Subject-Specific Patch-Based Denoising for Contrast-Enhanced Cardiac MR Images

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ABSTRACT

Many patch-based techniques in imaging, e.g., Non-local means denoising, require tuning parameters to yield optimal results. In real-world applications, e.g., denoising of MR images, ground truth is not generally available and the process of choosing an appropriate set of parameters is a challenge. Recently, Zhu et al. proposed a method to define an image quality measure, called Q, that does not require ground truth. In this manuscript, we evaluate the effect of various parameters of the NL-means denoising on this quality metric Q. Our experiments are based on the late-gadolinium enhancement (LGE) cardiac MR images that are inherently noisy. Our described exhaustive evaluation approach can be used in tuning parameters of patch-based schemes. Even in the case that an estimation of optimal parameters is provided using another existing approach, our described method can be used as a secondary validation step. Our preliminary results suggest that denoising parameters should be case-specific rather than generic.

Keywords: Patch-based methods, MRI denoising, Non-local means, Ground truth

1. INTRODUCTION

Cardiac MR imaging can provide very good soft tissue contrast and has the ability to delineate structurally disease myocardium (e.g. chronic infarct). The conventional MR method to identify such chronic lesions is based on so-called late-gadolinium enhancement (LGE), which requires an intravenous injection of a contrast agent. However, these LGE images are often noisy, hampering accurate detection of the infarct boundaries particularly at the lesion interface with blood and healthy tissue. There is also a large variability in image quality among cases caused by the image intensity, MR parameters, contrast agent kinetics, coil selection etc. Therefore, a robust post-processing denoising method that would significantly increase the CNR/SNR of poor quality LGE images would be desirable.

Recently, various patch-based methods have been proposed to denoise MR images. However, in validation of many patch-based algorithms on real data, ground truth is not generally available. Furthermore, the process of choosing an appropriate set of parameters that minimizes an objective function that typically relies on the ground truth, e.g. PSNR (Peak signal-to-noise ratio), can be challenging. Moreover, some patch-based methods require numerous datasets for training and testing of optimal parameters.[8] Thus, we hypothesize that a method that can be applied on a subject-specific case (i.e., where filter parameters are optimized per case) will lead to more accurate results.

In this manuscript, we focus on the well-known Non-Local means (NL-means) filter. NL-means and its variants perform denoising using similarity of patches in an image. In Section 2, we review the NL-means denoising filter. For a fixed patch-radius, choosing appropriate regularization parameter h and search radius are essential in evaluation of denoising. Here, we use the so called measure Q introduced in[3] to assess the quality of the NL-means algorithm when no ground truth is available. The method in[3] defines Q based on singular

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value decomposition of local image gradient matrix and provides a quantitative measure of true image content (i.e., sharpness and contrast as manifested in visually salient geometric features such as edges). In section 3, we present the results of our denoising experiments assessed by Q. Finally discussions and concluding remarks will be presented in Section 4.

2. METHODS

2.1 Review of the NL-Means Denoising

Consider the following image denoising problem,[1]

$$\mathbf{u} = \mathbf{x} + \mathbf{n},$$

where $\mathbf{u} \in \ell^2(\Omega)$ is a given observation, $\mathbf{n} \in \ell^2(\Omega)$ is additive white independent Gaussian noise with zero-mean and variance σ^2, and $\mathbf{x} \in \ell^2(\Omega)$ is the image to be recovered where

$$\Omega = [1, \ldots, M] \times [1, \ldots, N].$$

For any $x \in \Omega$, define the approximation of $\mathbf{x}$ denoted by $\widetilde{\mathbf{x}_{NL}}$ as

$$\widetilde{\mathbf{x}_{NL}}(x) = \frac{1}{C(x)} \sum_{y \in \Omega} w(x, y)\mathbf{u}(y), \text{ such that}$$

$$w(x, y) = \exp\Big(- \frac{\| \mathbf{u}(\mathcal{N}^d\{x\}) - \mathbf{u}(\mathcal{N}^d\{y\}) \|_{2,a}^2}{h^2} \Big), \text{ and}$$
$$C(x) = \sum_{y \in \Omega} w(x, y),$$

where the expressions $\mathcal{N}^d\{\ldots\}$ and $\| \, . \, \|_{2,a}^2$ are defined in the following way.

Neighbourhoods: For any point in the domain of observation $(i, j) \in \Omega$, define

$$\mathcal{N}^d\big\{(i, j)\big\} = \Big\{(i + i', j + j') \mid (i', j') \in \mathbb{Z}^2, \max\{|i'|, |j'|\} \leq d\Big\}.$$

Gaussian-weighted-semi-norm: For any image patch

$$\mathbf{y} \in \ell^2\big([1, \ldots, 2d + 1] \times [1, \ldots, 2d + 1]\big),$$

define $\| \, . \, \|_{2,a}^2$ as

$$\| \mathbf{y} \|_{2,a}^2 = \sum_{-d \leq i \leq d, -d \leq j \leq d} G_a(i, j)|\mathbf{y}(i + d + 1, j + d + 1)|^2$$

in which G_a is a two-dimensional Gaussian kernel of standard deviation a, centred at $(0, 0)$, and of the same dimension as $\mathbf{y}$.

The idea of the NL-means algorithm is that given a discrete noisy image $\mathbf{u}$, the estimated noiseless value $\widetilde{\mathbf{x}_{NL}}(x)$ is computed as a weighted average of all pixel intensities in the observed image, $\mathbf{u}(y)$, where the weights $w(x, y)$ depend on the similarity of neighbourhoods of the pixels x and y, and w is a decreasing function of the weighted Euclidean distance of the neighbourhoods.

The parameter h in the algorithm acts as a degree of filtering and controls decay of the exponential function and therefore the decay of the weights as a function of the Euclidean distances. Such an h plays the role of the regularization parameter of the inverse problem.

The denoising algorithm above is computationally intensive. A possibility to overcome the computational complexity is to restrict $y \in \Omega \cap \mathcal{N}^r\{x\}$, i.e., in a smaller search window or neighbourhood of x rather than the whole field of Ω in the corresponding equations. In[2,4,5,7] other approaches to overcome the high computational cost of the NL-means algorithm have been examined.

2.2 Quality Metric Q

We evaluate the quality of the denoising experiments without ground truth using metric Q. Algorithm 1 briefly outlines how Q is obtained. For details see.[3]

Algorithm 1 (Procedure for computing metric Q). .

1. *Given a noisy image, divide it into M non-overlapping patches of size $N \times N$, and calculate the local coherence R_k for each patch $k = 1, ..., M$.*
   (We use the acronym QPS when referring to the Q patch size, i.e., N.)
2. *Find (say $m \leq M$) anisotropic patches by thresholding the local coherence values as $R_k \geq \tau$. The threshold τ is determined by solving an equation with a given significance level δ.*
3. *Calculate the so called local metric Q_k on each anisotropic patch identified in step 2.*
4. *Return the value $Q = \frac{1}{M}\sum_{k=1}^{m} Q_k$ as the metric for the whole image.*

3. EXPERIMENTS AND RESULTS

The contrast-enhanced (i.e., late-gadolinium enhanced) MR data was obtained in two pigs with chronic myocardial infarction on a 1.5T GE scanner using a 5 inch surface coil. For image acquisition, we used a conventional 2D fast gradient echo (FGRE) pulse sequence approximately $15 - 20$min following a bolus of Gd-based intravenous injection. The MR scanning parameters were the following: repetition time TR= 7ms, echo time TE= 3.3 ms, inversion recovery time TI= 225ms, flip angle FA= 20, nr. of acquisitions NEX= 1, slice thickness = 5 mm, field of view FOV= 23cm and matrix 256×256 (yielding an approximately 0.9mm $\times$ 0.9mm in-plane pixel size).

The method described in[2] was used to denoise each of the two datasets (Case 1 and Case 2). We fixed the patch size to 3×3 and varied the search radius over the range of 3, 6, and 9. Size of patches in measuring Q (i.e. QPS) are varied in the range of 8 and 16.

The results are displayed in Figures 1 and 2. Vertical blue lines in all Figures correspond to optimal value of h obtained using the method introduced in.[2] In Figure 3, the result of the denoising is shown for sample slice 7 of the noisy datasets. Denoising result using the optimal h value introduced in,[2] and the result for h that corresponds to the peak of the curves in Figure 2 is displayed. Parameters for the results in Figure 3 are QPS= 8, search radius= 3, and patch size= 3, and noise is assumed to be Gaussian in all experiments.

4. DISCUSSION AND CONCLUDING REMARKS

We performed a set of patch-based denoising experiments on LGE MRI data and assessed the quality of each output image without ground truth. We measured the peak of the plotted Q curves over a number of different parameters.

In our experiments, no parallelization was performed to speed-up the process. However, parallel implementations may speed-up the process of finding nearly optimal parameters. The exhaustive method described in this paper can be used in tuning parameters of patch-based schemes. Even in the case that an estimation of optimal parameters is provided using another existing approach, our described approach can be used as a secondary validation step.

Our preliminary results suggest that denoising parameters should be case-specific rather than generic. Our experiments demonstrated the feasibility of using this denoising method for cardiac LGE and optimization on a subject-specific fashion. In future, the study can also be extended to more datasets.

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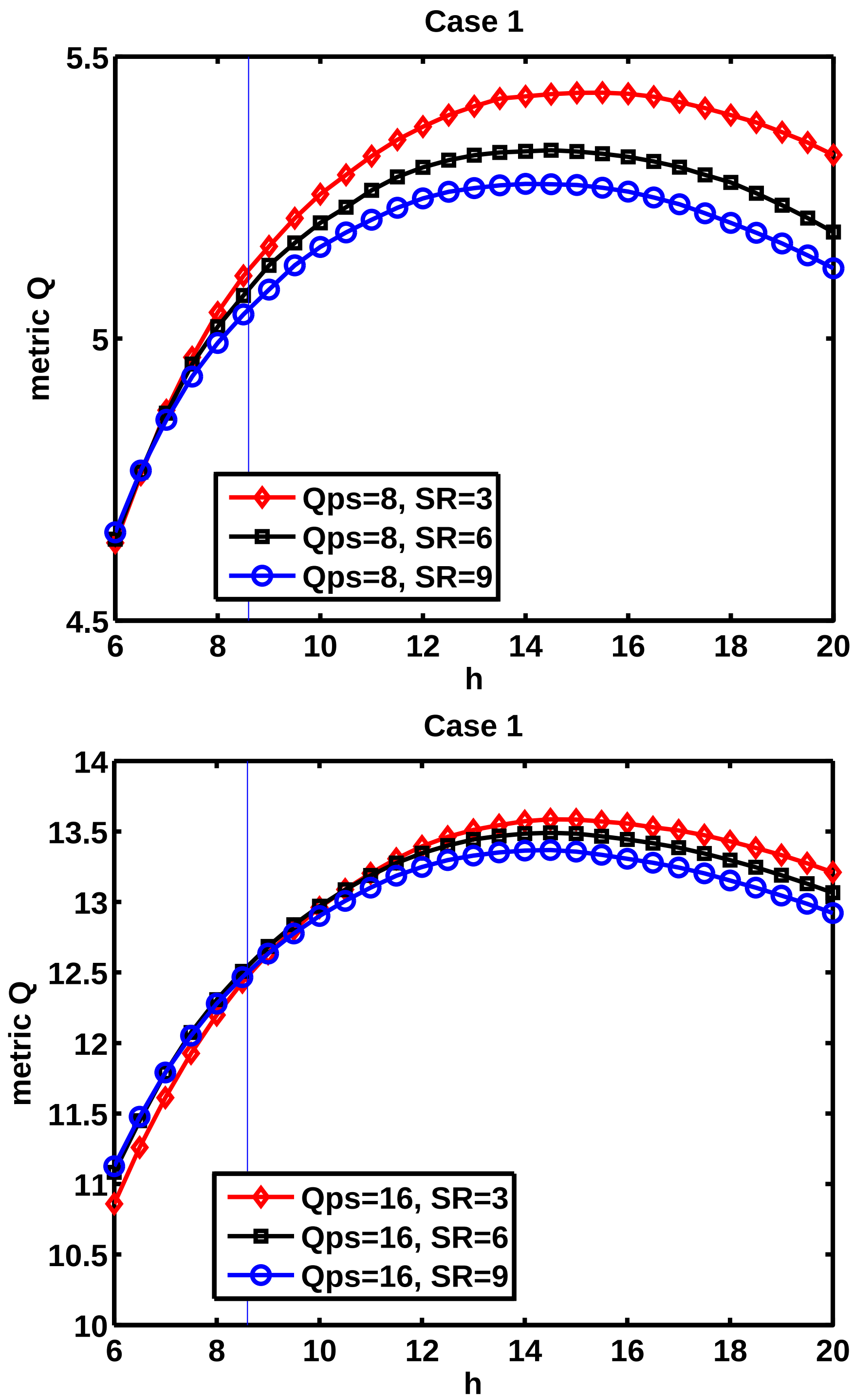

Figure 1. Evaluation of metric Q for the first dataset (case 1). Search radius (SR) is varied in the range of $3, 6, 9$, size of patches in measuring Q (QPS) are 8 in the top plot, and 16 in the bottom plot. Vertical blue line is the optimal h introduced in.[2]

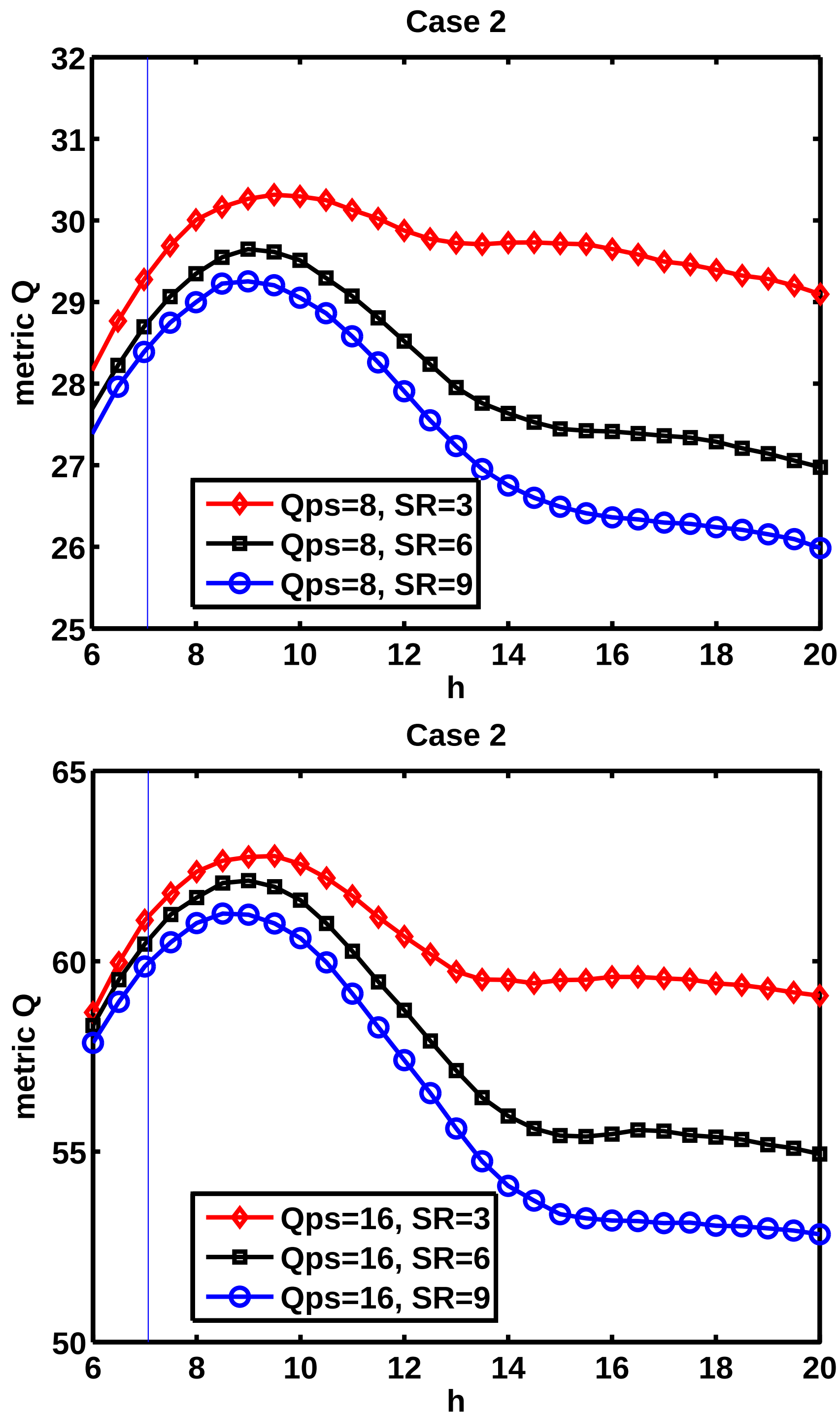

Figure 2. Evaluation of metric Q for the second dataset (case 2). Search radius (SR) is varied in the range of $3, 6, 9$, size of patches in measuring Q (QPS) are 8 in the top plot, and 16 in the bottom plot. Vertical blue line is the optimal h introduced in.[2]

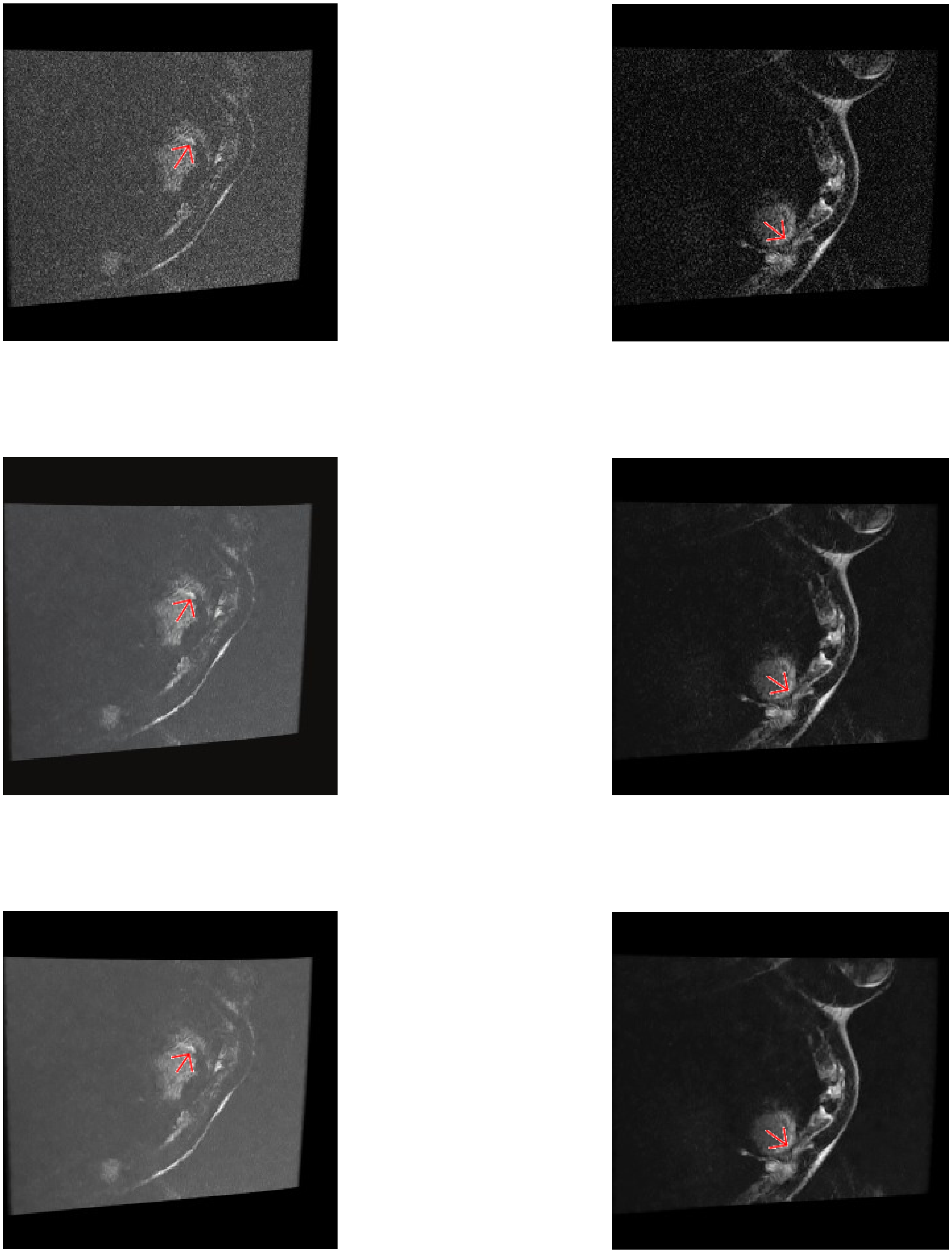

Figure 3. Top: Sample slice 7 of the noisy input dataset 1 (top left) and dataset 2 (top right), Middle: Denoising experiment using the optimal h introduced in,[2] Bottom: Denoising experiment for $h = 14.5$ and $h = 9.5$ that maximize the Q measure respectively in dataset 1 and 2, i.e. the value of h corresponding to peak of the red curves in the first row of Fig. 1. Parameters are QPS= 8, search radius= 3. Hyper-enhanced area indicates the infarct marked by arrow.

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