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Multi-objective noise estimator for the applications of de-noising and segmentation of MRI data

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ABSTRACT

The present study proposes the noise estimation of Magnetic Resonance Imaging (MRI) data using multi-objective particle swarm optimisation (MOPSO). This adaptive noise estimation is based on the maximisation of the multiple quality measures, which enable the algorithm to achieve de-noising along with enhancement in the image features. The paper proposes two filtering approaches to de-noise MRI data. In first, MOPSO based noise estimation is followed by non-local statistics based Kalman filter, whereas, in the second approach, MOPSO based noise estimation is followed by Linear Minimum Mean Square Error (LMMSE) filter. The impact of de-noising on segmentation of MRI data has also been studied, for this purpose enhanced fuzzy c-means algorithm has been applied on filtered MRI data. The de-noising and segmentation performance of MOPSO-non local Kalman filter and MOPSO-LMMSE filters has been evaluated and compared with Wavelet filter, Wiener filter, non-local mean filter, standard Kalman and standard LMMSE filter. The proposed noise estimation approach followed by filtering is giving better de-noising and segmentation results as compared to standard filters considered.

1. Introduction

MRI is an important modality of medical imaging as far as concern the structure of soft tissues, their details and disease characterisation. The advantages of this imaging technique are its non-ionization behaviour and better image quality with high tissue contrast resolution. This imaging technique produces different weighted images by varying in the sequences of radio frequency (RF) pulses, and these weighted sequences can be used to diagnose the various diseases [1,2]. However, the presence of artifacts and noise in the MRI data may affect the perception of the radiologists. Hence, an efficient de-noising as a pre-processing step should be implemented [3].

Previously, many filtering algorithms have been proposed to de-noise MRI data [4,5]. The conventional Wiener filters [6] are simple and process the local neighbourhood pixels. However, these filters assume Gaussian rather Rician distributed noise and hence often produce blur on resulting MRI data. An alternative to conventional Gaussian filtering, the approach based on Markov Random Field has the capability to preserve the shape of transitions in fMRI studies [7]. Recently, Fabio Baselice et al. have exploited the Markov Random Field for de-noising and edge preservation of 3D MRI data, and tunes the parameters by itself [8]. The transformation-based de-noising method utilises Wavelet-based filter [9], which has improved the visual appearance of diffusion-weighted MRI data as it preserves the edges and reduces the blur. The non-local means (NLM) filter [10] has shown elegant accuracy in preserving the edges, which averages the non-local pixels of the image while considering the self-similarity property that determines the weights. Further, the idea of NLM filter has been extended to other de-noising methods as well [11,12].

The recent trends are toward statistical estimation based de-noising approach for MRI data, which utilises quasi-Monte Carlo estimation has been instigated while considering local statistics of MRI data [13]. The maximum likelihood estimation method has been implemented in a non-local manner to de-noise the MRI data generated from multiple coils [14]. Jose V. Manjon et al. estimated the noise level of the MRI data followed by de-noising using non-local principle component analysis (PCA) [11]. Further, linear minimum mean square error (LMMSE) based techniques are another class of de-noising method and have the ability to produce a greater de-nosing performance. S. Aja-Fernandez et al. proposed iterative LMMSE approach for signal estimation in MRI data [15]. This LMMSE estimation based approach has been implemented on the local statistics of the data. Later on, the LMMSE approach has been exploited for non-local statistics for the 3D MRI data to obtain

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enhanced performance [16]. Apart from LMMSE, other filters such as patch based PCA filter have also used iterative approach [17]. These iterative filtering approaches assume the Rician distribution of MRI data at every iteration, however, the nature of resulting data changes after each iteration. Further, signal estimation based on non-recursive Kalman filter has been applied earlier to photographic images using local statistics for the enhancement of contrast and de-noising [18]. This work has performed de-noising without doing noise estimation, and hence, direct application of this standard Kalman filter it is not found very suitable for the de-noising of MRI data. V. Brion et al. proposed the parallel Kalman filter for real-time χ-noise correction of diffusion tensor imaging and High Angular Resolution Diffusion Imaging data [19]. Recently, a modified Kalman filter has been used, where Markov random field has been followed by standard Kalman filter to de-noise the image [20].

The present paper implements MOPSO for noise estimation followed by de-noising algorithms i.e. LMMSE based filter and modified Kalman based filter. The present study suggested that the noise need to be adaptively estimated in the process of filtering of MRI data. The previous recursive filtering methods have assumed MRI data as Rician distributed throughout all the iterations, however, the Rician nature of MRI data get modified after each iteration. Hence, in case of recursive filtering, adaptive estimation of noise after each iteration is primary requirement of the filtering. The non-recursive filters also get benefited from proposed approach, as MOPSO objectively maximizes the image quality parameters to estimate the noise from MRI data. Further, enhanced fuzzy c-means segmentation algorithm [21] also shows better segmentation results with proposed algorithms. The rest of the paper is organized as follows. The next section describes the problem formulation to estimate the noise. Section 3 formulates the non-local Kalman filter to de-noise the MRI data. Section 4 presents the material and proposed algorithm along with its working. Section 5 demonstrates the experiment results, and finally, Section 6 concludes the study.

2. Problem formulation

The complex-valued MRI data is reconstructedfrom the inverse Fourier Transform of *k-space* data and contains white Gaussian noise [22]. The magnitude MRI data follows the Rician distribution [23], as computation of magnitude MRI from complex-valued MRI data is a non-linear mapping process. The magnitude signal, which is the envelope of the complex signal can be expressed as follows:

$$M(x) = \left| A(x) + N(x) \right| \tag{1}$$

where $A(x)$ is noise free amplitude data and $N(x) = n_{Re}(x) + i\, n_{Im}(x)$ is the complex white Gaussian noise having zero mean, n_{Re}: real component of $N(x)$ and n_{Im}: the imaginary components of $N(x)$. The probability density function (PDF) of M can be expressed as Rician and represented as follows [24]:

$$p_M(MA,\ \sigma_n) = \frac{M}{\sigma_n^2} \exp\left(- \frac{M^2 + A^2}{2\,\sigma_n^2} \right) I_0 \left(\frac{A\,M}{\sigma_n^2} \right) \tag{2}$$

where σ_n^2 is noise variance and $I_0(x)$ is the first kind 0^{th} order Bessel function. As there is no signal in the background of the MRI data. Hence, the PDF of Rician can be converted to the Rayleigh distribution in this region [25], which is computed by putting $A = 0$ in the Eq. (2) and is expressed as follows:

$$p_M(M, \sigma_n) = \frac{M}{\sigma_n^2} \exp\left(- \frac{M^2}{2\,\sigma_n^2} \right) \tag{3}$$

2.1. Estimation of noise variance

Previously, the estimation of noise variance (σ_n^2) has been derived while using the background (or non-signal region) of the magnitude MRI, such as: the simple estimator based on method of moments has been proposed [26], which is given as $\hat{\sigma_n^2} = \frac{1}{2} \left\langle M^2 \right\rangle$, where $\langle . \rangle$ is sample estimator, M^2 is second order moment, and hence, $\left\langle M^2 \right\rangle$ is sample second order moment. Sijber J et al. has been estimated $\hat{\sigma_n}$ in the non-signal region, defined as: $\hat{\sigma_n} = \sqrt{\frac{2}{\pi}} \left\langle M \right\rangle$ [27], where $\left\langle M \right\rangle$ is sample mean. In an another study, the noise has been estimated for Rician distribution expressed as $\hat{\sigma_n^2} = \frac{1}{2} (\left\langle M^2 \right\rangle - (2 \left\langle M^2 \right\rangle^2 - \left\langle M^4 \right\rangle)^{1/4})$ [28]. Recently, a very efficient noise estimation methods have been suggested, which is based on the maximum distribution of sample local statistics [15], and is defined as $\hat{\sigma_n} \approx \frac{\sqrt{e}}{2}\, mode(\mu_{1_{ij}})$, where $\mu_{1_{ij}}$ is local mean.

The above-discussed approaches were proposed for Rician distribution of MRI data. However, in the process of filtering of MRI data, the recursive filters modify its Rician distribution after the first iteration, which results in non- Rician distribution of data in subsequent iterations [15]. Hence, there is a need for adaptive re-estimation of noise level after each iteration. Further, it is observed that the different values of the constant factor $\sqrt{\frac{1}{2}} \approx 0.707$, $\sqrt{\frac{2}{\pi}} \approx 0.797$, *and* $\frac{\sqrt{e}}{2} \approx 0.824$ has been proposed in literatures [26–28] to estimate the $\hat{\sigma_n}$. The noise estimation was based on the assumption that there is no bias field present in the data, however, there is the probability that bias field may be present in real MRI data. In the view of above reasons, the present study proposes the MOPSO based noise estimation approach.

Instead of a fixed value of constant factor in noise estimation, MOPSO selects the value of this factor adaptively. Hence, the expression of noise estimation can be defined as follows:

$$\hat{\sigma}_{opt} \approx k\, mode \left\langle \hat{\mu 1_{ij}} \right\rangle \tag{4}$$

where MOPSO randomly initialises the constant factor k within the search space and searches its optimum position for the maximization of two objectives i.e. image quality measures PSNR and image anisotropy quality index (AQI) [29].

The proposed noise estimation approach is further helpful in adaptive design of recursive as well non-recursive filters for de-noising and enhancement of MRI data effectively. The de-noising of the image can be quantified in terms of structure similarity index (SSIM), peak signal to noise ratio (PSNR) image quality based on local variance (IQLV) [30] and AQI. Previously, image qualities PSNR, AQI and IQLV has been found valuable to quantify the enhancement and de-noising [31–33], hence, the present study has chosen to adopt these image quality indexes. The higher value of these image quality measures represents the lower noise and better enhancement of the image.

2.2. Multi-objective particle swarm optimization (MOPSO)

MOPSO belongs to computational intelligence, which efficiently addresses complex problems. Recently, optimization algorithms have been used for the enhancement of MRI data [31,34]. Particle Swarm Optimization (PSO) is one of the most popular evolutionary algorithm [35], developed by the R. C. Elbert and J. Kennedy [36].The swarm of particles moves toward the optimum solution over the search space using an iterative process. The particles keep tracking its coordinates in the solution space, which is associated with the objective function, called personal experience. Additionally, particles keep tracking the whole population for a global experience. In every iteration, the movement of the particles depends on its previous direction $v_i(t)$, previous position $x_i(t)$, personal best experience