COMPARATIVE ANALYSIS OF VARIOUS FILTERS FOR NOISE REDUCTION IN MRI ABDOMINAL IMAGES

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Abstract: *Magnetic resonance imaging MRI is an imaging technique that is primarily used in medical diagnostics for the visualization of the structures and functions of tissues and organs in the body. It physically based on the principles of nuclear magnetic resonance (NMR), and in particular the field gradient NMR, and is therefore also known as magnetic resonance imaging (sometimes colloquially shortened to MRI). Compared to CT occur artifacts (distorted image) by the MRI diagnostic are more frequently and interfere usually more with the image quality. A wide variety of artifacts is routinely encountered on MR images. In this paper, various filtering algorithms are discussed and compared.*

Keywords: *MRI, noise, artifacts, filtration methods*

ACM Classification Keywords:

Introduction

The medical visual diagnostic is very important and widely used in the analyses of the human health and diseases. Nowadays it is almost unthinkable for doctors to make diagnose without the help of some kind of medical visualization technique. However it is still imposable for them to count on this visualization to be on hundred present accurate. The main reason of that is the unavoidable presence of noise and a variety of artifacts in the medical images. This justifies our research and observation of the filtration's methods of one of the widely used medical imaging - MRI.

In fact it has a various advantageous features, such as high-resolution capability, the ability to produce an arbitrary anatomic cross-sectional imaging, and high tissue contrast. Unfortunately, there are many potential sources of image artifacts associated with the technology of MRI. Many MR artifacts are neither obvious nor understandable from previous experience with conventional types of imaging. While some MR artifacts are machine specific, the majority are inherent in the imaging method itself. Many artifacts can be considered as noise.

The term noise in MR can have different meanings depending on the context. For example, it has been applied to degradation sources such as physiological and respiratory distortions in some MR applications and acquisitions schemes [Fern´andez and Vega, Kruger and Glover,2001], [Petridou and all,2009]. Even acoustic sources (the sound produced by the pulse sequences in the magnet) are sometimes referred to as noise [Fern´andez and Vega, Counter and all, 2000]. The presence of noise over the acquired MR signal is a problem that affects not only the visual quality of the images, but also may interfere with further processing techniques such as segmentation, registration or fMRI analysis [Fern´andez and Vega, McGibney and Smith, 1993, Gudbjartsson and all, 1995], [Aja-Fern'andez and all, 2008].

In the signal processing literature, many of the popular denoising algorithms suggested are based on wavelet thresholding [Sarode, Deshmukh, 2010-11]. These approaches attempt to separate significant features/signals from noise in the frequency domain and simultaneously preserve them while removing noise [Sarode, Deshmukh, 2010-11], [Chang and all, 2006]. If the wavelet transform is applied on MR magnitude data directly, both the wavelet and the scaling coefficients of a noisy MRI image are biased estimates of their noise-free counterparts [Sarode, Deshmukh, 2010-11],[Chang and all, 2006]. The difficulty with wavelet or anisotropic diffusion algorithms is again the risk of over- smoothing fine details, particularly in low SNR images [Sarode, Deshmukh, 2010-11, Bernsteinan all, 1989].

In this paper, various filtering algorithms are used to remove noise from MRI images as good as it is possible and to preserve the quality of them. These filtering algorithms have various advantages and disadvantages. There are different filters and none of them overcome others in all situations in respect to computation cost, noise removing and quality of denoised image. That is why noise removal method can be improved and it can be still an open research area.

MRI Imaging and Artifacts

Magnetic resonance imaging (MRI) is primarily used in medicine (radiology) to visualize detailed internal structure and limited function of the body. By MRI contrast between the different soft tissues of the body is much greater than those by computed tomography (CT). This makes it especially useful in neurological (brain), musculoskeletal, cardiovascular, and ontological (cancer) imaging. In MRI there is no ionizing radiation, but uses a powerful magnetic field to align the nuclear magnetization of (usually) hydrogen atoms in water in the body. Every MRI scanner has a powerful radio transmitter to generate the electromagnetic field which excites the spins. If the body absorbs the energy, heating occurs. For this reason, the transmitter rate at which energy is absorbed by the body has to be limited. It has been claimed that tattoos made with iron containing dyes can lead to burns on the subject's body.

It works as a radio frequency transmitter is briefly turned on, producing an electromagnetic field. In simple terms, the photons of this field have just the right energy, known as the resonance frequency, to flip the spin of the aligned protons. As the intensity and duration of the field increases, more aligned spins are affected. After the field is turned off, the protons decay to the original spin-down state and the difference in energy between the two states is released as a photon. It is these photons that produce the signal which can be detected by the scanner. An image can be constructed because the protons in different tissues return to their equilibrium state at different rates. Contrast agents may be injected intravenously to enhance the appearance of blood vessels, tumours or inflammation. Contrast agents may also be directly injected into a joint in the case of arthrograms, MRI images of joints.

MRI diagnostic is considered as generally very safe procedure. Nonetheless the strong magnetic fields and radio pulses can affect metal implants, including cochlear implants and cardiac pacemakers. In the case of cardiac pacemakers, the results can sometimes be lethal. MRI is used to image every part of the body, and is particularly useful for tissues with many hydrogen nuclei and little density contrast, such as the brain, muscle, connective tissue and most tumours. In clinical practice, MRI is used to distinguish pathologic tissue (such as a brain tumour) from normal tissue. One advantage of an MRI scan is that it is believed to be harmless to the patient. It uses strong magnetic fields and non-ionizing radiation in the radio frequency range. It can be used also during pregnancy. However, as a precaution, current guidelines recommend that pregnant women undergo MRI only when essential. MRI is rapidly growing in importance as a way of diagnosing and monitoring congenital defects of the fetus because it can provide more diagnostic information than ultrasound and it lacks the ionizing radiation of CT.

The artifacts in MR imaging can be grouped into two general categories. First, there are artifacts that are hardware related. These artifacts are relatively uncommon—fortunately, because they are often difficult to diagnose and usually require service personnel to correct. The second category consists of artifacts related to the patient or under operator control. This category is encountered much more commonly and may often be easily prevented or corrected once they are recognized.[Ruan]

In the literature there are a large amount of artifacts' groups, as follow: Motion Artifacts, Susceptibility Artifacts, Chemical Shift Artifacts, Wrap Around Artifacts, Partial Volume Artifacts, Gibbs Ringing Artifacts, Zebra Stripes, Slice-overlap Artifacts, RF Overflow Artifacts, Entry Slice Phenomenon, Zipper Artifacts, Cross-Excitation and Shading [Mirowitz, 1999]. In this study some of them are shown in the experimental part.

Motion is the most prevalent source of MR imaging artifacts. As the name implies, motion artifacts are caused by motion of the imaged object or a part of the imaged object during the imaging sequence.[Ruan, 2011] There are different reasons of motion artifacts and they can be grouped in: Respiratory motion, Cardiac motion and Vascular pulsation.

- Respiratory motion results in ghosting artifacts and blurring that can obscure or simulate lesions. A variety of methods have been used to reduce the effect of respiratory motion artifacts. Mechanical methods, such as use of an abdominal or thoracic binder or taking images with the patient in a prone position, are intended to restrict the amplitude of respiratory motion.

- Cardiac motion produces a series of ghost artifacts along the phase-encoding direction of the image, in addition to blurring and signal loss of cardiac and juxtacardiac structures [Ruan, Huber and all, 2001].
- Vascular pulsation artifacts are recognized by their alignment with the responsible vessel along the phase-encoding direction of the image. These artifacts reproduce the cross-sectional size and shape of the responsible vessel, but not necessarily its signal intensity.

Three different parameters—spin density ρ, spin-lattice relaxation $T1$, and spin–spin relaxation $T2$—determine the resonance signal. $T1$ and $T2$ time constants cannot be measured directly because signal strength is always

influenced by proton density and because field inhomogeneity hide the $T2$ effect. $T2$-enhanced images can be generated by the *spin echo* sequence. Hence, different sequences can be developed for enhancing either of the parameters a more detailed treatment can be found. It changes the appearance of different tissues in images (e.g., water and fat is bright in $T2$ images and tissue is darker while the opposite is true for a $T1$ image) [Toennies, 2012].

The single echo will be taken as the image. The time between the 90° impulse and the echo impulse is called *echo time TE*. The time between two measurements is called *repetition time TR*. Short *TE* (20 msec) and long *TR* (2000 msec) will produce a proton-density-weighted image. Using a shorter repetition time (*TR* = 300–600 msec) will produce a $T1$-weighted image because $T1$ relaxation is generally longer than 200–600 msec. A long *TE* (> 60 msec) and a long *TR* (2000 msec) produces a $T2$-weighted image.

Noise in MR images

In many cases the complex effect of the influence of some different artifacts can be presented as kind of noise. In Magnetic Resonance Images, raw data is intrinsically complex valued and corrupted with zero mean Gaussian distributed noise with equal variance.

A. Gaussian white Noise

Gaussian noise is statistical noise and it has a probability density function of the normal distribution (also known as Gaussian distribution). The probability density function *p* of a Gaussian random variable *z* is given by:

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{1}$$

where *z* represents the grey level, μ the mean value and σ the standard deviation.

It is widely used as additive white noise to yield additive white Gaussian noise (AWGN). Gaussian noise is properly defined as the noise with a Gaussian amplitude distribution. There is no information of the correlation of the noise in time or of the spectral density of the noise. Gaussian noise is labeled as 'white' because of the correlation of the noise.

After Fourier transformation, the real and imaginary images are still Gaussian distributed given the orthogonality and linearity of the Fourier transform. MR magnitude images are formed by taking the square-root of the sum of the square of the two independent Gaussian random variables (real and imaginary images) pixel by pixel. So the MR magnitude data can be shown to be Rician distributed. When SNR is high (SNR>2), the Rician distribution approaches a Gaussian; when SNR approaches 0, the Rician distribution becomes Rayleigh distributed.

B. Rician Noise

The image intensity in magnetic resonance magnitude images in the presence of noise is to be governed by a Rician distribution [Sarode, Deshmukh, 2010-11].

Rician noise is not additive noise, but is instead data-dependent [Coup´e and all, 2010], [Getreuer and all, 2011]. Consider a set of random numbers, which we take to be the intensity values of a noise-free MR image A defined on a discrete grid M so that $A = \{ai, i \ \in M\}$. Let σ be the standard deviation of Gaussian noise. There are two sets of Gaussian distributed random numbers $X = \{xi, i \in M\}$ and $Y = \{yi, i \in M\}$ with zero mean and identical standard deviations .Then the following are Rician distributed. [Sarode, Deshmukh, 2010-11]

$$mi = \sqrt{(ai + xi)^2 + y} \qquad (2)$$

"Rician noise" depends on the data itself, it is not additive, so to "add" Rician noise to data, what we really mean is make the data Rician distributed [Sarode, Deshmukh, 2010-11].

However, we can still use the two basic models of noise for the MRI images, too:

- additive;
- multiplicative

By the additive model the function that describes the noise doesn’t correlate the function of the image:

$$g(x, y) = f(x, y) + \eta(x, y) \quad (3)$$

where $g(x,y)$ is the real output image, $f(x,y)$ is the ideal not noised image and $\eta(x,y)$ is the noise.
The multiplicative model can be presented with:

$$g(x, y) = f(x, y) \times \eta(x, y) \quad (4)$$

Denoising

Denoising can be described as a process of removing noise from a signal, but in fact is more complicated. The methods of noise reduction are conceptually very similar regardless of the signal being processed. It is interesting that knowledge of the characteristics of an expected signal can mean the implementations of these techniques vary greatly depending on the type of signal [Tisdall and Atkins, 2005]. It is important, when we have a model for the degradation process, to be possible the inverse process to be applied to the image to restore it back to the original form. Denoising is a very important part of preprocessing in medical imaging where the physical requirements for 2 high quality imaging are needed for analyzing images of unique events, in regard to obtain better quality of medical images and more precise diagnostic of disease. Noise can be random or white noise with no coherence or coherent noise introduced by the devices mechanism or processing algorithm [Sarode and Deshmukh, 2010]. In magnetic tape, the larger the grains of the magnetic particles, the more prone the medium is to noise[Sarode and Deshmukh, 2010].

One of the most direct approaches to cope with acquisition noise in MRI (of course, not the only one) is signal estimation via noise removal. Traditionally, noise filtering techniques in different fields have been based on a well-defined prior statistical model of data, usually a Gaussian model. [Aja-Fern'andez and all, 2008]

There are different methods for filtration, which can be applied for noise reduction in MR images. For evaluation of noise reduction some parameters such as: peak signal-to noise ratio (PSNR), the effectiveness of filtration (Eff), which is equal to the difference of signal-to noise ratio in filtered image (SNRF) and signal-to noise ratio in noised image (SNRN), and noise reduction ratio (NRR) are used.

The visualization of result from filtration is another criterion, which can give visually information of the effectiveness of the applied method. This criterion is very important for the doctors. For evaluation of the methods is needed to obtain in the same time high values of PSNR and Eff and low value of NRR. These conditions can be implemented in the algorithm for calculation of the criteria. The main flow diagram of the algorithm is presented in Fig.1..

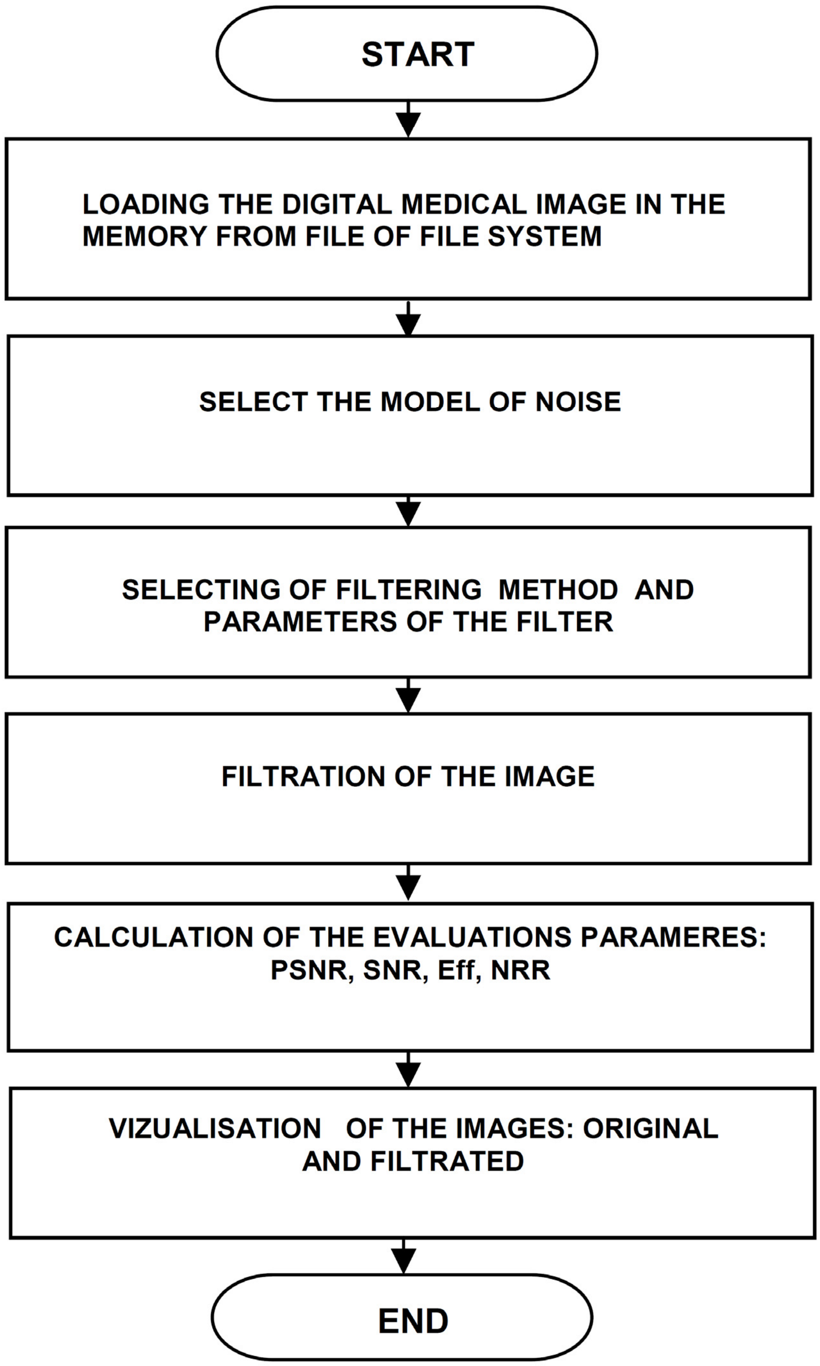


Fig.1 The flowchart of the algorithm for noise reduction

Filtration's methods

The filtration is applied in the spatial and frequency domain.

The filtration in the spatial domain represents an operation between the pixels that are located in the neighborhood. In this case, the neighbors of each pixel in the image are analyzed. The filtration function is represented as a matrix and is called mask of the filter. It has often the following size: 3x3, 5x5, etc., but in any case is smaller than the size of the image. Generally there are two types of filters in the spatial domain: linear (e.g. Gaussian filter) and nonlinear (e.g. Median filter).

The methods of treatment in the frequency domain are based on manipulation of the orthogonal transformation of the image, not on the image itself. The improvement of the image in this domain consists of several basic stages:

- Transformation from the spatial to the frequency domain using strait 2D discrete transformation of the image, e.g. two-dimensional discrete Fourier transformation (2D DFT), cosine-transformation, Hartley-Adamar transformation, Wavelet transformation, etc.(the choice depends on the application);
- Manipulation of transformation factors with operator M(multiplication with the function, which describes the function);
- Performance of reverse discrete transformation from the frequency to the spatial domain.

A. Gaussian Filtration

Significantly improvement of filtration can be achieved, when the mask of the filter coincides with the function that describes Gaussian distribution. In discrete form the Gaussian distribution can be approximated by binominal distribution (binominal Gauss filter) and so the filter becomes particularly suitable for filtration in the spatial domain. Because of the possibility for separately filtration in horizontal direction the sharpness of the image is retained. Another advantage of this filtration is the fast operation.

B. Median Filtration

Median filter is known as nonlinear method that is used to remove noise from MRI images. It is very effective at removing salt and pepper noise. The algorithm of median filter works by moving through the image pixel by pixel, replacing each value with the median value *N* of neighboring pixels. The pixel is calculated by the following order: first the entire pixel values from the pattern of neighbors are sorted into numerical order, and then the pixel being considered is replaced with median pixel value. Median filter is better able to remove noise without reducing the sharpness of the image.

C. Wiener Filtration

An optimization between inverse filtering and noise smoothing is the Wiener filter (nonlinear). This filter removes additive noise and deblurring concurrently. As prove for optimization is the reducing the overall Mean Square Error (MSE). There are two important parts of the operation: inverse filtering and noise smoothing. Wiener filters belong to a kind of optimum linear filters that have the noisy data as input which involves the calculation of difference between the desired output sequences from the actual output. Measurement of the performance can be shown using Minimum Mean-Square Error.

There is also Wiener2 filter that is a 2-D adaptive noise removal filter. This function works as applying a wiener filter which is a type of linear filter to an image adaptively, tailoring itself to local image variance. Wiener2 performs little smoothing by large variance. By small one, wiener2 performs more smoothing. That way leads often to better result than linear filtering. As comparison the adaptive filter is more selective than a comparable linear filter, preserving edges and other high frequency parts of an image. There are no design tasks, the wiener2 function handles all preliminary computations, and implements the filter for preliminary computations, and implements the filter for an input image. Wiener2 filter is best suitable to remove Gaussian noise.

D. Wavelet Filtration

Many of the popular de-noising algorithms suggested are based on wavelet thresholding [Overton and Weymouth, 1979], [Weaver, and all, 1991], [Nowak, 1999]. These approaches attempt to separate significant features from noise in the frequency domain and simultaneously preserve them while removing noise [Pizurica and all, 2006]. The wavelet function can be viewed as a high pass filter, which approximates a data set (a signal or time series). The result of the wavelet function is the difference between value calculated by the wavelet function and the actual data. The scaling function calculates a smoothed version of the data, which becomes the input for the next iteration of the wavelet function. In the context of filtering, an ideal wavelet/scaling function pair would exactly split the spectrum.

The difficulty with wavelet or anisotropic diffusion algorithms is the risk of over-smoothing fine details particularly in low SNR images [Plonka and Ma, 2008].

The general wavelet–based method for denoising and nonparametric function estimation is to transform the data into the wavelet domain, threshold the wavelet coefficients, and invert the transform. We can summarize these steps as:

1. Decompose

Choose a wavelet and a level N. Compute the wavelet decomposition of the image down to level N.

2. Threshold detail coefficients

For each level from 1 to N, threshold the detail coefficients. Hard and soft thresholding are examples of shrinkage rules. After we have determined the threshold, we have to decide how to apply that threshold to our data. The simplest scheme is hard thresholding. The hard thresholding preserves the wavelet coefficients whose absolute values are larger than the threshold, otherwise they are set to zero. In soft thresholding, wavelet coefficients whose absolute values are lower than the threshold are set to zero, otherwise this method shrinks them toward zero.

3. Reconstruct

Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

E. Homomorphic Wavelet Filtration

The homomorphic filtering technique works in frequency domain. However, before the transformation is taking place, logarithm function has been used to change the multiplication operation in Eq.(4) into addition operation. In the Fourier transform of traditional homomorphic filtering, spatial resolution is lower, and local contrast of image is not increased obviously. Lowpass filtering could reduce noise by smoothing, but the border of image will become to more indistinct. Highpass filtering could enhance the edge of image, but the noise of background will be increased. The standard homomorphic filtering schema can be presented in Fig.2, where DFT is 2D Discrete Fourier Transform, H(u,v) is a filter function, $(DFT)^{-1}$ is 2D Inverse Discrete Fourier Transform and *g(x,y)* is the output image. Using Wavelet Transform, block DFT will be changed with DWT and block $(DFT)^{-1}$ with IDWT.

Fig.2 The flowchart of standard homomorphic filtering

The filtration function H(u,v) is based on wavelet decomposition and thresholding of wavelet coefficients. Because the noise of wavelet transform usually concentrate on the state of high resolution, the method is useful to eliminate the noise. This method can be applied in MRI to decry a varying of the intensity in different tissues, which exists because of inhomogeneity of radio pulses.

Experimental part

For the experiments we have used a sequence of 22 MR-images in axial plane, in which the abdominal organs can be well seen (one of them is the spleen). The images are from a study of health in Pomerania (East Germany).The original images were in DICOM format and they were converted to BMP for visualization and experiments. The size of the images is 256x176 pixels and they are originally grayscale. The experiments for noise reduction are made by computer simulation in MATLAB, version 8.1 environment by using of IMAGE PROCESSING and WAVELET TOOLBOXES.

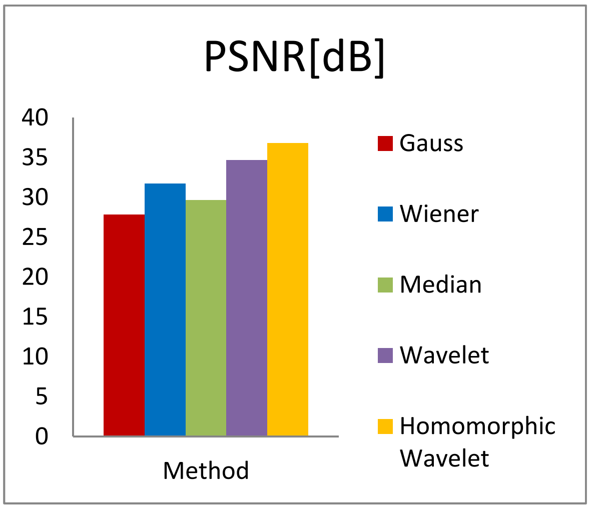
The best results after several filters used for the MRI sequence are achieved with four of them: Wiener filter, Median filter, Wavelet filter and Homomorphic Wavelet filter, which have been already described in the previous section. The best results are obtained by the following conditions: the median filter is with [3x3] neighborhood mask; the wavelet filter and the homomorphic wavelet filters are made on the base of the wavelet decomposition on level 1, using orthogonal wavelets and adaptive threshold of the transformed MR image.

For evaluation of noise reduction by different filters some parameters such as: peak signal-to noise ratio (PSNR), the effectiveness of filtration (Eff), which is equal to the difference of signal-to noise ratio in filtered image (SNR_F) and signal-to noise ratio in noised image (SNR_N), and noise reduction ratio (NRR) are used. The obtained averaging results from simulation are presented in Table 1.

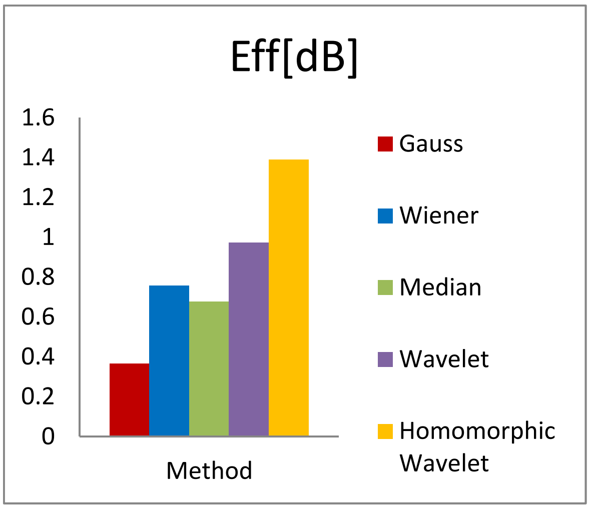
Table 1

Filter	**NRR**	**PSNR** [dB]	**SNR_N** [dB]	**SNR_F** [dB]	**E_{ff}** [dB]
Gaussian	0,671	27,824	21,6530	22,0194	0,3664
Wiener	0,395	31,737	21,6530	22,4101	0,7571
Median	0,463	29,653	21,6530	22,3285	0,6755
Wavelet	0,334	34,676	21,6530	22,6257	0,9727
Homomorphic Wavelet	0,232	36,822	21,6530	23,0404	1,3874

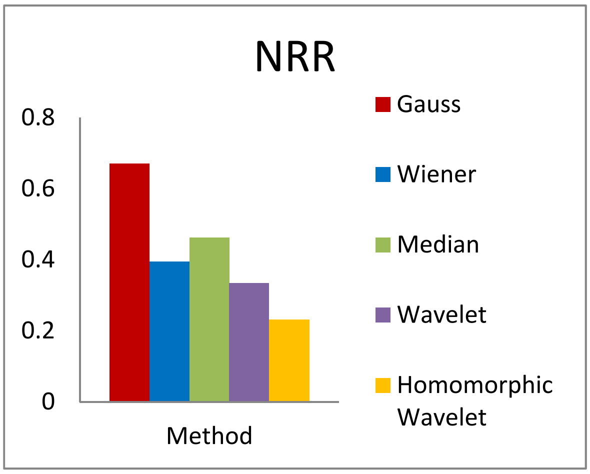
The graphical interpretation of PSNR, E_{ff} and NRR are given in Fig.3.



a)



b)



c)

Fig.3 Graphical presentation of the results obtained by investigated methods of filtration for: a) PSNR; b) Effectiveness of filtration (E_{ff}); c) NRR

For visualization of the best results were chosen three consecutive images from the sequence. They are given in Fig.4. These images represent as wholeness and in the best manner for observation the human spleen. The original image 1 and its modifications obtained after different filtering methods are given in Fig.5.

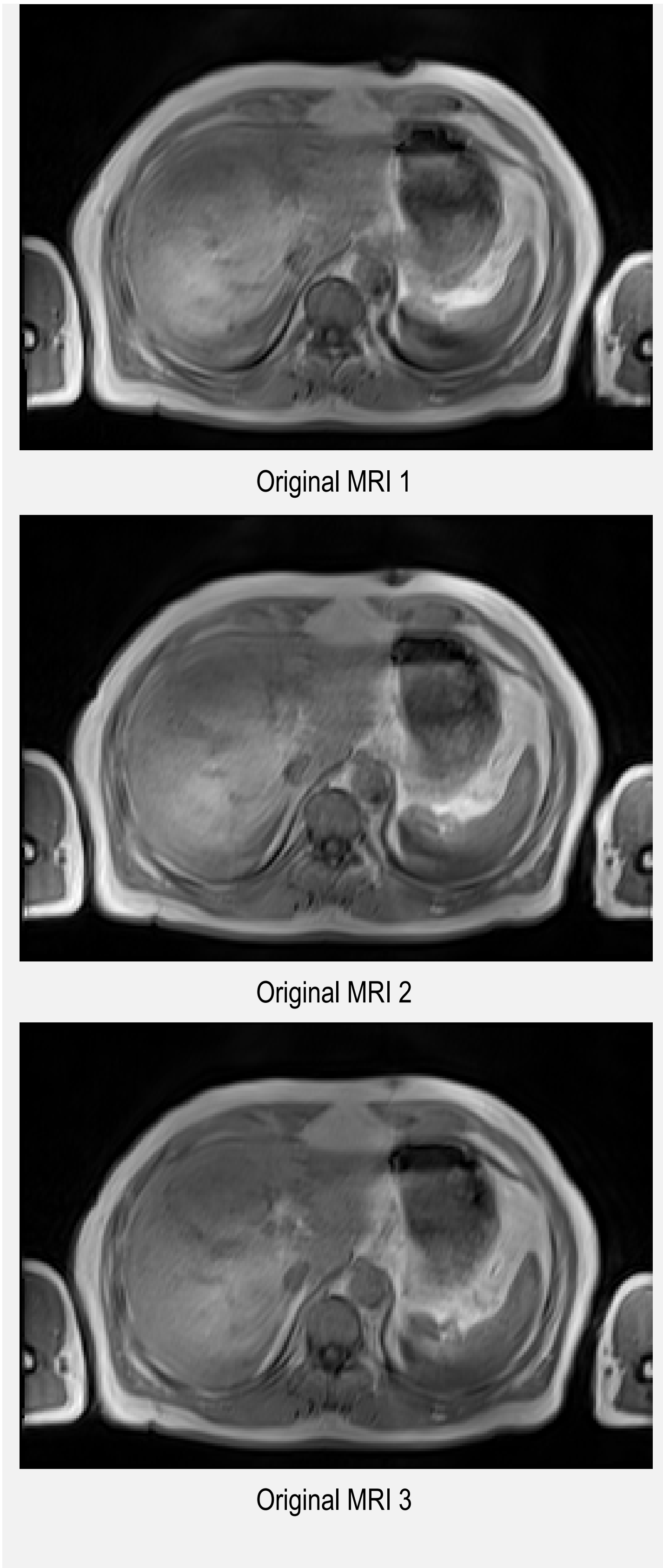


Fig.4 The original consecutive MR-images from the sequence representing the spleen in axial plane

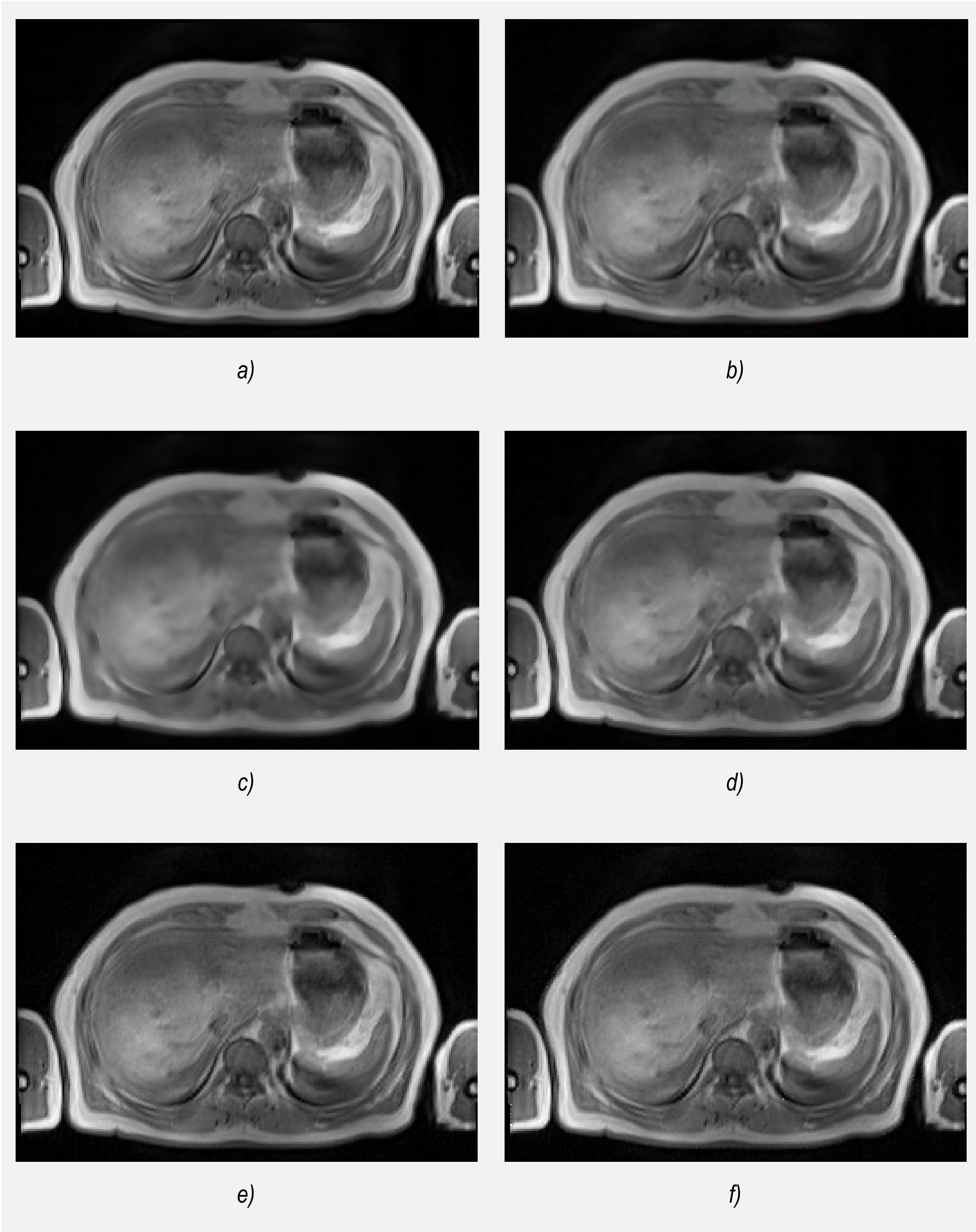


Fig.5 MRI 1 images obtained by noise reduction with investigated filters: a) original image; b) Gaussian filter; c)Wiener filter; d)Median filter; e)Wavelet filter; f)Homomorphic wavelet filter

The original image 2 and its modifications obtained after different filtering methods are given in Fig.6. The original image 3 and its modifications obtained after investigated filtering methods are presented respectively in Fig.7.

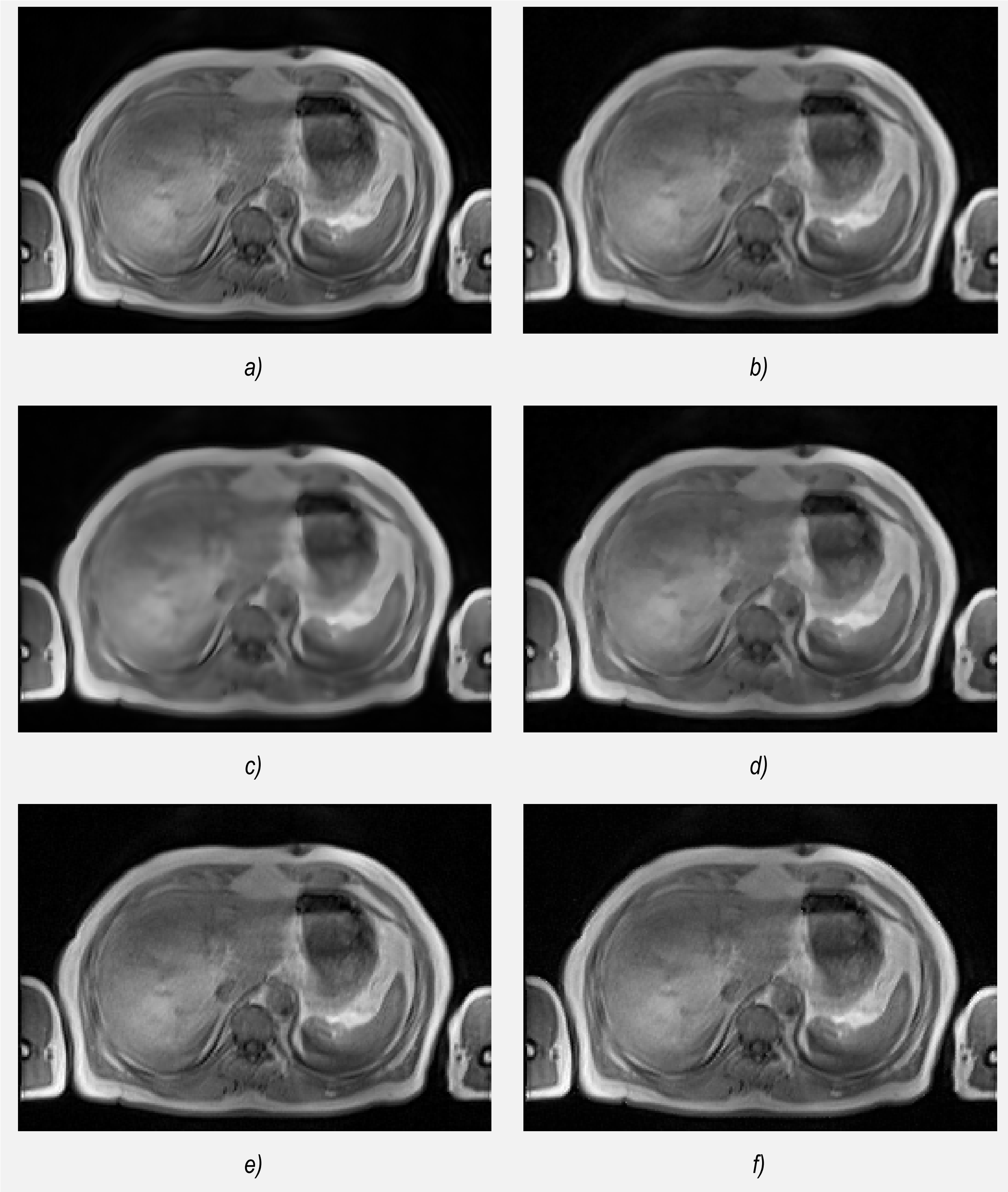
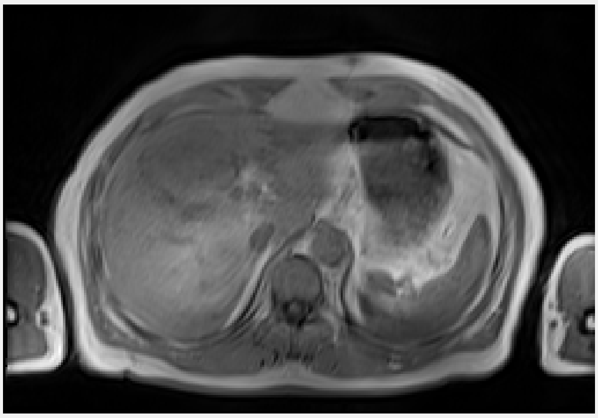
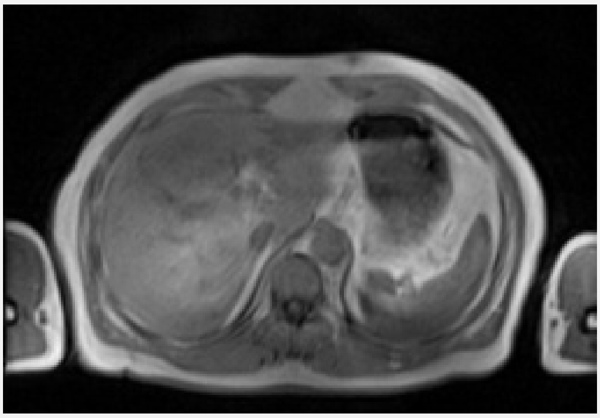
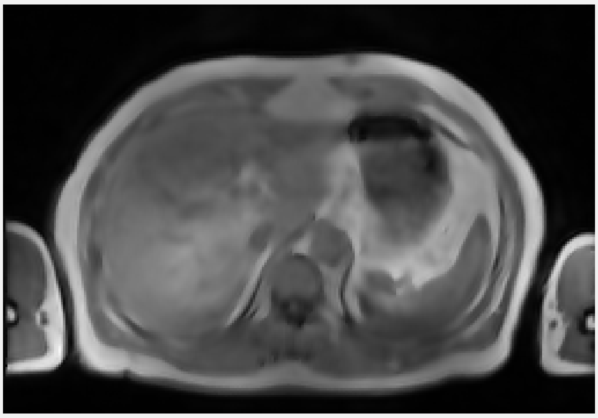


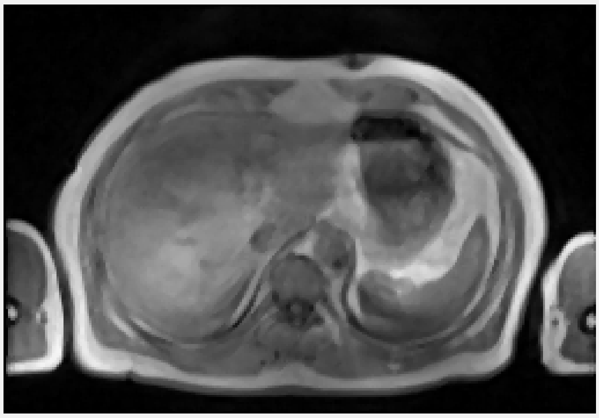
Fig.6 MRI 2 images obtained by noise reduction with investigated filters: a) original image; b) Gaussian filter; c)Wiener filter; d)median filter; e)Wavelet filter; f)homomorphic wavelet filter



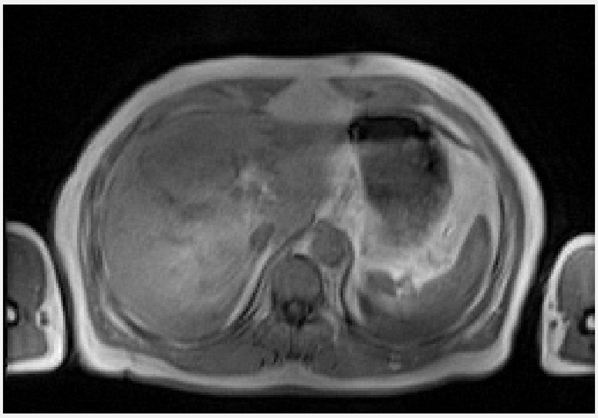


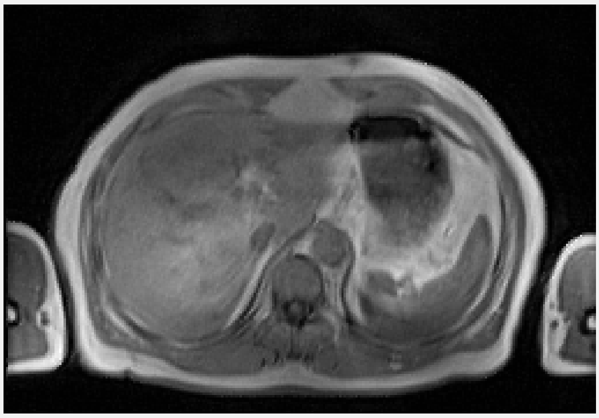
a) *b)*





c) *d)*





e) *f)*

Fig.7 MRI 3 images obtained by noise reduction with investigated filters: a) original image; b) Gaussian filter; c)Wiener filter; d)median filter; e)Wavelet filter; f)homomorphic wavelet filter

The implemented investigations and the obtained results from simulation have shown that by using of homomorphic filter the values of PSNR and the effectiveness of filtration are greater compering to the other filters. The average value of NRR is around 0.2 and shows that the noise is five times reduced. By noise reduction on the base of wavelet transformation and wiener filter the values of NRR are respectively 0.3 and 0.46. It shows that in these cases the noise is reduced respectively three times and two times. The best results from the homomorphic wavelet filter are obtained by wavelet decomposition on level 1, using orthogonal wavelets coiflet and adaptive threshold of the transformed MR abdominal images.

Conclusion

In this paper a comparative study of noise reducing techniques and various filtering algorithms are implemented on MRI series of abdominal images. MRI images when captured usually have Gaussian noise and Rician noise. Two basic models of noise are applied for investigation of the process of noise reduction for the specific case of the abdominal organs. To reduce the noise filtering algorithms are introduced. The results are analyzed and evaluated on the base of objective estimations parameters and visualization criterion. For evaluation of the methods we propose to be automatically analyzed and compared values of PSNR and Eff, which must be higher and the value of NRR, which must be low in the same time. This simple algorithm is applied and used for optimal choice of parameters of the filters. Median filter performs better result in compare to Gaussian filter. The Wiener filter works better, but more significant results we obtain by wavelet and especially by homomorphic wavelet filter.

In this case the boundaries of the organs are better preserved.

The implemented comparative study and obtained results can be applied:

- for future segmentation of the abdominal organs;
- for clinical diagnosis such as tissue classification;
- restoring textures;
- reconstruction by 3D model of the organs;

Our future investigation will be concentrated in improving of the investigated region of interest (ROI) and choice for suitable algorithm for segmentation of specific abdominal organs, especially of spleen.

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Bibliography

[Anisha and Krishnan, 2015] Anisha, S.R PG Scholar,Dr J Venugopala Krishnan. In: Comparison of Various Filters for Noise

Removal in MRI Brain Image, International Conference on Futuristic Trends in Computing and Communication (ICFTCC-2015) . Department of ECE, Jeppiaar Engineering College, Chennai-119.

[Aja-Fern'andez and all, 2008] S. Aja-Fern´andez, M. Niethammer, M. Kubicki, M. E. Shenton, C.-F. Westin, In: Restoration of DWI data using a Rician LMMSE estimator, IEEE Trans. Med. Imaging 27 (10) (2008) 1389–1403.

[Bernsteinan and all, 1989]M. A. Bernstein, D. M. Thomasson, and W. H. Perman, In: Improved detectability in low signal-to-noise ratio magnetic resonance images by means of phase-corrected real construction. Med. Phys., vol. 16,no. 5, pp. 813–817, 1989.

[Chang and all, 2006] S. G. Chang, Y. Bin, and M. Vetterli, In: Adaptive wavelet thresholding for image denoising and compression, IEEE Trans. On Image Processing, vol. 9, No. 9. pp. 1532-1546, Sept. 2006.

[Counter and all, 2000]A. Counter, A. Olofsson, E. Borg, B. Bjelke, A. H¨aggstr¨om, H. Grahn. In: Analysis of magnetic resonance imaging acoustic noise generated by a 4.7 t experimental system, Acta Oto-Laryngologica 120 (6) (2000) 739–743.

[Coup´e and all, 2010] P. Coup´e, J. V. Manj´on, E. Gedamu, D. Arnold, M. Robles, D. L. Collins, Robust Rician noise estimation for MR images, Med. Imag. Anal.14 (4) (2010) 483–493.

[Fern´andez and Vega] Santiago Aja-Fern´andez and Antonio Trist´an-Vega. In: A review on statistical noise models for Magnetic Resonance Imaging. LPI, ETSI Telecomunicaci´on, Universidad de Valladolid, Spain

[Georgieva,2015] Veska Georgieva, Technical University Sofia. In: Medical Image Processing. TU-Sofia, Bulgaria

[Getreuer and all, 2011] P. Getreuer, M. Tong, L. Vese, A variational model for the restoration of MR images corrupted by blur and rician noise, in: G. Bebis, R. Boyle,B. Parvin, D. Koracin, S. Wang, K. Kyungnam, B. Benes, K. Moreland, C. Borst, S. DiVerdi, C. Yi-Jen, J. Ming (Eds.), Advances in Visual Computing, Vol. 6938 of Lecture Notes in Computer Science, Springer Berlin / Heidelberg, 2011, pp. 686–698.

[Gudbjartsson and all, 1995] H. Gudbjartsson, S. Patz, In: The Rician distribution of noisy MRI data, Magn. Reson. Med. 34 (6) (1995) 910–914.

[Huber and all, 2001]Huber ME, Hengesbach D and Botnar RM, " Motion artifact reduction and vessel enhancement for free-breathing navigator-gated coronary MRA using 3D k-space reordering," Magn Reson Med 2001 Apr;45(4):645-52.

[Kruger and Glover,2001], G. Kruger, G. H. Glover. In: Physiological noise in oxygenation-sensitive magnetic resonance imaging, Magn. Reson. Med. 46 (2001) 1631–637.

[Lin and Willson, 1988] H. Lin and A. N.Willson Jr., In: Median filters with adaptive length. IEEE Trans. Circuits Syst., vol. 35, no. 6, pp.675–690, Jun. 1988.

[McGibney and Smith, 1993] G. McGibney, M. Smith. In: Unbiased signal-to-noise ratio measure for magnetic resonance images, Med. Phys. 20 (4) (1993) 1077–1078.

[Mirowitz, 1999] Mirowitz SA, "MR imaging artifacts. Challenges and solutions," Magn Reson Imaging Clin N Am

1999 Nov;7(4):717-32

[Nowak, 1999], R. D. Nowak. Wavelet-based Rician noise removal for magnetic resonance imaging. IEEE Trans Image Process 1999; 8:10:1408–1419.

[Overton and Weymouth, 1979] K. J. Overton and T. E. Weymouth,In: A noise reducing preprocessing algorithm. Proc. IEEE Computer Science Conf. Pattern Recognition and Image Processing, Chicago, IL, 1979, pp.498–507.

[Pizurica and all, 2006] A. Pizurica, A. M. Wink, E. Vansteenkiste, W. Philips, and J. B. T. M. Roerdink. A review of wavelet denoising in MRI and ultrasound brain imaging. Current Med Imag Rev 2006; 2:2:247–260

[Plonka and Ma, 2008] Gerlind Plonka and Jianwei Ma. Nonlinear Regularised Reaction-Diffusion Filter for Denoising of Images with Textures. IEEE Trans. Image Processing 2008; 17:8:1283–1294

[Ruan] Chun Ruan. In: MRI Artifacts: Mechanism and Control

[Sarode, Deshmukh, 2010-11] Milindkumar V. Sarode, Dr.Prashant R. Deshmukh. In: Performance Evaluation of Rician Noise Reduction Algorithm in Magnetic Resonance Images, Journal of Emerging Trends in Computing and Information Sciences. Department of Computer Science and Engineering Jawaharlal Darda Institute of Engineering& Technology, Yavatmal (M.S.) India Department of Computer Science & Engineering and Information Technology SIPNA's College of Engineering Amravati (M.S.) India.

[Sun and Neuvo, 1994] T. Sun and Y. Neuvo, In: Detail-preserving median based filters in image processing. Pattern Recognit. Lett., vol. 15, pp. 341–347, Apr. 1994.

[Tisdall and Atkins, 2005] D. Tisdall and M. S. Atkins. MRI denoising via phase error estimation. Proc SPIE Med Imag 2005; 646–654.

[Toennies, 2012] K.D.Toennies, Guide to Medical Image Analysis, Methods and Algorithms, Springer-Verlag London, 2012.

[Weaver, and all, 1991] J. B. Weaver, Y. Xu, D. M. Healy Jr., and L. D. Cromwell. Filtering noise from images with wavelet transforms. Magn Reson Med 1991; 21:2:288–295.

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