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Suppression of Interference Caused by Fragment Brownian Movement through the Utilisation of Fuzzy Formulation

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Abstract The proposed fuzzy composition-based filtering method aims to remove a presence of fractal Brownian noise in the MR brain images. The fractional Brownian motion (FBM) noise is a continuous time Gaussian processed noise and its very difficult to identify the positions and range of noise density level, due to a smoothed noise. The projected fuzzy scheme encloses an equivalent fuzzy interference scheme, a fuzzy average procedure and a fuzzy composition procedure. The noise subtraction scheme has been confirmed to be the finest while the depiction is tainted by means of *fractional Brownian motion*. With an average o/p Peak Signal to Noise Ratio(PSNR) of 37.22 and an average noisy image PSNR of 20.28, the average PSNR rate has improved by 16.94. In addition, the average mean square error (MSE) rate has decreased from 609.48 to 12.33 percent. An experimental result confirms that the fuzzy filtering achieves an outstanding eminence of reinstated images in terms of PSNR and MSE without the assistance of noiseless depiction.

Keywords FBM, parallel FIS, FM process, FC process, MRI brain, PSNR, MSE

1. Introduction

One vast area of real-world study and growth is clinical image and signal analysis. When diagnosing cells in the human body, a variety of pictures are acquired, including magnetic resonance imaging (MRI), computed tomography (CT), ultrasound (US), X-rays, and positron emission tomography (PET). When diagnosing diseases of the nervous system, pulmonary, renal, liver, etc., as well as detecting tumor or cancer existence and disease phase, MRI images are invaluable [21–25]. The

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goal of image restoration is to reduce or eliminate any shame associated with image perception through marginalization or diminution. Shadowing and contamination from electrical and photo-metric assets are the most common causes of depletion. When a metaphor's spectrum drops, it's usually because of a flawed illustrative layout style that uses prism architecture far from the point of focus to create a virtual shift between the camera and the source of light [12, 17]. Wherever possible, before any further arrangements, the image in question must be restored in the fields of photography, evaluation, study, and medicine. If that is the case, the aforementioned areas' preliminary processing pace is noise removal [19, 20].

The reduction of noise in images poses a significant challenge for researchers, as it results in the presence of shadows, a lack of clarity, and the introduction of unwanted artifacts into the original material [20]. The objective of image acquisition is to obtain MRI images without any noise. Various types of noise might be encountered, such as salt-and-pepper noise, arbitrary quantized impulse noise, white, speckle, and fractional Brownian noise (FBM), among others. Subtracting FBM from clinical photographs is a complex process [14]. Due to the sensitivity and delicacy of the data included in the image, any alterations to the image can significantly impact the decision-making process for disease diagnosis. Our objective is to eliminate the noise while preserving the integrity of the image data. Smoothed Gaussian noise reduces the sharpness of edge data and modifies the initial concentration variation in the spatial realm [2, 6].

1.1. Limited Brownian phenomenon

The class of fractional, or 1/f, interference is where Brownian interference shows up. In algebra, 1/f noise is expressed as a partial Brownian motion [9, 10, 15]. The mechanism of fractional Brownian movement follows a Gaussian distribution and is completely random [3, 4] [11–14]. For 1/f noise, Brownian intrusion is a special case. It is created by combining it with white noise. There have been several proposed strategies for noise removal; their operation depends on the type of image and any interference in the picture [7, 8, 15]. The interaction between fine-grained Gaussian white noise, which is unrelated to events, and stochastic action (Brownian motion) interference, which is related to percentage increases, gives rise to pink noise. Brownian motion is a mixture of white Gaussian noise, and the exponent α is raised by 2 when a signal is integrated, while it is dropped by 2 when a signal is differentiated. As a result, pink noise cannot be acquired using the simple formula of integrating or differentiating this appropriate source data. Such ways are proposed to enable a conventional statistical explanation [5, 6] that may be present in the distribution over the eventuality of signals. Conversely, the generally acknowledged major elucidation of pink noise has not been anticipated, except for a few acknowledged algebraic examples resembling fractional Brownian motion. Therefore, one of the earliest mysteries of contemporary physics and the scientific understanding of the universe is the pervasiveness of pink interference [1, 2, 10]. The research makes use of fuzzy clustering to categorize regression models suitable for fractional Brownian motion defects [19]. One fractal dimensions of FBM fractals that Chai (2020) suggested is based on random sets [18, 20]. Since it causes shadowing, dullness, and the introduction of artifacts to the source contents, noise reduction in images is a challenging problem for scientists [7, 8, 20].

There are numerous kinds of noise that can be introduced into magnetic resonance imaging (MRI), including salt and pepper, random-valued impulse, white, speckle, fractional Brownian noise, and so on. The objective of picture acquisition is to eliminate these noises. In medical pictures, one of the trickiest tasks is the subtraction of fractional Brownian noise. For the simple reason that any alterations to the visual, especially those involving light, will influence the decision-maker's ability to diagnose illness. Removing the noise without compromising the image data is therefore essential. By reducing the intensity of edge information and altering the initial intensity range in the spatial domain, the smoothed noise known as Gaussian noise is created.

1.2. Fuzzy membership

A membership utility, defined as the utility that circulates in the valid entity period and is divided between 0 and 1, is relevant to the fuzzy, which permits a steady appraisal of the membership characteristics of a group [16, 19]. Until it complies with fuzzy subset regulations, there are multiple ways to characterize membership functions for fuzzy sets.

1.2.1. Gbell function

The entire Gbell membership function depends on the three variables x, y, and z, as stated in [15],

$$f(a, w, x, y) = \frac{1}{1 + |\frac{a-y}{w}|^{2x}}. \tag{1.1}$$

In this context, the variable x is usually positive. The variable y determines the central position of the curve. The parameter vector f, denoted as the second dispute utilized for the generalized bell-shaped membership function as a vector consisting of the values w, x, and y, respectively [9].

1.2.2. π-formed function

The π-form is the result of the π-shaped MF building block's spline-based curvature, which in turn gives it a membership function. Either the left and right foundational orientations or "feet" of the curve are determined by the parameters w and x. The x and y coordinates determine the location of the "shoulders" of the curve, which are the upper and lower extremities. By multiplying S-shaped and Z-shaped membership functions, π-formed membership functions are then obtained:

$$f(a, w, x, y, z) = \begin{cases} 0, & a \leq w; \\ 1 - 2(\frac{a-x}{x-w})^2, & \frac{w+x}{2} \leq a \leq x; \\ 1 - 2(\frac{a-y}{z-y})^2, & y \leq a \leq \frac{y+z}{2}; \\ 2(\frac{a-z}{z-y})^2, & \frac{y+z}{2} \leq a \leq z; \\ 0, & a \geq z. \end{cases} \tag{1.2}$$

1.3. FBM noise generation

Produce a variety of noise interference ranges and combine them into a single signal, providing further support to the notion that low-frequency interference is more credible than higher-power interference. Produce (Gaussian) noise across a wide frequency spectrum, employing spline interpolation to achieve leveling. Then, combine everything in one go to achieve the highest level of FBM disruptive noise [1,2].

$$Noise\ Image = Noise\ free\ Image + FBM\ Noise. \tag{1.3}$$

2. Proposed methodology

The proposed noise removal method is very effective due to fuzzy interference system (FIS). The fuzzy composition process is very helpful for deciding the correct intensity range of pixel. The MRI brain images are used for testing this proposed fuzzy based filter and the FBM noise is generated based on the random valued spline interpolation. The Noise model is added to the input image and given to the proposed fuzzy based filter. The system consists of three major parts which are, Fuzzy Mean Process (FMP), Parallel Fuzzy Interference System (PFIS) and Fuzzy Composition Process (FCS). The Noisy image and processed PFIS and FMP are given to the fuzzy composition system (FCS), and then finally get the FBM noise removed image. The fuzzy interference system (FIS) contributes significantly to the efficacy of the noise removal method proposed here. The fuzzy composition process greatly facilitates the determination of the appropriate pixel intensity range. FBM noise is produced through the arbitrarily quantized spline approximation in order to evaluate the recommended fuzzy-based filtration on MRI brain images. With the source image and the suggested fuzzy-based filter, the noise framework is appended. FCM (Fuzzy Composition Process), PFIS (Parallel Fuzzy Interference System), and FMP (Fuzzy Mean Process) are the three primary components thereof. The fuzzy composition system (FCS) is provided with the noisy image and executes PFIS and FMP in order to eliminate the noise from the image prior to generating the FBM.

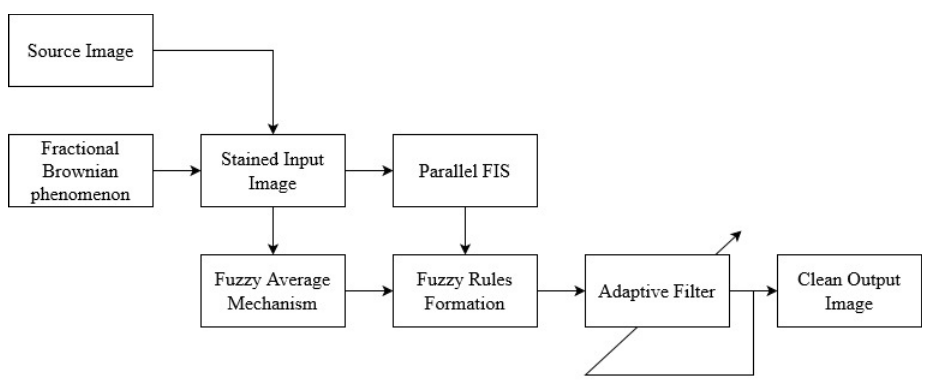

Figure 1. Block diagram of proposed fuzzy filter for FBM noise removal

2.1. Concurrent fuzzy presupposition preparation

The concurrent fuzzy presupposition method locates the current and adjacent pixel ranges using the provided LS. As a result, it can be utilized for both fuzzy average and fuzzy composition practice in order to filter noise from FBM. Each intensity value is divided into five distinct ranges as follows: High dark (HD), dark (DA), Average (AV), Intense (IN) and High Intense (HI).

$$out_n = gbellmf(X_n, L_S); \qquad X_n is L_S \tag{2.1}$$

and $X_n \ \epsilon \ \{X_1, X_2, X_3 X_n\}$ and $L_S \ \epsilon \ \{HD, DA, AV, IN, HI\}$, where HD= [10 30 d1], Da= [30 d1 d2], AV= [d1 d2 d3], IN= [d2 d3 200], HI= [d3 200 255].

$$gout_n = \begin{cases} {out_n}^2, & if \ \text{“}very\text{”} \ (\lambda = 2.0); \\ out_n, & if \ \text{“}normal\text{”} \ (\lambda = 1.0); \\ {out_n}^{0.5}, & if \ \text{“}more\ or\ less\text{”} \ (\lambda = 0.5). \end{cases} \tag{2.2}$$

$$P_{fis} = \begin{cases} \frac{\sum_{r=1}^{n^2}(x_r * gout_r)}{\sum_{r=1}^{n^2}(gout_r)}, & if \ \sum_{r=1}^{n^2}(gout_r) \geq 0; \\ 0, & otherwise. \end{cases} \tag{2.3}$$

2.2. Fuzzy average function

A four-factor trapezoidal membership function enables access to fuzzy mean behaviour, which is one of the few significant linguistic fuzzy sets. Expression (2.4) illustrates the fuzzy mean approach by using equations (2.5) and (2.6).

$$Y_{mean} = \begin{cases} \frac{\sum f_{low}}{\sum f_{mean}}, & if \ \sum f_{mean} \geq 0; \\ 0, & otherwise, \end{cases} \tag{2.4}$$

where

$$f_{lown} = f_{meann} * X_n. \tag{2.5}$$

$$f(x, 0, \alpha, \beta, 255) = \begin{cases} \frac{x}{\alpha}, & 0 \leq x \leq \alpha; \\ 1, & \alpha \leq x \leq \beta; \\ \frac{255 - x}{255 - \beta}, & \beta \leq x \leq 255, \end{cases} \tag{2.6}$$

where $\alpha = d4; \beta = d5$.

2.3. Fuzzy composition process

Fuzzy composition is the combination of two distinct language sets, namely the fuzzy average procedure and the distributed fuzzy interference process. Equation (2.7) illustrates the final result of fuzzy composition. The output of the FBM noise reduction filter is obtained by solving equations (2.8)-(2.13). The output of the π-shaped membership function with the relevant input of f_e is given by equations (2.10) and (2.11). For each noisy pixel X_n, there is an absolute difference between the values of f_m and f_e.

$$f_{comp} = f_x\ high + f_x\ low, \tag{2.7}$$

$$f_m = |min(P_{fis}) - Y_{mean}|, \tag{2.8}$$

$$f_e = |f_m - X_n|, \tag{2.9}$$

$$f_{Fhigh} = pimf(f_e, [0\ 10\ Low\ High]), \tag{2.10}$$

$$f_{Flow} = pimf(f_e, [Low\ High\ 225\ 255]), \tag{2.11}$$

where Low=d6, High=d7;

$$f_x high = f_m * f_{Fhigh}, \tag{2.12}$$

$$f_x low = X_n * f_{Flow}. \tag{2.13}$$

3. Result & discussion

This work selects 59 MRI brain pictures with a size of 512x512 from five patient datasets. To eliminate FBM noise, we first reduce these photos to 256x256 pixels. For the purpose of evaluation, this work tabulates ten picture results. Figure 2 displays the results of the test images. By combining the 2(c) original image with the randomly generated FBM noise image in figure 2(a), we obtain the figure 2(b) image. Figure 2(b) shows an example of processing an FBM noise image using the suggested fuzzy filter. Finally, the result of the suggested fuzzy filter is shown in figure 2(d), a rebuilt image from a noisy one. Figure 3 displays the three-dimensional perspective of the test photos from Figure 2. The proposed fuzzy filter performs optimally at [64;108;152;50;190;50;70;] for [D1;D2;D3;D4;D5;D6;D7]. The outcome of the noise reduction process is dependent on the fixed values d1 and d7. We consider both MSE and PSNR when evaluating the system's efficiency.

$$PSNR = 20 * log_{10} \frac{255}{MSE}\ in\ dB, \tag{3.1}$$

$$MSE = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (x_{i,j} - y_{i,j})^2}{M * N}. \tag{3.2}$$

Here $x_{i,j}$ is a noise free image pixel concentration at i, j. $y_{i,j}$ is the reconstructed image pixel concentration at i, j. M and N is row & column of noise free image. The input MSE & PSNR values are obtained from noise-free image and FBM noise image and also output MSE & PSNR values are obtained from noise-free image and reconstructed image.

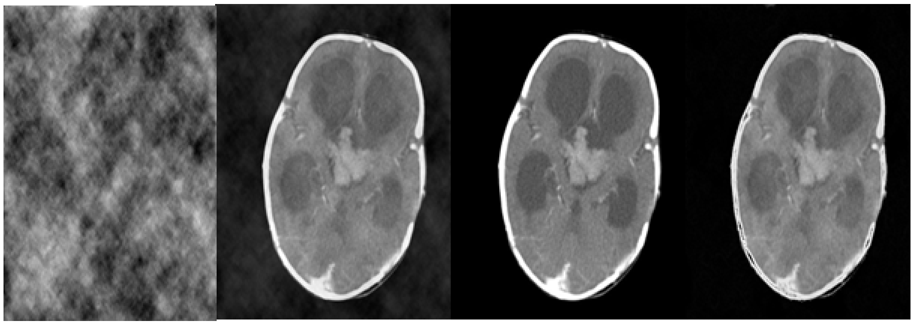

Fig. 2. (a) FBM Noise; (b) FBM Noisy Image; (c) Original Image; (d) Restored Image

Figure 2. 2D-response of proposed fuzzy filter for FBM noise removal

To demonstrate some visual responses of the suggested scheme, in Figure 2 the original MR images and their noisy variants with the presence of 30% FBM noise are shown. A fuzzy filter is used to remove noise in the MR image, and PSNR (dB) values are presented for each image. A comparison of the suggested approach with various noisy images is presented in Table 1. The proposed method produces higher image quality in terms of PSNR values, as demonstrated in Figure 3.

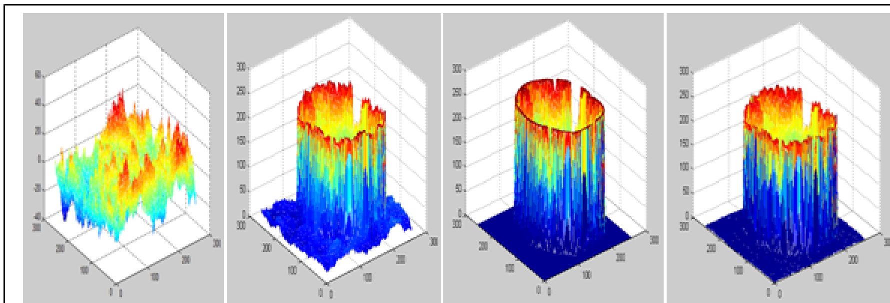

Fig. 3. (a) FBM Noise; (b) FBM Noisy Image; (c) Original Image; (d) Restored Image.

Figure 3. 3D-response of proposed filter

The average peak signal-to-noise ratio (PSNR) values of each tested filter (Adaptive Wiener filter, Median filter, and Adaptive Median filter) are compared to the suggested filtering scheme in Table 2. To remove the FBM noise, each filter is employed. A noise density of 10-30% is applied to the MRI image. Table 2 shows that when all four filters are compared, the proposed fuzzy filter performs better. In comparison to the Median, Weiner, and Adaptive Weiner filters, the fuzzy filter has a greater PSNR.

4. Conclusion

The proposed fuzzy based filter is used for removing FBM noise from the MRI brain images. The achievement of the recommended filter relies on the fuzzy membership

Image	1	2	3	4	5	6	7	8	9	10
i/p MSE	606.9	594.3	583.2	580.2	585.3	608.3	616.4	624.9	637.8	657.5
o/p MSE	13.38	12.43	11.92	12.00	11.86	12.80	12.40	12.22	12.01	12.29
i/p P-SNR	20.30	20.39	20.47	20.50	20.46	20.29	20.23	20.17	20.08	19.95
o/p P-SNR	36.86	37.18	37.37	37.33	37.40	37.06	37.20	37.26	37.33	37.24

Table 1. Proposed fuzzy filtering result

FBM Noise	10%	20%	30%
Wiener	43.2096	40.7198	29.4058
Median	51.9813	50.0028	36.8096
Adaptive Median	38.9811	36.6111	35.5311
Proposed Fuzzy Filter	54.8327	51.4818	37.3787

Table 2. Proposed fuzzy filtering result PSNR comparison with different filtering methods

input parameters, and these ranges of parameter values determine the result of the proposed system. So it can efficiently detect and replace the right value for the noisy pixel through the function of PFIS, FMS and FCS modules. The average PSNR rate improvement is 16.94 from the average o/p PSNR value 37.22 and average noisy image PSNR value 20.28. And also average MSE rate is reduced from 609.48 into 12.33. The future improvement of the proposed system focus on fixing the right values to input parameters of the fuzzy membership.

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