applications are concerned NSs are achieved as main technique for de-noising. Medical image procedure has comprised in image segmentation, registration, three dimensional rebuilding as well as motion analysis. Additional study direction is depended on precise image segmentation.

In discovering the numerous diseases intensity, discrete professional specialists may result in incorrect diagnosis. With the objective of performing diagnosis instinct in the medical images, several image processing techniques have been investigated in Neutrosophic theory to interpreting intrinsic insecurity, as well as imprecision.

Purpose of speckle noise involved in Optimal Coherence Tomographic (OCT) images was eliminated [1] via Iterative contraction algorithm based on Chi-square similarity and fuzzy logic. Here the OCT image was split to image blocks with low rank group matrix. During fuzzy logic, singular values were obtained via dissimilar weights. Also, denoising effect was enhanced. With this the PSNR was said to be improved. However, the running time required in denoising was said to be compromised due to lack in optimization policy.

Deviations involved in the imaging system were focused in [2] Saliency Map and Neutrosophic Set Theory (SMNS). First, guided filter was employed in image using different channels to focus on the weak edges. Image foreground information was highlighted to generate saliency map. Followed by Neutrosophic Set area with which the results were interpreted as true, indeterminate and false. As a result, SMNS method saw an improvement in precision, recall and running time. However, the noise ratio (i.e., Peak Signal-to Noise Ratio – PSNR) was not focused.

Noise data was determined in [3] during mathematical model. Owing to reason that noise has a great influence on uncertainty of gray stage. Direct method was employed for determining noise variance. Here, the image noise variance was determined from fuzziness of noisy image employing polynomial model. However, the noise affected uncertainty of gray step as well as fuzziness of image. In addition, peak signal-to-noise ratio was not improved.

An improved FCM algorithm was introduced in [4] with anti-noise capability. In this work, noise reduction was performed in novel image segmentation algorithm with dictionary learning. Grayscale features was extracted in an accurate manner. However, computational cost involved in denoising was not reduced by employing improved FCM algorithm.

1.1 Objective and Contributions

Our study aims to accurately perform image denoising even in the presence of uncertainty from brain MRI images. We develop an end-to-end image denoising model based on Kalman Bucy Filtering algorithm. With this, denoised images, uncertainty issue is handled by employing Neutrosophic Neuro Fuzzy set, which are fed to image processing for producing finally detected output. Following the research line of previous works Chi-square similarity and fuzzy logic [1] and Saliency Map and Neutrosophic Set Theory (SMNS) [2], mathematical model in MR images [3] and improved FCM algorithm [4], several modifications are introduced to such a method to further enhance its performance and applicability for robust medical image denoising.

The key contributions of our paper are the following:

- To design a Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) method for reducing noisy artifacts by higher PSNR in a computationally efficient fashion.

- A novelty of Kalman Bucy Filtering-based Image Denoising algorithmis examined in denoised images is achieved in a computationally efficient manner by means of Kalman Bucy Gain function.
- A new algorithm called Neutrosophic Neuro Fuzzy set in an accurate manner which help of Neutrosophic Fuzzy set subjected to deep neural network also addressed uncertainty involved through denoising.
- Simulation outcome of KBF-NNFID achieves better medical diagnosis in terms of PSNR, execution time as well as true positive rate in comparison with the other medical diagnosis methods.

1.2 Road map

Article planned as: Related works concerning image denoising introduced in Section 2. Thereafter in the Section 3, the proposed KBF-NNFID is designed. Section 4 presents Experiments. Section 5 explains discussion via table and graphical representations. Lastly, Section 6 demonstrates summary.

2. Literature Survey

With contemporary evolution in technology, several healthcare techniques escalate and filtrate in each and every medical diagnosis therefore paving new mechanisms for disease diagnosis. As a result, electronic healthcare has made an appearance as a state-of-the-art tendency in our society. Moreover, these mechanisms are fundamentally a guideline to the evolution of medical diagnosis. But the presence of noise makes the medical images indistinguishable and may confuse disease identification and analysis. Therefore, medical image denoising is a mandatory technique for medical image processing.

Deep learning is the expeditious growing area in artificial intelligence and is significant used in several domains, including medication. In [5], an extensive profile was provided on studies accomplished on the region of medical image analysis. However, yet it remains a challenging issue for segmenting tumor accurately owing to the speckle noise and inconsistency observed in the tissue background image. To overcome these issues, breast tumor segmentation employing neutrosophic set (NS) was proposed in [6]. However, it failed to identify noisy images. Most of gradient basis of edge detection techniques is highly susceptible to image noise that in turn results in less efficiency.

Some of challenges, issues and advantages of applying deep learning for edge detection were investigated in [7]. Neutrosophic set theory [8] was employed that in turn preserved image characteristics as well as minimization of false occurring due to noise. However, the object quality was not focused. To address on this aspect, a Modified Neutrosophic Set Segmentation method was proposed in [9] that with the aid of 3D modeling not only improved the image quality but also the PSNR.

Neutrosophic set has preferable course of action for image quantifying due to the reason that indeterminacy. With example, medical diagnosis images obtained via CCTV footage can included several blur pixels. These characteristic can be addressed via neutrosophic sets where each pixel is classification based on three factors, extent of truth, extent of falsity and extent of indeterminacy.

In [10], Pythagorean fuzzy set was introduced as an innovative model that with the aid of thresholding function obtained best results on separating of the object into its variants accurately. In [11], Linguistic Neutrosophic Cubic Set (LNCS) was proposed to handle data uncertainty via aggregation operators. Yet another convolutional neural network was applied in [12] that with the aid of sparseness factor not only ensured security but also denoised efficiently.

An enhanced self-learning weighted fuzzy algorithm that included distinct weights for calculating distance via continuous iterative self-learning was proposed in [13]. Followed by which, distance evaluated in addition to the weights obtained were utilized based on self-learning with the purpose of enhancing segmentation performance and robustness. DL was investigated [14]. An in-depth analysis of conventional ML, DL and certain potential methods were designed in [15].

Both one as well as two-sample hypothesis testing issue concerned in [16] by Neutrosophic fuzzy Sign set. In [17], DCNN and whale optimizer were presented by early medical diagnosis. The integration model along with the gradient descent-based model also enhanced the accuracy rate involved in the medical diagnosis. Yet another Jarque-Bera test was applied in [18] under the fuzzy environment for obtaining accurate inter valued data. A comprehensive approach for detection and classification of tumors was designed in [19] to not only reduce the noise but also resulted in accuracy via morphological operators. Identical lesion region was determined via hybrid fuzzy c means with more similarity in an accurate manner was presented in [20].

In [21], trigonometric similarity measures of NHSSs are performed. But, cosine and cotangent similarities were not discovered. Neutrosophic Dombi fuzzy graph is carried in [22] as well as Advanced Multi-Criteria Decision Making (MCDM) techniques designed in [23] to applications of multiple recent and innovative healthcare analytics problems. Emergency branch obtained in [24] via plithogenic set method. Several optimization systems designed in [25] to decision analytics, and data science in applying defined set of smart environments.

2.1 Research gap

In this work, a novel method called, Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) for medical image denoising is proposed. Disadvantages of traditional techniques were obvious. Simple as well as invariant features formerly used for designing novel image denoising. This schemes performance plateaus that create them critical to improve.

3. KBF-NNFID Method

Owing to the presence of noise, uncertainty and fuzziness compute assisted diagnosis for medical images are said to be confined. Such constrains may influence decisions involving disease diagnosis while ascertaining the type of the disease and the grade of the disease as well. Fuzzy sets are considerably utilized in minimizing the uncertainty and fuzziness in diverse applications. However, those models disregard the spatial aspects of the pixels owing to noise. To control such disadvantages of the fuzzy-based methods, neutrosophic set is utilized alternatively.

As a consequence, different types of image denoising methods were explored on the basis of the neutrosophic theory for throwing light on the ambiguity and vagueness in medical image denoising. In this section a method called, Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) for reducing the noisy artifacts with higher PSNR at computationally efficient manner is designed. KBF-NNFID diagram is given in Figure 1. .

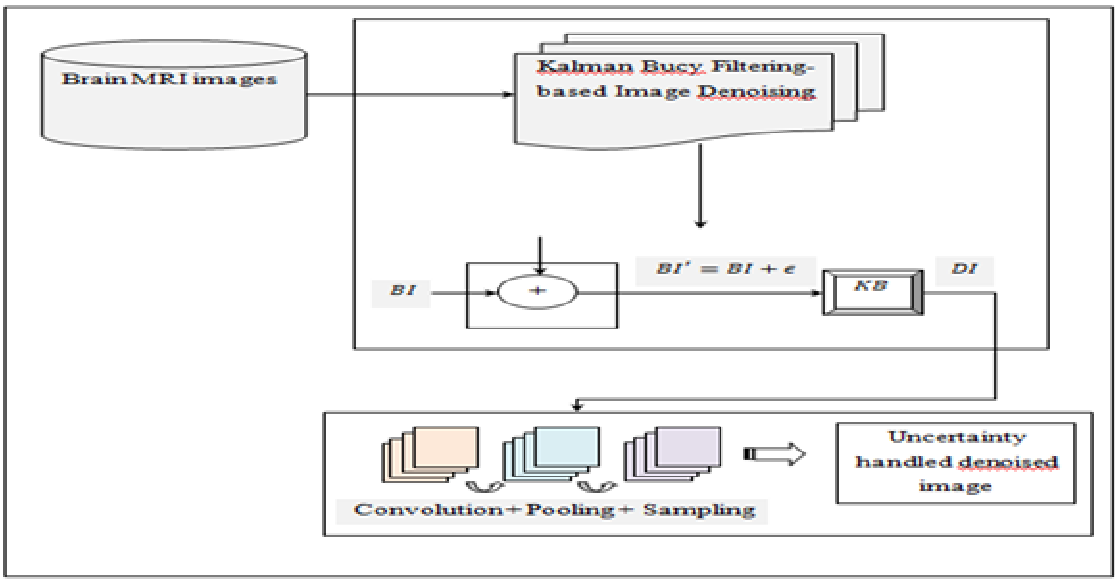

Figure 1 Block diagram of Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising

As shown in the above figure with the Brain MRI LGG segmentation dataset provided as input, the overall KBF-NNFID method is split into two sections. They are image denoising model to reduce the noise in Brain MRI images by employing Kalman Bucy Filtering algorithm and handling uncertainty of noisy image by means of Neutrosopic Neuro Fuzzy set.

3.1 Dataset description

This Brain MRI LGG segmentation dataset consists of brain MR images as well as taken from The Cancer Imaging Archive (TCIA). First, patients who did not have preoperative FLAIR were excluded. As of 120 cases remained, furthermore 10 patients were excluded for whom pertinent genomic information are not obtainable. Final examined cohort of 110 patient's data included as five institutions. They correspond to 110 patients included least FLAIR sequence as well as genomic cluster data. Each images offered in tif format by 3 channels per image. In 101 cases, 3 sequences were found to be accessible as well as dataset is said to be prepared in 110 folders. Every folder have MR images by naming convention: `TCGA_<institution-code>_<patient-id>_<slice-number>.tif`. In 9 cases, post-contrast sequence has absent as well as pre-contrast sequence has lost in 6 cases. Via FLAIR, absent sequences were restored for constructing each images 3-channel.

3.2 Kalman Bucy Filtering-based Image Denoising model

Over the recent few years, image prior learning has materialized as an efficient instrument for image denoising that makes the most of prior knowledge to obtain sparse coding and employ them in reconstructing the clean image from noisy one. However, these image prior learning models are not said to be free from limitations and therefore failed attempts in enhancing performance and efficiency concurrently. In this section, objective of noise in Brain MRI images minimized via Kalman Bucy Filtering. Formulate the estimate of unknown variables depending on the single measurement using joint probability distribution over variables for every timeframe. Kalman Bucy Filtering-based Image Denoising model plan is shown in Figure 2.

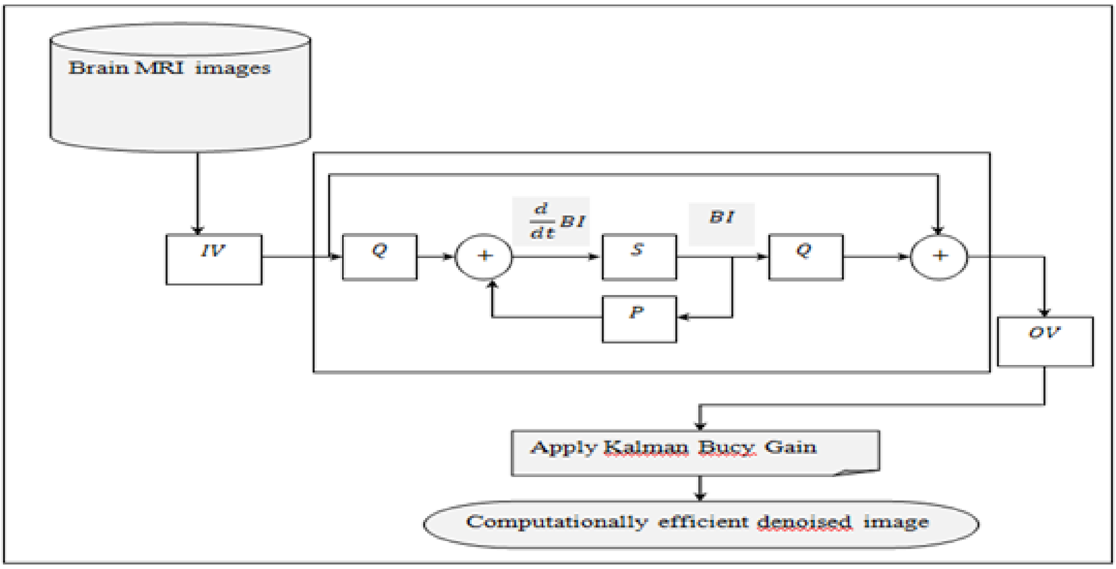

Figure 2 Block diagram of Kalman Bucy Filtering-based Image Denoising model

In figure, input of Brain MRI images assume and stored in form of vector represented as input vector '*IV*' is subjected to state space model for obtaining time series images. Followed by which a Kalman Bucy Gain function is applied to generated denoised images. Let us consider a Brain MRI images as input '*BI*' be a two dimensional function '*BI(a,b)*', 'a' and 'b' are spatial coordinates with amplitude of ' *BI*' at any location '(a,b)' refers to the intensity of the image at that point. As illustrated in the above figure, the degradation process is modeled with the aid of a noise term, '€', that functions on an input Brain MRI image 'BI' to produce a degraded image, '*BI*'. Given this noisy inference, with certain perception of the noise term, the restoration process capitulates an estimate, '*BI*', of the original image '*BI*'. Then, a Brain MRI input image '*BI*' of size 'a*b' pixels with gray level function is mathematically formulated as given below.

$$BI = (BI_{a,b}), where\ \ a,b = 1,2,\ldots.,A,B (1)$$

The noisy Brain MRI input image 'BI'' with gray level function is then defined as given below.

$$BI' = (BI'_{a,b}) + \epsilon_{a,b}, where\ \ a,b = 1,2,\ldots,A,B \quad (2)$$

Then, with the above two formulations as given in (1) for original image and (2) for noisy image, the objective of applying the filtering during denoise process remains in estimating the signal or pixels at each time 't' making entire utilization of the information (i.e., feature information like, patient ID, gender, age, race, ethnicity and so on) furnished by the observations up to that specific time. The Kalman Bucy filtering applied in our work is said to be recursive in 't' and hence said to be Gaussian. The Kalman Bucy filtering for denosing Brain MRI images with 'i' inputs, 'j' outputs and 's' state variables (i.e., probable subset of image pixels) is then represented in the form of state space model and is mathematically formulated as given below.

$$\frac{d}{dt}BI(t) = P(t)BI(t) + Q(t)IV(t) + \epsilon_1(t) \quad (3)$$

$$OV(t) = R(t)BI(t) + \epsilon_1(t) \quad (4)$$

From the above equations (3) and (4), at each time ‘t’, ‘$P(t)$’ denotes the state matrix (i.e., ‘$\dim[P(.)] = s * s$’), ‘$Q(t)$’ denotes the input matrix (i.e., ‘$\dim[Q(.)] = s * i$’), ‘$R(t)$’ denotes the output matrix (i.e., ‘$\dim[R(.)] = j * s$’), ‘$BI(.)$’, ‘$IV(.)$’ and ‘$OV(.)$’ representing the state vector, input vector and output vector respectively. Then, the Kalman Bucy filter with series of measurement observed over a time period ‘t’ comprises of two differential equations. The state estimate series of measurement observed over a time period ‘t’ to denoise Brain MRI image ‘BI'’ is then mathematically expressed as given below.

$$\frac{d}{dt}BI'(t) = P(t)BI'(t) + Q(t)IV(t) + KB(t)[OV(t) - R(t)BI'(t)] \quad (5)$$

In a similar manner, the covariance series of measurement observed over a time period ‘t’ to denoise Brain MRI image ‘BI'’ with intensities ‘$Int_1(t)$’ (i.e., the tumor location in our work) is then mathematically expressed as given below.

$$\frac{d}{dt}CV(t) = P(t)CV(t) + CV(t)P^T(t) + Int_1(t) - KB(t) \quad (6)$$

From the above two equations (5) and (6), the Kalman Bucy gain to denoise the Brain MRI image ‘BI'’ using joint probability distribution is mathematically formulated as given below.

$$DI(t) = KB(t) = CV(t)R^T(t)Int_1^{-1}(t) \quad (7)$$

From the above equation (7), Kalman Bucy gain ‘$KB(t)$’ at time ‘t’ is evaluated based on the intensity of the noise ‘$\epsilon_1(t)$’, therefore finally producing the denoised images. The pseudo code representation of Kalman Bucy Filtering-based Image Denoising is given below.

Input: Dataset ‘DS’, Features ‘$F = F_1, F_2, \ldots, F_n$’, Brain MRI Images ‘$BI = BI_1, BI_2, \ldots, BI_m$’
Output: PNSR-improved Brain MRI Images ‘$DI(t)$’
1: Initialize ‘n’, ‘m’, time ‘t’ **2: Begin** **3: For each Dataset ‘DS’ with Features ‘F’ and Brain MRI Images ‘BI’** **4: Formulate Brain MRI input image with gray level function as in equation (1)** **5: Formulate Brain MRI noisy image with gray level function as in equation (2)** **6: For ‘i’ inputs, ‘j’ outputs and ‘s’ state variables** **7: Formulate the state space representation for the corresponding Brain MRI Images ‘BI’ as in equations (3) and (4)** **8: Estimate state estimate series of measurement observed over a time period ‘t’ as in equation (5)** **9: Evaluate covariance series of measurement observed over a time period ‘t’ as in equation (6)** **10: Obtain Kalman Bucy gain as in equation (7)** **11: Return denoised images ‘DI’** **12: End for** **13: End for** **14: End**

Algorithm 1 Kalman Bucy Filtering-based Image Denoising

As given in the above Kalman Bucy Filtering-based Image Denoising algorithm, initially, the gray level functions are obtained separately for Brain MRI input and Brain MRI noisy images. Second, a state space representation with separate matrix for input, output and state is obtained. Third, over a succession of time period, state and covariance series are estimated. Finally, denoised images are obtained via Kalman Bucy gain. With this, the PSNR is improved in computationally efficient manner.

3.3 Neutrosopic Neuro Fuzzy set (NNFS)

Indeterminacy of all elements cannot measure as well as simply evaluated in traditional set. On other hand, fuzzy set occupied its application for handling uncertainty. In certain applications not only true membership must be considered. In addition, inclusion of false as well as indeterminacy of membership plays a major role.

To name a few applications being the processing of medical images that in turn would possess certain amount of indeterminacy value. As a result it is found to be laborious and cumbersome process to be addressed by employing the traditional fuzzy set. Neutrosopic Neuro Fuzzy set (NNFS) is used to tackle the uncertainty with help of the membership grade.

In our work, via truth, indeterminacy as well as falsity membership grades, neutrosophic set (NS) is utilized for handling the uncertainty of noisy image. An efficient image denoising process is carried out with higher PSNR. Figure 3 shows the block diagram of Neutrosopic Neuro Fuzzy set model.

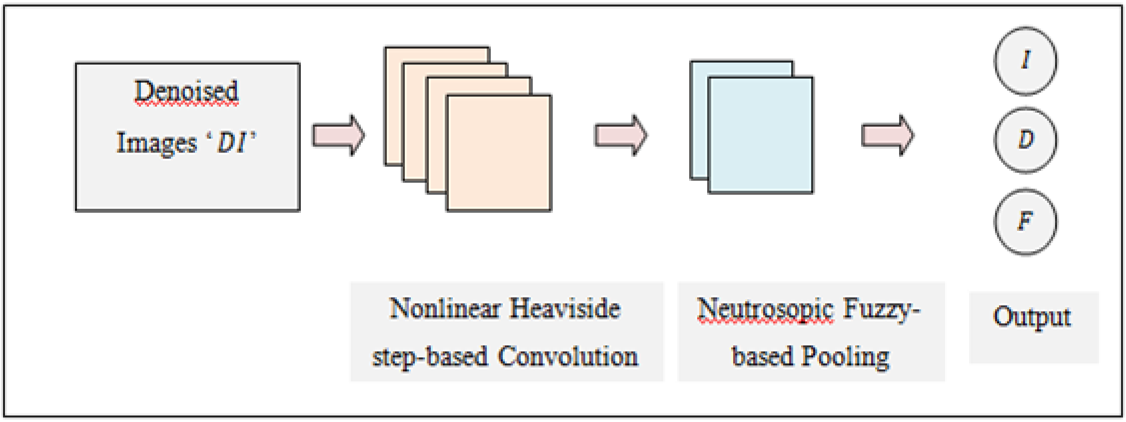

Figure 3 Structure of Neutrosopic Neuro Fuzzy set model

As shown in the above figure, in our work, deep neural network is integrated with neutrosophic fuzzy set Neutrosopic Neuro Fuzzy set for handling uncertainty issue in denoised brain MRI images. The neutrosophic denoised image is characterized by three subsets 'T', 'I' and 'F' respectively. With the aid of the above sets, '$T(m,n)$', '$I(m,n)$' and '$F(m,n)$' in neutrosophic are network's weights are updated. Finally, the updated weights were reused for new sets of images. Let us consider a pixel ' Pi ' in neutrosophic denoised image described as '$Pi(m,n)\{T(m,n), I\ (m,n), F(m,n)\}$'. As a result, for each pixel in the neutrosophic denoised image, the truth set 'T', false set 'F' and indeterminacy set 'I' has to be evaluated. Therefore, a pixel in the neutrosophic denoised image is represented as given below.

$$DI_{NS}(m,n) = \{T(m,n), I(m,n), F(m,n)\} \quad (8)$$

From the above formulation, '$t\%$' represents true (i.e., set of white pixels), '$i\%$'represents indeterminate (i.e., set of boundaries) and '$f\%$' represents false (i.e., set of non-white pixels), where '$t \in T$', '$i \in I$', and '$f \in F$' respectively. Let us further assume layer '$l-1$', '$m-th$' input denoised image as '$DI^{l-1}(m)$' and '$W^{l}(m,n)$' represents the weight that associates '$n-th$' feature of the output layer to the '$m-th$' feature of the input layer. Then, the convolution layer for the corresponding input denoised image is mathematically stated as given below.

$$DI^{l}(n) = HF\ \left[\sum_{m}\left(DI^{l-1}(m) * W^{l}(m,n) + B^{l}(n)\right)\right] \quad (9)$$

From the above equation (9), '$B^{l}(n)$' represents the bias of the convolution layer with '$*$' denoting the convolution operation and 'f is a nonlinear Heaviside step function which is acquired by

$$HF(DI) = \frac{d}{dDI} MAX\{EI, 0\} \quad (10)$$

From the above equation (10), Heaviside step function 'HF' is evaluated for each denoised image 'DI' based on the derivative results. Followed by which in the pooling layer, '$DI^{l}(n)$' is obtained as given below.

$$DI^{l}(n) = POOL\ \left[DI^{l-1}(n)\right] \quad (11)$$

From the above equation (11), '$POOL$' denotes the sampling function applied to the denoised image 'DI' at the '$l-1$' layer and during the training phase, three functions '$T(m,n)$', '$I(m,n)$' and '$F(m,n)$' are evolved as given below.

$$T(m,n) = \frac{LMV(m,n) - LMV_{min}}{LMV_{max} - LMV_{min}} \quad (12)$$

$$LMV(m,n) = \frac{1}{(w*w)} DI(m+u, n+v) \quad (13)$$

$$I(m,n) = \frac{\delta(m,n) - \delta_{min}}{\delta_{max} - \delta_{min}} \quad (14)$$

$$\delta(m,n) = ABS[LMV(m,n)] \quad (15)$$

$$F(m,n) = 1 - T(m,n) \quad (16)$$

From the above equations (12) and (13), '$LMV(m,n)$', 'LMV_{min}' and 'LMV_{max}' denotes the local mean value, minimum local mean value and the maximum local mean value of the pixel 'm,n' respectively. The local mean value is obtained by utilizing neighboring pixels possessing similar intensity value with 'w' representing the window size of the 'DI'. Also from (14) and (15), the indeterminate resultant value '$I(m,n)$' is arrived at by means of the absolute value of local mean value '$\delta(m,n)$', average minimum value 'δ_{min}' and average maximum value 'δ_{max}' respectively. Finally, the falsified resultant value is obtained in equation (16). With this uncertainty was removed from denoised brain MRI images. With the design of this novel neutrosophic nonlinear Heaviside step function which was based on the local mean value utilizing neighboring pixels this deep neural network model considered uncertainty with the aid of membership grade. This in turn handled uncertainty by means of additional domain 'I' that increases the efficiency of dealing with uncertainty in case of denoised images. The pseudo code representation of Neutrosopic Neuro Fuzzy set is given below.

Input: Dataset 'DS', Features '$F = F_1, F_2, \dots, F_n$', Brain MRI Images '$BI = BI_1, BI_2, \dots, BI_m$'
Output: Uncertainty resolved denoised image
1: Initialize denoised images 'DI' **2: Begin** **3: For each Dataset 'DS' with Features 'F' and denoised images 'DI'** **4: Formulate neutrosophic denoised image as in equation (8)** **5: Formulate convolutional layer as in equations (9) and (10)** **6: Evaluate '$DI^l(n)$' in the pooling layer as in equation (11)** **7: For each denoised image 'DI' at the '$l-1$' layer** **8: Formulate true (i.e., set of white pixels) set as in equations (12) and (13)** **9: Formulate indeterminate (i.e., set of boundaries) set as in equations (14) and (15)** **10: Formulate false (i.e., set of non-white pixels) set as in equation (16)** **11: Return** **12: End for** **13: End for** **14: End**

Algorithm 2 Neutrosopic Neuro Fuzzy set

As given in the above Neutrosopic Neuro Fuzzy set algorithm, the application of Neutrosopic Fuzzy set for denoised brain MRI images are applied in the deep neural network framework. With the denoised images obtained as input, the pixel representation of the neutrosophic denoised image is first obtained. Second, convolution layer for the corresponding input denoised image is performed using nonlinear Heaviside step function. Finally, in the pooling layer, three functions are evolved and network's weights are updated. Finally, the updated weights are utilized for the other sets of images.

4. Experimental setup

Quantitative outcomes for estimating the image denoising based on neutrosophic fuzzy set methods with simulations performed in Matlab. In experiments, performance of the image denoising based on neutrosophic fuzzy set method called, Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) is compared with [1] and SMNS [2]. Several factors such as PSNR, execution time and true positive rate have been used for the evaluation of aforementioned methods using Brain MRI LGG segmentation dataset.

5. Results

KBF-NNFID for medical image denoising in the presence of uncertainty using three different performance metrics by making detailed comparison with [1], [2] are provided.

5.1 PSNR

It has refers to percentage among highest feasible importance of a brain MRI as well as potentiality of corrupting noise to influences precision of its categorization. It is utilized in quantifying rebuilding quality during denoising process. The PSNR value is mathematically stated as given below.

$$PSNR(dB) = 10log_{10}\frac{255^2}{MSE} \quad (17)$$

Where, '$PSNR$' measured with mean square error 'MSE'.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[BI(m,n) - DI(m,n)]^2 \quad (18)$$

Where, 'MSE' evaluated depended on square dissimilarity pixel values among processed denoised image size '$DI(m,n)$' as well as original brain MRI image '$BI(m,n)$' by higher probable pixel value as 255. The PSNR is estimated in terms of decibel (dB). KBF-NNFID method on medical image denoising with [1] [2] using similar brain MRI image dataset is compared in Table 1.

Table 1 PSNR measure of the proposed KBF-NNFID method and other state-of-the-art methods

Image size (KB)	PSNR (dB)		
	KBF-NNFID	Iterative contraction algorithm based on Chi-square similarity and fuzzy logic	SMNS
28.7	64.65	58.25	55.32
36.5	62.15	56.66	53.14
27.7	60.22	56.81	55.32
52.3	58.63	52.25	48.70
56.4	64.95	56.66	51.40
33.9	63.31	58.25	53.14
51.3	66.24	62.68	58.25
46.5	61.73	56.66	54.72
40.7	57.63	53.14	50.64
31.7	60.22	55.32	54.16

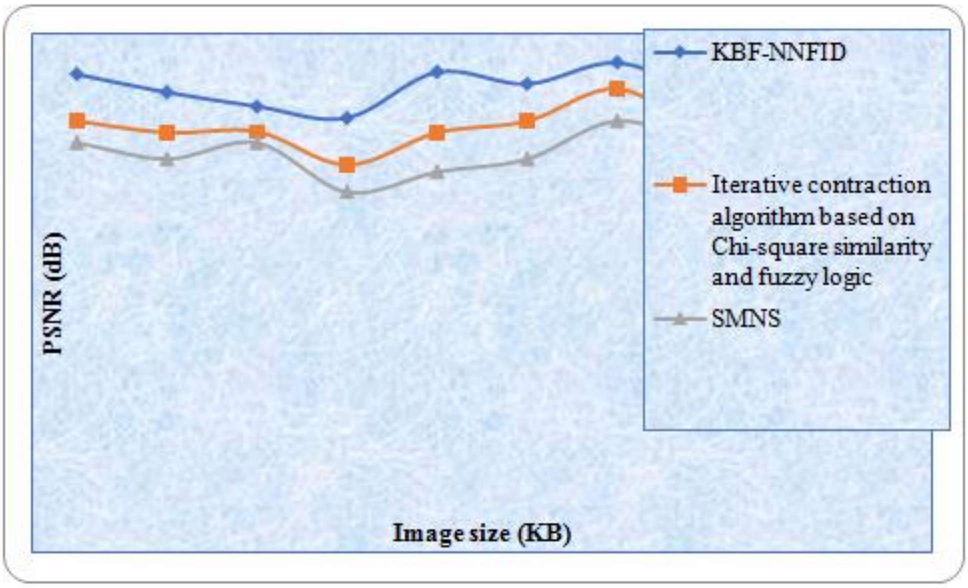

Figure 4 PSNR versus image size

PSNR demonstrated in Figure 4. From the above figure, by dissimilar image sizes concerned in medial image denoising even in the presence of uncertainty, PSNR as well be different. But, performance result of PSNR using the KBF-NNFID than [1] and [2]. Image size of 28.7KB considered, KBF-NNFID of PSNR is 64.65dB, and 58.25dB and 55.32 dB using [1] and [2]. On contrary to existing, KBF-NNFID better. Neutrosopic Neuro Fuzzy set algorithm in Neutrosopic Fuzzy set for denoised brain MRI images in deep neural network framework. Here, first the pixel representation of the neutrosophic denoised image was first obtained. Next, with the aid of nonlinear Heaviside step function convolution was performed for respective input denoised image. Finally with the three functions obtained in the pooling layer, network's weights were updated. As a result, the PSNR rate using KBF-NNFID method was said to be improved by 9% compared to [1] and 16% compared to [2].

5.2 Execution time

Image denoising execution time is second factor. Image denoising execution time is mathematically formulated by.

$$ET = \sum_{i=1}^{n} BI_i * Time \ \left(KB(t)\right) \tag{19}$$

From the above equation (19), the image denoising execution time 'ET' is measured based on the brain images images 'BI_i' as well as '$Time \ \left(KB(t)\right)$' is time needed at image denoising. It has estimated in milliseconds (ms). Performance of the proposed KBF-NNFID method on image denoising with previous work Iterative contraction algorithm based on Chi-square similarity and fuzzy logic [1] and SMNS [2] conducted on medical images using similar Brain MRI image dataset in Table 2.

Table 2 Execution time measure of the proposed KBF-NNFID method and other state-of-the-art methods

Images	Execution time (ms)		
	KBF-NNFID	Iterative contraction algorithm based on Chi-square similarity and fuzzy logic	SMNS
10	0.35	0.41	0.46
20	0.42	0.55	0.7
30	0.48	0.65	0.85
40	0.53	0.68	0.95
50	0.55	0.74	1.25
60	0.59	0.8	1.4
70	0.65	0.85	1.55
80	0.68	0.92	1.7
90	0.75	1.15	1.85
100	0.82	1.35	2.05

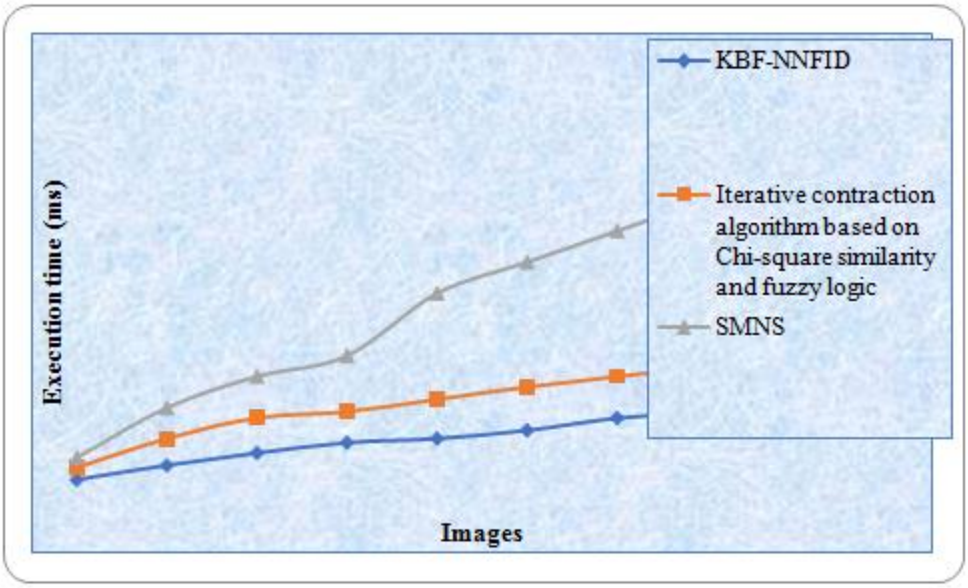

Figure 5 Execution times versus images

Execution time illustrated in Figure 5. From figure, horizontal axis is number of sample images as well as vertical axis is execution time evaluated in milliseconds (ms). Image denoising execution time has straightly enhancing to samples. Nevertheless, experiments carried out by 10 samples demonstrated KBF-NNFID, [1] [2] execution time is 0.35ms, 0.41ms and 0.46ms. On contrary to conventional, ET of KBF-NNFID is lesser. Kalman Bucy Filtering-based Image Denoising algorithm utilized. initially gray level functions were evaluated distinctly for Brain MRI input and Brain MRI noisy images. Moreover, a state space representation with separate matrix for input, output and state were obtained. With this the execution time involved using KBF-NNFID method were found to be comparatively lesser by 26%, as well as 50% than [1] [2].

5.3 True positive rate

True positive rate plays main task. Maximum values of true positive rate establish consistency of image denoising scheme employed. True positive rate is for denoise image even in presence of uncertainty in a successful manner with real positive range, i.e., to properly discover denoised image as denoised and vice versa. This is mathematically expressed as given below.

$$TPR = \frac{TP}{TP+FN} * 100 \quad (20)$$

From the above equation (20), true positive rate 'TPR', true positive is 'TP', false negative is 'FN'. TPR comparison is given in Table 3 in KBF-NNFID [1] [2] .

Table 3 True positive rate measure of the proposed KBF-NNFID method and other state-of-the-art methods

Images	True positive rate (%)		
	KBF-NNFID	Iterative contraction algorithm based on Chi-square similarity and fuzzy logic	SMNS
10	90	80	70
20	88.35	79.35	68.45
30	88	79	65.35
40	87.45	78.15	65
50	87	78	64.15
60	86.55	77.34	64
70	86.25	77	63.85
80	86	75.35	63.25
90	84.35	75	63
100	84	73.15	61

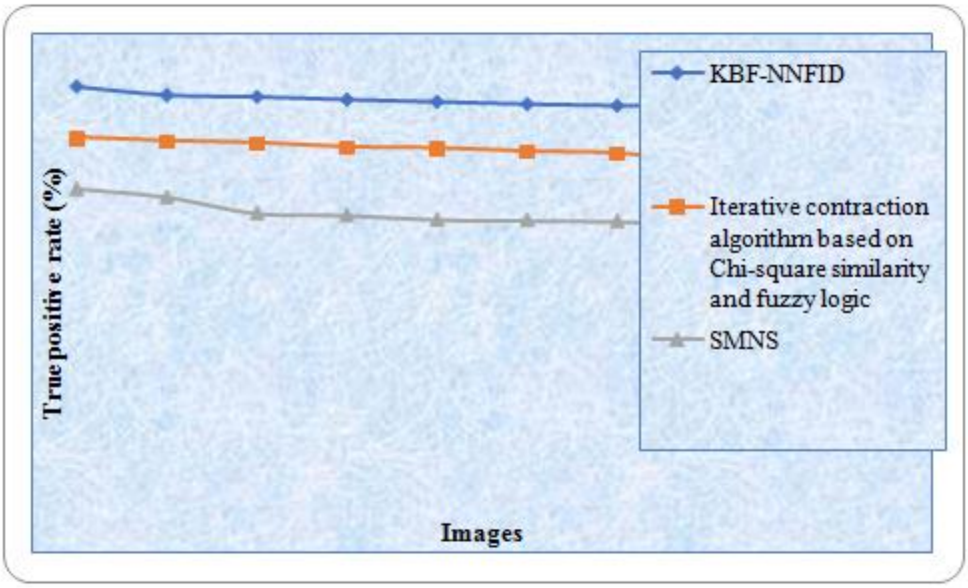

Figure 6 True positive rate time versus images

TPR proved in Figure 6.In figure, TPR for three techniques are found to be inversely relative to number of images. But, 10 images are taken for measuring simulation then TPR is 9% by KBF-NNFID, 80% and 70% by [1] and [2]. KBF-NNFID of TPR has better than existing [1], [2]. KBF-NNFID of TPR has better than [1], [2]. Symmetric Convolute layer employed for extract features. TPR enhanced by 5%, 11% than 1], [2].

6. Summary

Novel Kalman–Bucy Filtered Neutrosophic Neuro Fuzzy Image Denoising (KBF-NNFID) method is developed for medical image denoising even under uncertainty from brain MRI images. We developed the KBF-NNFID method by integrating Kalman Bucy Filtering and Neutrosopic Neuro Fuzzy set for minimum noisy artifacts with enhanced PSNR in computationally efficient fashion. A novelty of Kalman Bucy Filtering-based Image Denoising algorithmis determined in denoised images is achieved in a computationally efficient manner by means of Kalman Bucy Gain function. The state space model and series of measurement were observed over a time period by means of Kalman Bucy Filtering. Next, by employing nonlinear Heaviside step function that initially convoluted the denoise images and then performed pooling via local mean value.A new algorithm called Neutrosophic Neuro Fuzzy set in an accurate manner which help of Neutrosophic Fuzzy set subjected to deep neural network also addressed uncertainty involved during the denoising process. In this manner the brain MRI images were denoised even under uncertainty in a timely way. An image denoising was performed for preserving the geometrical features by means of Kalman Bucy Filtering-based denoising model for removing the noise. Second with the denoised brain MRI images as input, Neutrosopic Neuro Fuzzy set algorithm was applied that handled uncertainty via indeterminate functions. We used the Brain MRI Images Dataset for medical image denoising. Experimental evaluation is carried out using medical images with different performance metrics such as 13% enhanced PSNR, 38% minimum ET and 14% improved TPR.

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