Medical Magnetic Resonance Image Denoising by Adjusted Non-Local Means Algorithm

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Abstract: Medical images represent a very important class of digital imeges because they faciliate significant improvements in diagnostics, which is a cornerstone of any medical treatment. Magnetic resonance images are one of the latest and most powerful ways of looking into the human body and differentiating various tissues and organs. Like any physical system, magnetic resonance imaging is prone to interferences and imperfections which appear in the resulting images as different types of noise. Hence, magnetic resonance images are a very important class of medical images and their enhancement is very significant for the quality of diagnostic process. In this paper we presented an algorithm for improving magnetic resonance images of the brain. We tested our proposed adjusted non-local means filter for removing random noise in the magnetic resonance images of the brain on several standard benchmark images. Several evolution metrics were used to prove the quality of the proposed method.

Key–Words: Magnetic resonance images, magnetic resonance noise, non-local means filter, magnetic resonance images denoising

1 Introduction

Digital images were widely used during recent years. Many different fields use applications that include digital images and some image processing, including quality control [1], astronomy [2], meteorology [3], etc. Image processing can be at the lower lever (denoising [4], contrast enhancement [5], etc.) or higher level (segmentation [6], thresholding [7], [8], [9], shape recognition that includes optical character recognition [10], [11], [12], face recognition [13], skin detection [14], lip detection [15], etc.)

One of the areas in which digital image processing is very necessary is medicine since digital images are very important for medical diagnosis. In the field of medical imaging, techniques for digital image processing began to be used first in late 1960's and early 1970's. There are several types of medical images that are used such as magnetic resonance imaging (MRI), ultrasound imaging (US) and computed tomography (CT).

Magnetic resonance is used in medicine radiology to diagnose and report the diseases like tumors or cancer. Also it is used for treatment monitoring. This method does not use damaging radiation which makes this method very popular. Magnetic resonance imaging uses a magnetic field and pulses of radio wave energy in order to make pictures of organs and structures inside the human body. Reading MRI can give different information about organs. Some of that information can be seen using other medical imaging methods such as X-ray, computed tomography and others, but MRI may also presents some problems that cannot be seen using other methods.

For making MRI images, the area of the body that need to be studied is placed inside a special machine that creates strong magnetic field. That magnetic field makes protons in the body to align with the field. Radio-frequency pulses through the patient, which stimulates protons to spin out and strain around the magnetic field. After turning off the radio-frequency field, the MRI sensors detect released energy of the protons. Time necessary for the protons to realign with the magnetic field and the amount of energy that was released are changing based on the environment as well as on the chemical nature of the molecules. Pictures from an MRI scan are digital images that can be saved and stored on a computer for further study. The images also can be reviewed remotely, such as in a clinic or an operating room. In some cases, contrast material may be used during the MRI scan to show certain structures more clearly. Advantage of the MRI is that it generates high resolution images of soft tissues that are found in the human body. Most complex soft organ in human body is the brain.

For medical image processing noise is one of the major problems which undesirably corrupts medical images. Procedure of image denoising in image processing has a role to remove a noise from image, while retaining its quality. Noise removal is applied to various medical images enhancements. There are different types of noise that appear in digital images. Some types include Gaussian noise, salt and pepper noise, speckle noise, Rician noise, fractional Brownian motion noise, etc.

Gaussian noise often appears in natural images, speckle noise is observed in ultrasound images, Rician noise affects magnetic resonance images while random noise can appear in any type of images. Model of the noise depends on its source [16]. In digital images is very difficult to remove the noise that has a low frequency because it is difficult to distinguish low frequency noise from the real signal [17]. Generation of noise can arise because of poor instruments in image processing or interface. Noise on digital images may be obtained by compression, error in transmission or some other factors. MRI images are corrupted by various types of noise [18].

For the mentioned types of noise, denoising techniques should consider the image quality. Better image quality contributes to better diagnosis of the disease. In the diagnosis of a tumor an important role plays accurate detection and location of tumors [19]. A brain tumor represents an abnormal growth of tissue. Normal tissue mass, whose cells grow and multiply uncontrollably make a brain tumor [20]. Brain tumors can be primary or metastatic, and either malignant or benign, may be localized or extended while secondary tumors could be in different locations. Primary brain tumors include any tumor that starts in the brain and it can start from brain cells, the membranes around the brain, nerves, or glands. It is important to diagnose brain tumor on time since tumors can destroy and damage brain cells on many different ways such as by producing inflammation, placing pressure on other parts of the brain, increasing pressure within the skull, etc. A metastatic brain tumor is a cancer that has spread from elsewhere in the body to the brain. Brain tumor is the second leading cause of cancer death [21]. The occurrence of brain tumor that grows quickly, is more common in older people in comparison with the younger population. The tumor can directly destroy all the healthy cells of the brain because it spreads rapidly inside or around the brain. On the other hand, it can indirectly cause brain inflammation, swelling and pressure inside the skull.

It should be careful when dealing with sensitive organs like the brain and hence most commonly techniques like computed tomography (CT) and magnetic resonance imaging (MRI) are used to locate brain tumor. Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to visualize internal structures of the body in detail.

Magnetic resonance imaging technique is effective without ionizing radiation and risk for the patient. The technique of magnetic resonance imaging provides high quality and contrast of anatomical structures and functional images of various organs of the human body. Soft tissue structures such as the heart, brain or lings can be clearly seen through magnetic resonance rather than through other techniques. The technique of magnetic resonance imaging provides a lot of information, but it is widely used as a method for diagnosis and treatment planning [22]. Lately, more and more researchers are engaged by improving image quality, so as to allow easier and more precise analysis of magnetic resonance images. The most common researches performed upon magnetic resonance images of the brain. Using magnetic resonance image different states in which the brain can be found, such as cysts, bleeding, swelling or inflammatory condition can be determined. Also, it can determine whether the brain damage caused by injury or stroke.

In the processing of digital images, denoising technique aims to eliminate noise that affected the picture during transmission or making image while preserving its quality. In the medical field images obtained using magnetic resonance imaging is the most common tool for diagnosis disease. Magnetic resonance images are often affected by random noise occurring in the acquisition images. Noise generated in images produced undesirable visual quality and reduces the visibility of objects with low contrasts [23]. In health care, elimination of noise is of crucial importance in order to improve the recovery of details that can be hidden in the data. Magnetic resonance images are usually damaged with noise that render medical diagnosis. But the process of removing noise should not degrade the useful features in the image, especially the edges that represent important features of magnetic resonance images.

In this paper we proposed an algorithm for removing random noise from MRI brain images. We proposed a non-local means filter and we evaluated results using several metrics.

The remainder of this paper is divided into five sections. Section 2 provides literature overview of techniques and methods used for magnetic resonance image denoising. That section describes different types of transformations used for denoising. Section 3 describes various types of noise that can be found in magnetic resonance images and their characteristics. Section 4 presents the proposed algorithm to eliminate random noise from magnetic resonance images of brain which is based on non-local means filter. Section 5 presents the results obtained during the processing of magnetic resonance images with the proposed algorithm and evaluation metrics. Evaluation metrics were used for comparison of some calculation results. At the end in Section 6 conclusion is given.

2 Literature Review

Medical digital image processing represents wide scientific field. Diversity of medical digital images as well as numerous different organs and disease provide many research topics. Algorithms for processing medical digital images from different sources can be significantly distinguish. In this paper we are dealing with MRI images of brain.

In the case of MRI brain images one of the most common task is image segmentation [24], [25], [26]. The MRI brain image segmentation as a result detects and marks the tumors or lesions. Methods for image segmentation usually contains some thresholding techniques. Finding the optimal threshold values represent hard optimization problem. Swarm intelligence algorithms are rather popular method for solving hard optimization problems. In the last decade many different optimization algorithms were proposed, including fireworks algorithm [27] and enhanced fireworks algorithm [28], firefly algorithm [29], [30], [31], artificial bee colony [32], [33], [34], ant colony optimization [35], [36] and others.

Beside already mentioned problem of MRI image segmentation, MRI image classification is also common research topic. Problem is to find a method that based on given MRI image label it as normal or abnormal [37]. More precise analysis can include tumor detection [38]. For all this task, first step is the same. It is necessary that MRI image is the best as it can be. As mentioned before, one of the common degradation on MRI images is noise and it should be removed in order to advance analysis become more precise and accurate.

There are different methods and filters for noise reduction in magnetic resonance images. One of the filters which removes noise like Rician noise is based on Wiener filter [39]. This filter uses neutrosophic set which is applied in image domain. The image is transformed to neutrosophic set domain which uses three sets: True, Indeterminacy and False. Wiener filter method is used to remove noise for True and False sets to decrease Indeterminacy. Magnetic resonance images can be found from database Brainweb that contains images affected by the Rician noise. Performance of the Wiener filter could be compared with some other filters, like a non-local means filter or anisotropic diffusion filter.

Magnetic resonance images may be affected by random noise which limits accuracy of measurements. Removing the noise of this type from an image can be done through a non-local means filter which has its own parameters. For this method it is necessary to find the optimal parameters for different levels of noise so that the filter be adaptable to the characteristics of the noise in the magnetic resonance images. This technique was successfully tested by Manjon et al. [40].

In the magnetic resonance images one of the common sources of noise is thermal noise. Image reconstruction is performed by inverse discrete Fourier transformation. Noise which was reconstructed is complex white Gaussian noise. Signal magnitude is used for computerized analysis and diagnosis. The method that can be used over noisy MRI images is bilateral filter in underestimated wavelet domain [41]. The wavelet transform allows to ensure the presence of coefficients that are noisy. Bilateral filter is applied to the transformed coefficients and it removes noisy coefficients. Compared with classical wavelet domain denoising, reconstructive MRI data will give higher peak to signal ratio.

Using magnetic resonance imaging the brain tumor can be extracted by applying a mathematical morphological reconstruction. MRI images of the brain are affected by noise pulses. This method is explained by Sharma and Meghrajani [42]. In the preprocessing the magnetic resonance image global threshold technique is applied. On the processed image mathematical morphological reconstruction operation was used in order to segment the brain tumor. Proposed algorithm was adjusted to segment non-uniform intensity regions of brain tumor. Salt and pepper noise was removed by mathematical morphological operator.

Denoising based on wavelet transform has the possibility to improve the magnetic resonance imaging. Usually, uniform spatial distribution of the noise is required which is not the case in the images obtained with parallel MRI. Delakis et al. in [43] proposed a new algorithm for filtering parallel magnetic resonance images. This algorithm takes out edges from the original image and than generates a noise map from wavelet coefficients. With the aim to save the spatial resolution, at locations of edges noise map was set to zero. Directional analysis was used to calculate noise in the area where edges have a low contrast. The performance of this algorithm was compared with other methods and the results showed that proposed algorithm is comparable with them.

Magnetic resonance images can be affected by fractional Brownian motion noise. To reduce this kind of the noise from the brain MRI images methods that use wavelet-based thresholding techniques can be used. Some of these techniques of thresholding are: visu shrink, sure shrink and Bayes shrink. In [18] Rajeswaran and Gokilavani compared mentioned techniques. For comparing performance evaluation metrics were used. Evaluation metrics included calculation for: peak signal to noise ratio (PSNR), absolute error, fractal dimension, image enhancement factor (IEF), structural content, structural similarity index metric (SSIM), average difference (AD) and maximum difference (MD). These metric are also used in this paper.

In the literature there are various image processing methods used for denoising. Many of the proposed algorithms for denoising are based on wavelet thresholding [44]. These approaches attempt to separate significant features from noise in the frequency domain and simultaneously preserve them while removing noise. If the wavelet transform is applied on MR magnitude data directly, both the wavelet and the scaling coefficients of a noisy MRI image become biased estimates of their noise-free counterparts. The difficulty with wavelet or anisotropic diffusion algorithms is again the risk of over-smoothing fine details particularly in low SNR images. From these points, it is understood that all the algorithms have the drawback of over-smoothing fine details.

Wavelet based method for image denoising is usually a good choice and researched a lot in the recent years. Wavelet shrinkage enables efficient removal of noise from the preservation of a high frequency based on the dis-balancing of the energy of such representations. The technique for denoising image in the orthogonal wavelet domain, where each coefficient is thresholded, if the coefficient is smaller than the threshold, it is set to zero, otherwise it is kept or modified. The effectiveness of denoising wavelet shrinkage method largely depends on the choice of threshold parameter. The most popular methods based on wavelet thresholding are visu shrink, sure shrink and Bayes shrink. Visu shrink uses a universal threshold. In addition, subband adaptive systems have superior performance, such as sure shrink, which is a data driven system. Bayes shrink is data driven sub-band adaptive technique that surpasses visu shrink and sure shrink. Rayan and Kaimal implemented Bayesian shrinkage technique for denoising [45].

For denoising magnetic resonance images discrete wavelet transform algorithm can also be used. In [23] technique based on discrete wavelet transform and wavelet thresholding at different levels for removing random noise was proposed. Different wavelet families for denoising magnetic resonance images of the brain such as Haar transform, DB2, DB4, Sym2, Sym4 and others were used. Evaluation metrics were used for comparing the results. In [23] it was concluded that quality of denoised magnetic resonance image with the Haar wavelet transform were better in visual terms.

Magnetic resonance images affected by the random noise limit the accuracy of quantitative measurements from the data. There are some digital image filter methods used in MRI denoising. This techniques has an aim to increase the acquisition accuracy [46]. Most denoising methods are based on the signal averaging principle or statistical estimates, such as mean filter, median filter and Gaussian filter, but they have the disadvantage of blurring edges.

Median filters is often used in image processing because important details such as the edges are persevered when removing noise. The median filter represents a non-linear filter. Weighted median (WM) filters are a natural extension of median filters, which exploit not only rank-order information but also spatial information of input signal. Median filters can do an excellent job of rejecting certain types of noise such as impulse noise in which some individual pixels have extreme values [47]. In the median filtering operation, the pixel values in the neighborhood window are ranked according to intensity, and the middle value (the median) becomes the output value for the pixel under evaluation.

Magnetic resonance imaging is used in various fields of medicine to determine a disease such as cancer or tumor. Noise corrupts medical images and contributes to the fact that brings bad diagnosis of the diseases. Therefore, the methods of removing noise and keeping important signal in the best possible condition are very important for further medical research of illness that occurred in a patient.

3 Magnetic Resonance Image Noise

MRI technique is often used in the diagnostics of tumors of different parts of the body. With this technique a high quality image of the human body should be obtained that reveals a possible disease. The patient is scanned using an MRI machine while the MRI images are generated via computer [48].

In this paper we consider MRI images of the brain. MRI images can contain some kind of degradation such as noise. In the MRI images of the brain there are several various types of noise which can be present. Some MRI images can be affected by Gaussian noise, Rician noise, fractional Brownian motion noise, speckle noise, random noise and others.

Technique for generation of fractional Brownian motion noise was explained and implemented in [18] by Rajeswaran and Gokilavani. Fractional Brownian motion is non-stationary stochastic process and it represents continuous Gaussian process that has mean equal to zero. Parameter of this noise is Hurst parameter H $0 < H < 1$, and it determines the kind of the process. Special case is for $H = 1/2$ [49]. Fractional Brownian motion is defined by the following equation:

$$B_H(t) = \frac{1}{\Gamma(H+1/2)} \int_0^t (t-s)^{H-1/2} dB(s) \quad (1)$$

where $B(t)$ represents standard Brownian motion and $H \in (0,1)$ represents Hurst parameter. This equation gives poor results for applications with fractional Brownian motion because of its over-emphasizing of the origin [50]. Instead of Eq. 1 Weyl's integral was introduced:

$$B_H(t) = B_H(0) + \frac{1}{\Gamma(H+1/2)} * \quad (2)$$
$$\Big[\int_{-\infty}^{0} ((t-s)^{H-1/2} - (-s)^{H-1/2}) dB(s) + \int_0^t (t-s)^{H-1/2} dB(s)\Big]$$

Another equation for fractional Brownian motion represented with time-frequency and dual-frequency were described by Oigard et al. in [51].

Second common type of noise in MRI images is Gaussian noise. Noise is distributed evenly over the image, at each pixel of the image random value from Gaussian distribution was added. Gaussian distribution of noise is implemented using the following equation:

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(g-m)^2}{2\sigma^2}} \quad (3)$$

where g is gray level, m is average or mean of the function and σ is the standard deviation. Gaussian noise is a statistical noise, which includes the probability density function of the normal or also called Gaussian distribution. Noise values were obtained from the Gaussian distribution. Gaussian noise is properly defined as the noise with a Gaussian amplitude distribution [52].

Rician noise can be obtained from complex Gaussian noise. Rician noise is another noise that can corrupt magnetic resonance images. This noise had probability density function for intensity x given by the following equation:

$$p(x) = \frac{x}{\sigma^2}\ e^{-\frac{x^2+A^2}{2\sigma^2}}\ I_0(\frac{xA}{\sigma^2}) \quad (4)$$

Rician noise dependents on the signal in magnetic resonance image, which is not zero-mean. Distribution of Rician noise is closer to Gaussian in bright regions. Denoising the Rician noise with Wiener filter was implemented by Nowak in [53]. This method refers errors between observed data and intensities of the magnetic resonance images. Magnetic resonance images which had Rician noise could also be denoised using wave atom shrinkage [54].

Magnetic resonance images are mostly corrupted by noise during acquisition or transmission. Noise can also be produced due to imperfect instrument that is used. Image noise can be defined as random variation of brightness or color information image produced by the sensor and circuitry of the scanner. For digital images of magnetic resonance noise is low as well as high frequency component. Removing high frequency components is easier comparing to low frequency components removing. It is difficult to distinguish real low signal and the low frequency noise. Noise that is found in magnetic resonance images is usually from Riccian distribution. Riccian noise affects the image in both quantitative and qualitative manner so it is very important that image analysis, interpretation and feature detection be done properly. Noise reduction methods require to remove noise and to retain the original image quality as much as possible. The important thing about the image denoising is how to preserve the edges, so it is necessary to find an efficient denoising technique to avoid such data corruption [55].

Multiplicative noise also known as speckle noise, appears in different imaging systems as well as in magnetic resonance images. Speckle noise in medicine images often appeare in images that can provide useful diagnostic information about the disease in the human body. This noise is caused by errors in data transmission. Speckle noise can be based on gamma distribution and in that case it can be defined by the following equation:

$$F(g) = \frac{g^a}{(a-1)!\ a^\alpha}\ e^{-\frac{g^2}{a}} \quad (5)$$

As it was mentioned before, magnetic resonance imaging techniques can be an effective way to determine the diagnosis of the patient. Magnetic resonance images can be damaged by random noise.

Random noise limits the image analysis when processing on computers. It is difficult to carry out an assessment based on MRI that is affected with this kind of noise. Denoising technique makes it possible to eliminate the noise in order to obtain a more certain diagnosis of the patient. Denoising technique uses a filter through which the noise is removed. Methods of filtering can have a defect, such that high-frequency signals are eliminated from the component causing blurred edges in magnetic resonance images. Removing the random noise in the magnetic resonance images using a filter is explained in the next section.

4 Proposed Algorithm

The proposed algorithm for removing noise from images of magnetic resonance technique is non-local means (NL-means) which is based on non-local averaging of all the pixels in images. Non-local means filter for denoising takes a mean of all pixels contained in the image. The measurement is performed between the pixels and the extent of their similarity to the marked pixel. Compared to the local means algorithms, non-local means algorithm gives clearer filter results so less detail is lost in images. Non-local means algorithm was proposed by Buades et al. [56]. The Non-Local Means assumes that the image contains an extensive amount of redundancy [57]. These redundancies can be used when removing noise form the images.

Non-local means filter is an efficient method for denoising magnetic resonance image, because it keeps the borders of tissue in the right way. This type of filter has its limitations, because the calculation of similarity weight is exercised over the whole space in the neighborhood. The impact of noise in magnetic resonance imaging significantly affects the accuracy of similarity weight. Non-local algorithm calculates pixel similarity weight of the entire neighborhood. The accuracy similarity weights depend on the level of the noise intensity.

Non-local means algorithm is based on a process of averaging to incorporate all pixes in the image. In the filter processing, the process of averaging may be restricted to $M \times M$ window matrix that includes only some pixels, so that the window matrix $M \times M$ is smaller than the dimensions of the entire image. Value of centered pixel of window matrix is calculated as weighted average of pixels that belong to that window. In our proposed method we used window of the size 3×3 biased by the empirically determined weighted mean of the larger 9×9 window. Non-local means algorithm is based on the definition of the concept of similarity in the local context intensity in the neighborhood of each pixel rather than the intensity which is related only to the pixel itself. Non-local means algorithm is defined by the following equation:

$$u(p) = \frac{1}{C(p)} \int_{\Omega} v(q) f(p,q) dq \tag{6}$$

where Ω is the area of the image, p and q are two points within the image, $u(p)$ is filtered value of the image at point p while $v(q)$ is unfiltered value of the image at point q. Weighting function is $f(p,q)$. The integral is evaluated over $\forall\ q \in \Omega$. $C(p)$ presents a normalizing factor, defined by following equation:

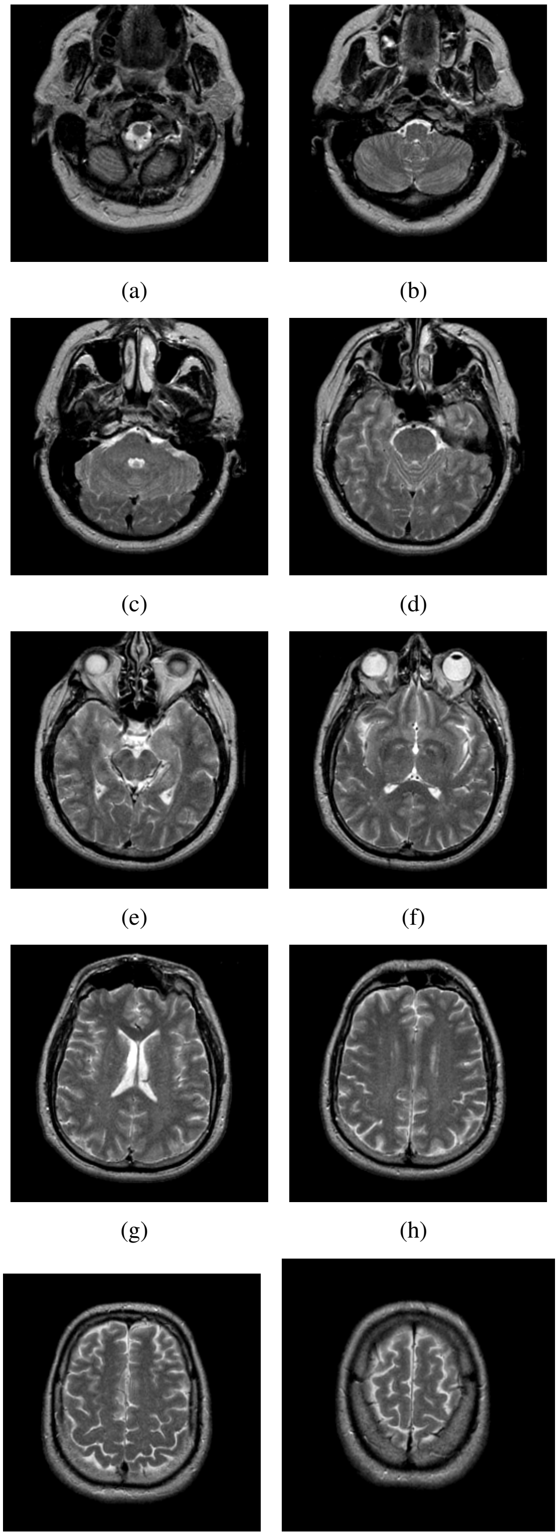
$$C(p) = \int_{\Omega} f(p,q) dq \tag{7}$$

For non-local means method which is used to remove the noise of the magnetic resonance images, there are some criteria for testing the performance of this algorithm [58], [18]. There are different types of evaluation metrics for testing the performance such as MSE (mean square error), PSNR (peak to signal ratio), NK (normalized cross correlation), AD (average difference), SC (structural content), MD (maximum difference), NAE (normalized absolute error) and IEF (image enhancement factor). Different metrics give different information about performance of the alorithm. Definition of evolution metrics as well as values of metrics obtained by our proposed algorithm will be presented in the next section.

5 Experimental Results

In this paper experiments for magnetic resonance images denoising were implemented using the following system: Intel ® Core$^{\text{TM}}$ i7-3770K CPU at 4GHz, 8GB RAM, Windows 10 Professional OS. Proposed algorithm has been implemented in the $Matlab$ version R2015a. Magnetic resonance images used for testing of the proposed method are from dataset of brain MRI and they can be found free for download at [59]. All test images are downloaded images from web-based medical image depository and all images are 256 gray scale images of the size 256×256. Five axial, T2-wighted brain MRI slices are considered. The images are in .png format. The original images are shown in Fig. 1.

Random noise was generated and inserted into the mentioned magnetic resonance images. At each pixel a random value from the range $[-15, 15]$ from uniform distribution was added. After that proposed non-local means filter algorithm was used to remove random noise from images.



(a) (b)

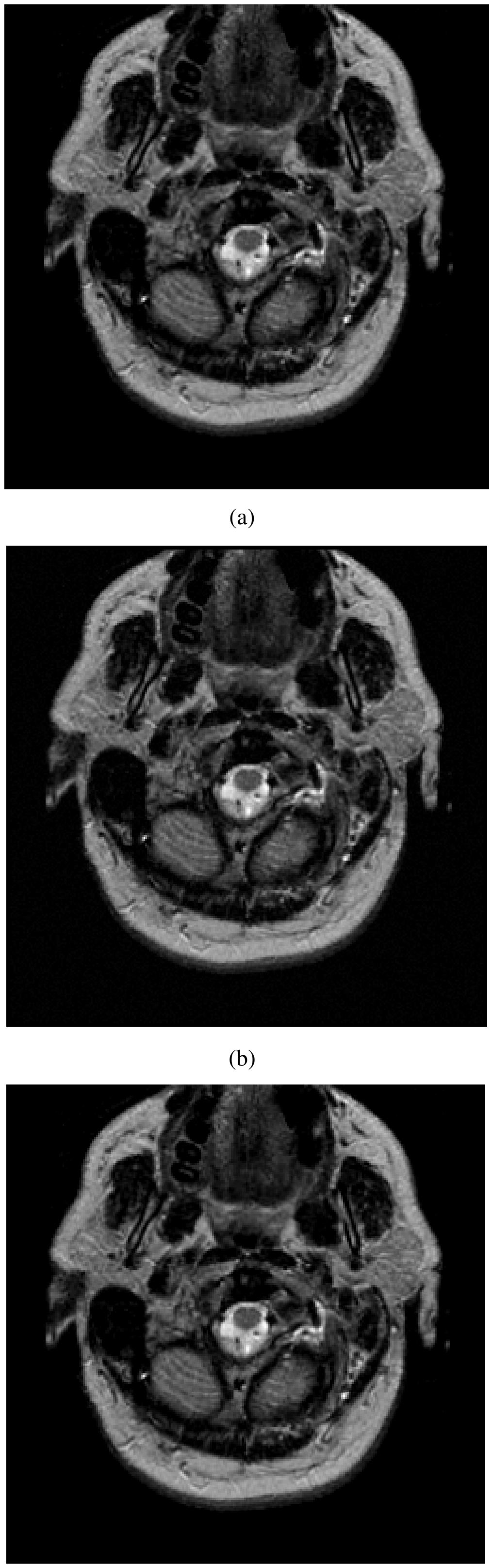
(c) (d)

(e) (f)

(g) (h)

(i) (j)

Figure 1: Original magnetic resonance images (a) Slice 22, (b) Slice 32, (c) Slice 42, (d) Slice 52, (e) Slice 62, (f) Slice 72, (g) Slice 82, (h) Slice 92, (i) Slice 102, (j) Slice 112



(a)

(b)

(c)

Figure 2: Slice 22 (a) Original MRI, (b) MRI with noise, (c) Denoised MRI

Table 1: Calculation of evaluation metrics

Evaluation metrics	MSE	PSNR	NK	AD	SC	MD	NAE	IEF
Slice 22								
with noise	39.2341	32.1942	1.0345	3.7775	0.9266	15	0.0909	-
denoised	23.4604	34.4275	0.9929	2.6506	1.0082	168	0.0710	1.6697
Slice 32								
with noise	43.7980	31.7163	1.0320	3.7648	0.9313	15	0.0856	-
denoised	31.7724	33.1103	0.9915	2.9381	1.0099	80	0.0726	1.3749
Slice 42								
with noise	40.3466	32.0727	1.0308	3.7539	0.9351	15	0.0789	-
denoised	37.9051	32.3438	0.9918	3.1320	1.0092	99	0.0711	1.0684
Slice 52								
with noise	38.7754	32.2452	1.0327	3.7016	0.9323	15	0.0710	-
denoised	36.7468	32.4786	0.9919	3.1905	1.0095	59	0.0657	1.0662
Slice 62								
with noise	38.4724	32.2793	1.0303	3.7062	0.9377	15	0.0637	-
denoised	38.0105	32.3318	0.9930	3.2856	1.0082	81	0.0602	1.0161
Slice 72								
with noise	42.9648	31.7997	1.0291	3.5327	0.9386	15	0.0916	-
denoised	39.7771	32.1345	1.0017	3.2483	1.0089	65	0.0708	1.0214
Slice 82								
with noise	35.9739	32.5709	1.0298	3.2944	0.9949	15	0.0893	-
denoised	32.1126	33.0641	1.0010	2.9242	1.0037	72	0.0696	1.0278
Slice 92								
with noise	29.6449	33.4113	1.0284	3.2647	0.9917	15	0.0884	-
denoised	23.1833	34.4791	0.9982	2.9407	1.0089	57	0.0656	1.5536
Slice 102								
with noise	28.6425	33.5607	1.0289	3.2552	0.9891	15	0.0967	-
denoised	23.2534	34.4659	0.9975	2.9736	1.0105	44	0.0817	1.5176
Slice 112								
with noise	26.3440	33.9240	1.0216	3.2351	0.9908	15	0.1021	-
denoised	22.9728	34.7187	0.9980	2.9831	1.0093	65	0.0731	1.5071

Graphical result of denoising image Slice 022 is shown in Fig. 2. Fig. 2(a) shows original image, Fig. 2(b) represents the magnetic resonance image of brain affected by random noise and finally Fig. 2(c) shows the image where the noise is removed by the proposed method.

Evolution metrics that we used to test efficiente of the proposed algorithm are some of standard metrics used in literature [58], [18]. As metioned before, we used mean square error, peak to signal ratio, normalized cross correlation, average difference, structural content, maximum difference, normalized absolute error and image enhancement factor.

The mathematical formula for calculating mean square error (MSE) is defined by the following equation (smaller is better):

$$MSE = \frac{1}{N * N} \sum_{i=1}^{N} \sum_{j=1}^{N} (x^*_{i,j} - x_{i,j})^2 \tag{8}$$

where $x^*_{i,j}$ represents pixels of the original image, $x_{i,j}$ represents pixels of the restored image and N is the dimension of the image.

For peak to signal noise ratio (PSNR) mathematical equation is presented by (larger is better):

$$PSNR = 10 \log \frac{65025}{MSE} \tag{9}$$

The equation for normalized cross correlation (NK) is presented by (closer to 1 is better):

$$NK = \frac{\sum_{i,j}^{N} \sum_{i,j}^{N} x^*_{i,j} x_{i,j}}{\sum_{i,j}^{N} \sum_{i,j}^{N} (x^*_{i,j})^2} \tag{10}$$

The equation for average difference (AD) is presented by (smaller is better):

$$AD = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (x^*_{i,j} - x_{i,j})}{N * N} \tag{11}$$

Structural content (SC) is defined by the following equation (closer to 1 is better):

$$SC = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} x^2_{i,j}}{\sum_{i=1}^{N} \sum_{j=1}^{N} (x^*_{i,j})^2} \tag{12}$$

Next metrics that can be used for quality estimation of denoising image techniques is maximum difference (MD). Maximum difference can be calculated by the following equation (smaller is better):

$$MD = \max(|x^*_{i,j} - x_{i,j}|) \tag{13}$$

Normalized absolute error (NAE) is defined by the following expression (smaller is better):

$$NAE = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |x^*_{i,j} - x_{i,j}|}{\sum_{i=1}^{N} \sum_{j=1}^{N} x^*_{i,j}} \tag{14}$$

Last metric that was used in this paper is image enhancement factor (IEF). This metric is presented by the following expression (larger is better):

$$IEF = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |x^{noise}_{i,j} - x^*_{i,j}|}{\sum_{i=1}^{N} \sum_{j=1}^{N} |x_{i,j} - x^*_{i,j}|} \tag{15}$$

where $x^{noise}_{i,j}$ is image with noise, $x^*_{i,j}$ is original image and $x_{i,j}$ is denoised image.

All this formulas are used for the estimation of the results of denoising the magnetic resonance images using the proposed method.

In the Table 1 the calculation of evaluation metrics MSE, PSNR, IEF, NK, AD, SC, MD and NAE are presented. Evolution metrics were calculated to compare the original and noisy image as well as to compare original and denoised image. Comparing the valus of the metrics for one MRI image it can be seen that our proposed method improved denoised image and made it more similar to the original image. Based on mean square error, the best resuts were achived for Slice 112. This MRI image contains larger black area and compared to the other images that were used in this paper has less edges. Non-local mean filter preserve more details than local mean filter, but it still causes some smoothing. If the image contain sharp edges, degradation will be more visible.

The best image enhancement factor was achived for Slice 22. This metric shows how much the image was improved. This means that in the case of the image Slice 22, our proposed algorithm removed noise better then in the case of the other images.

Based on the results presented in the Table 1 it can be concluded that our proposed algorithm successfully removed random noise from MRI images of brain.

6 Conclusion

An algorithm with the adjusted non-local means filter was constructed for removal of the random noise from magnetic resonance images. In our proposed method we used window of the size 3×3 biased by the empirically determined weighted mean of the larger 9×9 window. The proposed algorithm was tested on different magnetic resonance images of brain from the standard database [59]. For the quality of results different measures of quality evaluation metrics were used that included MSE (mean square error), PSNR (peak to signal ratio), NK (normalized cross correlation), AD (average difference), SC (structural content), MD (maximum difference), NAE (normalized absolute error) and IEF (image enhancement factor). In all cases results were satisfactory. Future research can include different types of means filters like weighted median filter and testing can be carried on images of other human organs.

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