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Spatially-variant noise filtering in magnetic resonance imaging: A consensus-based approach

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ABSTRACT

In order to accelerate the acquisition process in multiple-coil Magnetic Resonance scanners, parallel techniques were developed. These techniques reduce the acquisition time via a sub-sampling of the ***k***-space and a reconstruction process. From a signal and noise perspective, the use of a acceleration techniques modify the structure of the noise within the image. In the most common algorithms, like SENSE, the final magnitude image after the reconstruction is known to follow a Rician distribution for each pixel, just like single coil systems. However, the noise is spatially non-stationary, i.e. the variance of noise becomes ***x***-dependent. This effect can also be found in magnitude images due to other processing inside the scanner. In this work we propose a method to adapt well-known noise filtering techniques initially designed to deal with stationary noise to the case of spatially variant Rician noise. The method copes with inaccurate estimates of variant noise patterns in the image, showing its robustness in realistic cases. The method employs a consensus strategy in conjunction with a set of aggregation functions and a penalty function. Multiple possible outputs are generated for each pixel assuming different unknown input parameters. The consensus approach merges them into a unique filtered image. As a filtering technique, we have selected the Linear Minimum Mean Square Error (LMMSE) estimator for Rician data, which has been used to test our methodology due to its simplicity and robustness. Results with synthetic and *in vivo* data confirm the good behavior of our approach.

1. Introduction

Magnetic Resonance Imaging (MRI) acquisitions suffers from different sources of degradations and artifacts that corrupt the original signal. One of the most dominant sources of degradation is noise. Thermal noise in MR scans is mainly originated by the subject or object to be imaged, followed by electronics noise during the acquisition of the signal in the receiver chain. Since noise is related to stochastic motion of free electrons, it is intrinsically imbricated with the acquisition process and therefore it is unavoidable. Some modern acquisition sequences are particularly affected by noise, like those ones in which the signal is attenuated, such as diffusion sequences with high *b*-values. It is also the case in those techniques that demand large amounts of data: in order to reduce the acquisition time, the number of excitations (NEX) is also reduced. As a consequence, the noise power is increased proportionally to the square root of the speedup.

The degradation pattern introduced by noise affects the visual image quality and can negatively lead to an adequate interpretation and analysis of the data. Not only visual inspection is affected by the presence of noise, but also many common post-processing tasks (image registration, tissue segmentation, diffusion tensor estimation) and the obtaining of precise measures and quantitative imaging bio-markers.

The direct approach to minimize the influence of noise over the final image is the use of noise removal techniques, also known as de-noising or, from a statistical perspective, as signal estimation. Traditionally, noise filtering in medical imaging are based on well-defined prior statistical models of data. The Gaussian model is the usual assumption in many algorithms. The definition of more evolved noise models for MRI have allowed the natural extension

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of well-known image processing techniques to cope with features specific of MRI. Many examples can be found in the literature, such as the Conventional Approach (CA) [26], Maximum Likelihood (ML) [31], linear estimators [1], or adapted Non-Local Mean (NLM) schemes [24,34].

In the simplest case, when single-coil acquisitions are considered, the complex spatial MR data is typically assumed to be a complex Gaussian process, where real and imaginary parts of the original signal are corrupted with uncorrelated Gaussian noise with zero mean and equal variance σ^2. Thus, the magnitude signal calculated as the envelope of the complex signal is known to be Rician distributed [18,19]. This Rician model has been the standard in MRI modeling for many years, and it has been the base for a myriad of filtering techniques as well as noise estimation algorithms [1,22,24,34].

With the advent of multiple-coil systems to reduce acquisition time, Parallel Magnetic Resonance Imaging (pMRI) algorithms are used, predominating among them Sensitivity Encoding (SENSE) [29] and GeneRalized Auto-calibrating Partially Parallel Acquisitions (GRAPPA) [17]. From a statistical point of view, the reconstruction process carried out by pMRI techniques is known to affect the spatial stationarity of the noise in the reconstructed data; i.e. the features of the noise become position dependent. Instead of assuming a single σ^2 value for each pixel within the image, the variance of noise varies with $\boldsymbol{x}$, i.e. $\sigma^2(\mathbf{x})$ [2,5].

If SENSE is considered, the reconstruction process yields to the magnitude value of a complex Gaussian, and therefore, the final magnitude signal can still be considered Rician distributed, but with a different $\sigma^2(\mathbf{x})$ for each $\mathbf{x}$ [2,5,13]. This way, many algorithms proposed for single coils systems can still be used if SENSE is considered, as long as the non-stationarity of the noise is taken into account. However, the estimation of the spatial pattern of $\sigma^2(\mathbf{x})$ is an issue that presents serious difficulties and some prior information is needed, such as the sensitivity maps in each coil. Unfortunately, this information is not always available. Recently, some estimation methods have adopted a non-parametric approach to estimate these non-stationary noise maps. These methods do not rely on a specific processing pipeline; the only requirement is that a statistical model has to be adopted for the acquisition noise: Gaussian, [2,16,23,27], Rician [2,7,12,21,25], or nc-χ [28,32].

In this paper we propose a novel approach to noise filtering in MRI assuming non-stationary Rician noise in which the parameter σ depends on the position, $\sigma(\mathbf{x})$. That is the case, for instance of SENSE acquisitions, but not only. It can also be found, for instance, in GRAPPA if the data from each coil is merged using a spatial matched filter instead of the sum of squares. The filtering method is based on the consensus of different realizations of a given signal estimator for different σ^2 values. The idea is to generate a wide variety of candidates that are merged in a global solution without the need of a $\sigma^2(\mathbf{x})$ estimation. Since the representative inputs are not known in advance, we use a set of aggregation functions to merge the realizations. Then, for each pixel, a penalty step will select the aggregated value that presents less dissimilarities with respect to the inputs, as proposed in [9,10]. The final image is obtained with the information contained in the different candidates, showing a consistent spatially-variant behavior.

The work here presented is not a novel filtering method *per se*, but a methodology to adapt well-known statistical-based filters to a particular problem in which input parameters are unknown. It can be seen as an extension of the consensus framework for image processing proposed in two previous works: [15], where a general non-stationary Gaussian model where assumed; and in [14], where the uncertainty to deal with is the model of the noise that corrupts the image. The former approach deals with non-stationary noise in a similar way we do in this paper, while the latter considers stationary noise. The main advantage of the approach we propose in the current work, is that the existence of a well-defined prior noise model increases the amount of information available, which translates in a decrease of the uncertainty of the problem.

As a restoration algorithm, we consider the Linear Minimum Mean Square Error (LMMSE) estimator for Rician noise in [1], due to its simplicity and robustness, which is the natural extension of the Wiener filter to Rician noise. However, the method can be applied to other signal estimators.

The paper is organized as follows. Section 2 introduces the non–stationary Rician model in MRI as well as the LMMSE estimator and the consensus method. The aggregation and penalty functions are also explained. In Section 3 the proposed approach is presented. Then, in Section 4 different experiments are discussed for synthetic and real MR magnitude images using the new approach with LMMSE, to present our conclusions in Section 5.

2. Background

The method proposed in this paper is grounded in three different topics: (1) the non-stationary Rician model present in some MRI acquisitions; (2) the LMMSE estimator for Rician data and (3) the consensus methodology for decision taking when some information is missing. Next, we review the three of them.

2.1. The non-stationary Rician noise model in MRI

In MRI acquisitions, due to the reconstruction process and some post-processing done by the scanner, the noise in the final magnitude image can turn non-stationary, i.e. the variance of noise σ^2 becomes dependent on the position $\mathbf{x}$: $\sigma^2(\mathbf{x})$. This is the case when pMRI techniques are used.

Although the formulation of any specific pMRI method is beyond the scope of this work, as an illustration, let us assume that the reconstruction process combines the data of the different coils using a weighted sum to obtain the single complex image [2,4]:

$$S^{\mathcal{R}}(\mathbf{x}) = \sum_{l=1}^{L} \omega_l(\mathbf{x}) S_l^{\mathcal{S}}(\mathbf{x}). \tag{1}$$

where $\omega_l(\mathbf{x})$, $l = 1, \cdots, L$ is a set of reconstruction weights that may depend on several parameters, such as the sensitivity of the coils; $S_l^{\mathcal{S}}(\mathbf{x})$ are the sub-sampled signals acquired in each coil and $S^{\mathcal{R}}(\mathbf{x})$ the reconstructed signal. This model, for instance, is the one we find in the case of pMRI data reconstructed with SENSE in its original formulation. The linear operations over the Gaussian data generate correlated Gaussian data, affecting the stationarity of the noise in the resulting image, which becomes corrupted with complex Additive Colored Gaussian Noise whose variance depends on the position [2,4]:

$$S^{\mathcal{R}}(\mathbf{x}) = A^{\mathcal{R}}(\mathbf{x}) + N^{\mathcal{R}}(\mathbf{x}; \sigma^2_{\mathcal{R}}(\mathbf{x})), \tag{2}$$

where $N^{\mathcal{R}}(\mathbf{x}; \sigma^2_{\mathcal{R}}(\mathbf{x})) = N_r^{\mathcal{R}}(\mathbf{x}; \sigma^2_{\mathcal{R}}(\mathbf{x})) + j \cdot N_i^{\mathcal{R}}(\mathbf{x}; \sigma^2_{\mathcal{R}}(\mathbf{x}))$ is no longer white, neither stationary. The final magnitude image is obtained by using the absolute value:

$$M(\mathbf{x}) = |S^{\mathcal{R}}(\mathbf{x})| \tag{3}$$

and therefore it follows a non-stationary Rician distribution, with the parameter $\sigma^2_{\mathcal{R}}(\mathbf{x})$ being spatially variant. The specific value of $\sigma^2_{\mathcal{R}}(\mathbf{x})$ will depend on the reconstruction weights ω_l and on the covariance matrix $\mathbf{\Sigma}$. The final value of the variance of noise at each point will depend on the covariance matrix between coils of the original data (prior to reconstruction) and on the sensitivity map of each coil, but not on the data themselves. This model has been observed for SENSE by different authors through experimental and theoretical studies (see for instance the studies in [5,29,30,33]).