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4D non-local means post-filtering for cardiac gated SPECT

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Abstract

Cardiac gated images often suffer from increased noise in single photon emission computed tomography (SPECT) due to reduced data counts compared to non-gated studies. We investigate a spatiotemporal post-processing approach based on a non-local means (NLM) filter for suppressing the noise in gated SPECT images. In this filter, the output at a voxel location is computed from a weighted average of voxels in its four-dimensional (4D) neighborhood, wherein the filter coefficients are adjusted according to the similarity level in the local image pattern of individual voxels with respect to the output voxel. This adaptive property allows the filter to achieve noise reduction while avoiding excessive blur of the heart wall. In the experiments, we first evaluated the accuracy of the proposed NLM filtering approach using simulated SPECT imaging data. We then demonstrated the approach on eight sets of clinical acquisitions. In addition, we also explored the robustness of the NLM filter with imaging dose reduced by 50% in these clinical acquisitions. The quantitative results show that 4D NLM filtering could effectively reduce the noise level in gated images, leading to more accurate reconstruction of the myocardium. Compared to spatial filtering alone, using temporal filtering in NLM could reduce the mean-squared-error of the myocardium by 55.63% and improve the left ventricle (LV) resolution by 19.92%. It could also improve the visibility of perfusion defects in gated images. Similar results are also observed on the clinical acquisitions both at standard dose and at 50% reduced dose. The 4D NLM results are also found to be comparable to that of a motion-compensated 4D reconstruction approach which is computationally more demanding.

Keywords

Cardiac-gated SPECT; non-local means filter; spatiotemporal processing; 4D reconstruction

1. Introduction

Single photon emission computed tomography (SPECT) is an important technique in use today for detection and evaluation of coronary artery diseases. In cardiac gated SPECT, the data acquisition is synchronized to the electrocardiography (ECG) signal, which can provide valuable information about both myocardial perfusion and ventricular function [1]. Due to the lowered counts in individual gate intervals, the gated images often suffer from increased noise.

In recent years a growing number of spatiotemporal (aka 4D) methods have been studied to improve the image quality in gated SPECT [2–10]. These methods can be divided into two broad categories: (1) post-filtering approach, and (2) joint reconstruction approach. Both approaches aim to exploit the correlation of the signal components among the different gated frames in a cardiac sequence for noise reduction. In the post-filtering approach, the individual gated frames are reconstructed independently, followed by filtering along spatial and temporal directions [9,10]. In the joint reconstruction approach, the gated frames are reconstructed jointly from the entire collection of data, wherein a smoothing prior is used to complement the acquired noisy data [3–5]. For example, in our recent work [3,4] we developed a joint 4D approach for cardiac gated reconstruction, where we demonstrated that motion-compensated smoothing among the different gates can be much more effective for improving the reconstruction accuracy than spatial smoothing. The added cost of this approach is that it involves motion estimation among the different gates.

While joint reconstruction methods can yield reconstruction results that are potentially more accurate, post-filtering methods are often preferred in the clinics owing to their lower computational complexity and the level of smoothing can be easily controlled through adjusting the bandwidth of filtering. The latter is especially attractive when iterative reconstruction is used, because the level of smoothing can be adjusted without the need to re-run the reconstruction. However, compared to joint reconstruction methods, post-filtering methods often suffer from image blur associated with wall motion in gated images. This issue can be more pronounced when the imaging dose is reduced, as the bandwidth of filtering needs to be reduced in order to accommodate the increased noise.

In this work we investigate a both spatially and temporally adaptive filtering approach for cardiac gated images without using an explicit motion prior in reconstruction. Specifically, we employ a spatiotemporal non-local means (NLM) filter [11], in which we extend its similarity-based filtering to utilize the similarity of the cardiac image signal among the temporal gates in a cardiac sequence. In NLM filtering, the output at a given pixel (or voxel) of an image is formed by a weighted average of a group of pixels in the neighborhood of the pixel location according to their similarity levels. We exploit this property in the spatiotemporal NLM filter by extending the neighborhood to include the temporal dimension such that the smoothing is performed primarily along the trajectories of cardiac motion, thereby avoiding the potential pitfall of motion blur in the output.

In the experiments, we demonstrated the proposed NLM approach first on simulated imaging data in which the ground truth is known for quantitative evaluation. We evaluated the accuracy of the reconstructed myocardium using a number of metrics. We then demonstrated the proposed approach on eight sets of clinical acquisitions. Furthermore, to demonstrate the robustness of the proposed approach, we also tested it on clinical imaging data acquired with reduced dose (by 50%), which is of increased interests in recent years [12–14]. We note that this work is based on our preliminary study in [15], where we first explored the feasibility of spatiotemporal NLM filtering on gated images. In this study, we further develop this approach by modifying the filter to use one common parameter for controlling both spatial and temporal smoothing, and expand the evaluation study by using

additional quantitative measures (on wall resolution and lesion detectability). In addition, we have also included more human studies (8 subjects) and quantified their wall resolution.

We note that, because of their adaptive processing properties, NLM methods recently have been used for noise suppression in many applications [16–19]. For a detailed review, the interested readers are referred to [20–22]. In emission tomography, NLM filtering was applied to improve the resolution of SPECT images by incorporating anatomical information derived from computed tomography (CT) [18,19]. NLM filtering was also used for denoising in positron emission tomography (PET) images [16,17]. To the best of our knowledge, NLM filtering has not been explored for cardiac gated images.

The rest of paper is organized as follows: In Section 2, we describe the proposed spatiotemporal NLM filter and implementation issues for gated images. In Section 3, we describe the experiments and evaluation methods. In Section 4, we present the evaluation results and discussions. Finally, we give the conclusions in Section 5.

2. Spatiotemporal NLM filtering for cardiac gated images

2.1 Imaging model

In gated cardiac SPECT, the acquired projection data are binned into K gate intervals by using the ECG signal. For a given gate interval k , the imaging model is described by the following:

$$E[\mathbf{g}_k] = \mathbf{H}\mathbf{f}_k + \mathbf{s}_k, k = 1, \dots, K \quad (1)$$

where $\mathbf{g}_k$ and $\mathbf{f}_k$ are vectors representing the acquired data and the source distribution (i.e., original image), respectively, in gate k , $\mathbf{s}_k$ is the corresponding scatter component, $\mathbf{H}$ is the system matrix describing the imaging process, and $E[\cdot]$ is the expectation operator. In this study, both the collimator response and attenuation effect are incorporated into the system matrix $\mathbf{H}$.

As mentioned in the introduction, due to the limited count level in the gated data $\mathbf{g}_k$ and ill-conditioned nature of the system matrix $\mathbf{H}$, a direct reconstruction of the individual gates $\mathbf{f}_k$ from (1) would lead to very noisy images. This issue is further exacerbated when the imaging dose is reduced. In this study, we investigate using a spatiotemporal filtering approach to suppress the noise in the reconstructed images by exploiting the correlation among the individual gates.

2.2 Spatiotemporal NLM filtering of cardiac gated images

To facilitate the description of our NLM filtering approach for gated images, below we begin with a spatial NLM filter for processing the individual gates. Afterward, we extend it to allow for temporal processing across the different gates.

(1) Spatial NLM filtering—In this approach, a spatial filter is applied to the individual cardiac gates $\mathbf{f}_k$ one by one independently. Thus, the processing of different gates will have no effect on each other, which can avoid any potential temporal blurring.

Consider the image $\mathbf{f}_k$ of gate k , which is three-dimensional (3D) spatially in our application. For convenience, let's denote the voxels in $\mathbf{f}_k$ by using a single index variable (e.g., j). At a given voxel i , the output of an NLM filter is computed as a weighted average over a group of voxels in a neighborhood of voxel i [11]. Mathematically, the filter output at voxel i is given by:

$$\hat{f}_k(i) = \frac{1}{Z_k} \sum_{j \in N_i} w_k(i, j) f_k(j) \quad (2)$$

where $w_k(i, j)$ is a weight factor defined according to the similarity between voxels i and j , and N_i denotes the collection of voxels in a specified neighborhood of voxel i . In (2), Z_k is a normalization factor for the filter to have unit direct current (DC) gain.

In (2), it is noted that the filter coefficients $w_k(i, j)$ are allowed to vary among the different voxel locations i in the image. In practice, these coefficients are designed such that those voxels that are more similar to voxel i will contribute more to the filter output at i , thereby achieving spatially adaptive processing according to the image content. Because of this, NLM filter is reported to have edge preserving properties [11,20].

To measure the similarity level between voxels i and j [for defining $w_k(i, j)$], in this work we simply compare the image intensity values in their respective local neighborhoods. That is, we take a group of pixels (called a patch) around i and compare their differences with the corresponding patch around j . This patch difference is then used to define the similarity between the two voxels with an isotropic Gaussian kernel as [11]:

$$w_k(i, j) = \exp\left\{-\frac{1}{h^2} \sum_{m \in P_i} [f_k(l_i^m) - f_k(l_j^m)]^2\right\} \quad (3)$$

where l_i^m denotes voxel m within the patch around i (denoted by P_i), and l_j^m denotes the corresponding voxel within the patch around j . In (3), h is a parameter used to control the level of smoothing (a larger value leads to more smoothing) [11]. In our experiments this parameter was varied over a wide range in order to optimize its effect.

In this study the similarity measure in (3) is computed directly from the gated (noisy) image itself as in most of the applications of NLM filters [11]. However, we point that it could also be derived from a different (less noisy) source when available. For example, CT images were used for such measure in reconstruction of SPECT images [18,19].

(2) Spatiotemporal NLM filtering—To exploit the similarity of the cardiac image signal among the different gates, below we extend the processing of the NLM filter in (2) by also

including the temporal dimension. The goal is to have those similar pixels from neighboring gates also contribute to the filter output, thereby maximizing noise reduction in the filter output. Specifically, for gate k , the output of the filter at voxel i is now expanded as the following:

$$\hat{f}_k(i) = \frac{1}{Z_k} \sum_{k' = k, k \pm 1, \dots} \sum_{j \in N_i^{(k')}} w_{k'}(i, j) f_{k'}(j) \quad (4)$$

where $N_i^{(k')}$ denotes a neighborhood of voxel i in gate k' within the periodic cardiac cycle. In (4), Z_k is a normalization factor for the filter to have unit DC gain, i.e.,

$$Z_k = \sum_{k' = k, k \pm 1, \dots} \sum_{j \in N_i^{(k')}} w_{k'}(i, j) \quad (5)$$

In (4), the weight factor $w_{k'}(i, j)$ is modified from (3) accordingly as:

$$w_{k'}(i, j) = \exp\left\{-\frac{1}{h^2} \sum_{m \in P_i} [f_k(l_i^m) - f_{k'}(l_j^m)]^2\right\} \quad (6)$$

where l_i^m denotes voxel m within the image patch P_i around i (in gate k), and l_j^m denotes the corresponding voxel within the patch around j (in gate k').

In (4), the summation term is formed by the contribution from similar voxels within gate k and the contribution from the neighboring gates (i.e., temporal smoothing). From (6), it can be seen that the weight factor $w_{k'}(i, j)$ assumes its maximal value when voxel i (and its neighborhood) in gate k achieves a perfect match with voxel j in gate k' . This happens when the two voxels correspond to exactly the same physical point in the myocardium between neighboring gates. Consequently, the filter output will have the most contribution from those voxels that are located on the motion trajectory of voxel i in neighboring gates. Therefore, the NLM filter in (4) in essence achieves temporal filtering by following the motion trajectory of a voxel among different gates. As to be seen later in the results, this property is the key for the spatiotemporal NLM filter to achieve noise reduction while avoiding causing motion blur across the neighboring gates. This temporal smoothing property is noted to be similar in spirit to motion-compensated 4D reconstruction [3] where a smoothing prior is used explicitly to enforce smoothing along the direction of image motion.

In our initial study [15], we explored using two different parameters for spatial and temporal smoothing. When the noise level is similar between two neighboring gates (due to similar acquired counts), the contribution from a similar voxel in a neighboring gate should be no different from that in the same gate. Thus, we have chosen to use a common parameter h for

both the spatial and temporal components in (6). This will greatly simplify the parameter selection in our evaluation study.

For convenience, from this point on the spatiotemporal NLM filter in (4) is referred to as NLM-ST, whereas the spatial NLM filter in (2) as NLM-S.

2.3 Implementation of the spatiotemporal NLM filter

(1) Choice of parameters—For implementing these filters, the following parameters need to be specified: 1) the neighborhood $N_i^{(k)}$ in (4) which defines the spatial extent of the filter, 2) the image patch P_i in the similarity measure in (3), 3) the bandwidth parameter h for controlling the level of smoothing, and 4) for NLM-ST, the number of neighboring temporal gates in (4).

In our experiments, the neighborhood $N_i^{(k)}$ was set to a small window of size $w \times w \times w$ centered at voxel i in gate k . For optimizing the results, the window size w was incrementally varied as 3, 5, and 7. Similarly, the image patch P_i was also set as a small window centered at voxel i [21]. In addition, the number of neighboring gates in (4) was varied from 2 (i.e., $k' = k \pm 1$) to 6 (i.e., $k' = k \pm 1, k \pm 2$, and $k \pm 3$). These parameter settings were based on the consideration that the thickness of the LV wall is typically only a few voxels (between 2 and 4 voxels, depending on the image resolution), and that the motion magnitude at a given location on the LV is less than 1 voxel between two neighboring gates.

Finally, to optimize the smoothing effect, the bandwidth parameter h was varied incrementally in steps over the range from 0 to 1.5.

(2) Normalization of individual gates—In cardiac gated SPECT images, the image intensity of the LV wall is known to exhibit variations among the reconstructed individual gates due to the partial-volume effect [22]. To reduce the impact of such variations on the patch similarity measure and the filter output, we first normalized each gate such that the intensity of the heart region is within a common range [0,1] prior to applying the NLM-ST filter. Afterward, the filtered image was rescaled back to its original count level for each gate.

3. Experiments and evaluation study

3.1 Imaging datasets

We first quantified the accuracy of the reconstructed gated images using simulated imaging data wherein the ground truth is known. We then demonstrated the proposed approach on eight sets of clinical acquisitions. To demonstrate the robustness of the approach, we also tested it with reduced dose in these clinical acquisitions.

(1) Simulated imaging data—The 4D NURBS-based cardiac-torso (NCAT) 2.0 phantom [23] was used to simulate gated SPECT imaging with Tc-99m labeled sestamibi as the imaging agent. The simulation was based on a Philips Prism 3000 SPECT system with a low-energy high-resolution (LEHR) collimator. The projection data were 64×64 bins with

pixel size of 0.634 cm. For a circular camera rotation of 28.5 cm radius, 64 projection sets were collected for each gate for a total of 16 gates. The average spatial resolution at the location of the heart in the image slices was approximated 1.3 cm in full-width at half-maximum (FWHM). Monte-Carlo simulation with SIMIND [24] was used for the projection data. Both attenuation and scatter were included in the simulation. For attenuation correction, the averaged attenuation map over all cardiac gates was used. For scatter correction, the triple energy window (TEW) method [25] was applied. The photopeak window was 20% centered at 140 keV, and a 3.5 keV window abutted to the lower side of the photopeak window was used for scatter correction. Poisson noise at a level of 8 million total counts was introduced for the entire acquisition as in a typical clinical acquisition. The phantom was generated with the following body dimensions: 35.2 cm, 26.7 cm, and 41.7 cm in long-axis, short-axis, and height, respectively; the corresponding rib dimensions were 30 cm, 22.7 cm, and 37.3 cm, respectively. The following relative activity levels were introduced for the different organs: heart (ventricular and atrial walls) 1.0, liver 1.0, kidney 1.0, spleen 1.0, gall bladder 0.8, and tissue background 0.053. Two datasets were generated for the phantom, one normal, and one with perfusion defects. The defect dataset has a transmural perfusion defect with 30% intensity reduction located in the anterior-lateral region of the LV wall; the extent was 15 degrees in the circumferential dimension, and 3 voxels in height along the long-axis dimension. It is noted that the contrast level had been set to be low. This would allow us to assess how smoothing would affect lesion detection particularly for those that are subtle and small in size. Both datasets include 30 noise realizations for our quantitative evaluation.

(2) Clinical acquisitions—As a preliminary demonstration, we also tested the proposed approach on eight sets of clinical data, which were acquired under institutional review board (IRB) approval with informed content. Among these 8 subjects (5 male, 3 female), 6 were interpreted as being normal and 2 as having perfusion defects. The dataset was acquired in list-mode with an IRIX system with 64 projections (3-degree steps) and a 128×128 matrix. The pixel size was 0.467 cm. The acquisition started from right anterior oblique, passed through anterior and left anterior oblique, and ended at left posterior oblique. A total of 8 gates were used. Events were recorded within a symmetric energy window centered on 140.5keV with a width of 15%. A scatter window was also acquired which was centered at 120keV with a 5% width. Sequential transmission imaging was used for the estimation of attenuation maps. These studies were acquired at normal dose (acquisition time 10.67 min, injected dose 30–36 mCi adjusted according to body mass index). Among the 8 subjects, the total number of counts of acquired was between 14.67 and 20.12 million (17.32 ± 1.73 million). For reconstruction, TEW method [25] was used for scatter correction.

Furthermore, from the acquisitions of these 8 subjects, we also derived a reduced dose version in which the acquired photon counts in list-mode were statistically down-sampled to only 50% of the original level [12]. For each subject, the photon events acquired in list-mode were statistically resampled such that each event detected at standard dose was randomly accepted or rejected according to a binomial distribution with success probability equal to 1/2.

3.2 Reconstruction methods for comparison

To demonstrate the proposed NLM filtering approach for gated SPECT, we first reconstructed the individual gates in (1) separately using maximum-likelihood (ML) estimation; for faster convergence, the ordered subset expectation maximization (OS-EM) algorithm [2] (16 subsets and 10 iterations) was used in reconstructing the gated images. Afterward, the spatiotemporal NLM filter in (4) (NLM-ST) was applied to further process the reconstructed images. To demonstrate the benefit of temporal processing, we also provide results obtained with the spatial NLM filter in (2) (NLM-S).

For comparison, we also considered reconstruction results obtained by a clinical spatiotemporal filtering method, denoted by ST121. In this method, the images were first reconstructed by filtered backprojection (FBP), then processed spatially with a Butterworth filter of order 2.4 and cutoff frequency of 0.2 cycles/voxel, and further processed along the gate dimension with a temporal filter with impulse response 1/4, 1/2, 1/4.

Furthermore, we also considered a joint motion-compensated 4D reconstruction approach previously developed for gated SPECT images [27]. This approach was demonstrated to yield improved reconstruction of the myocardium over several alternative methods [3,4]. The parameters for 4D were set according to the reconstruction accuracy as in [27]. Note that for the independent 3D reconstruction, we used the same number of iterations as in 4D; this was to achieve the same level of resolution recovery in reconstruction.

3.3 Numerical Evaluation Metrics

(1) Overall error level of myocardium—To quantify the overall accuracy of the reconstructed myocardium, we computed the mean squared error (MSE) of a volumetric region containing the entire myocardium and nearby surrounding voxels; a 2D slice of this region is shown in Figure 1. The MSE is computed over all the cardiac gates for this region. The definition of MSE is given in Appendix A.

As reference, the reconstruction from the noiseless projection of the source (without attenuation) is used. This represents the ideal case of reconstruction without any distortion in the acquisition (referred to as ‘Ideal’ hereafter).

(2) Region bias-standard deviation (std) analysis—To quantify the regional accuracy of the reconstructed left ventricle (LV), we conducted bias-std analyses on an ROI selected on the LV wall (as indicated in Figure 1). Such analyses provide results on both the bias and noise levels of the regional intensity of the LV in the reconstruction. In our experiments, a total of $Q = 30$ noise realizations were used. A detailed description of the bias-std analysis procedure is given in Appendix A.

(3) Intensity Profile—We assessed the effect of NLM filtering on the spatial resolution of the heart wall by plotting the intensity profile for a cross section of the LV (Figure 2(a)). To quantify the wall resolution, we computed the FWHM of this cross-section in both ED and ES gates. This is to demonstrate how the filtering may affect the wall thickening effect associated with wall motion.

(4) Lesion Detectability—To demonstrate how NLM filtering may affect the visibility of perfusion defects in gated images, we quantified the detectability of a perfusion defect (Figure 2(b)) in the reconstructed images using a channelized Hotelling observer (CHO) [26]. In the CHO, four rotationally symmetric, non-overlapping input channels were used and internal noise was included [24]. In the experiments a total of 60 noise realizations (30 lesion-present and 30 lesion-absent) were used and the reconstructed images by each method were assessed by the CHO. The detection performance was summarized using the area under the receiver operating characteristic (ROC) curve (denoted as A_z). This ROC study represented a “signal-known exactly” and “background-known exactly” observer study.

4. Results and discussions

4.1 Quantitative evaluation with simulated imaging data

(1) Overall accuracy of reconstructed myocardium—In Figure 3(a) we show a plot of the MSE results of the reconstructed myocardium obtained by the NLM-ST filter with different parametric settings. In the plot, each curve was obtained by incrementally varying the smoothing parameter h for a given setting of the filter. For example, the curve labelled by “NLM-ST2 w3” corresponds to the setting of 2 neighboring gates and neighborhood window size of $3 \times 3 \times 3$ in the filter. In these results, the number of neighboring gates was varied as 2, 4, or 6 and the window size was set as $3 \times 3 \times 3$ or $5 \times 5 \times 5$. These results were from an average of 30 noise realizations. For comparison, the optimal MSE result obtained with 4D reconstruction is also shown in Figure 3(a).

From these results it can be seen that use of NLM filtering can greatly reduce the MSE level in the reconstructed images when compared to no filtering (i.e., $h = 0$). The window size of $3 \times 3 \times 3$ could yield a lower MSE than the size of $5 \times 5 \times 5$ when the same of number of neighboring gates was used. Moreover, the best $MSE = 5.04$ was achieved with the number of neighboring gates at 4 and $h = 0.2$. At this setting, the MSE is noted to be very close to that of 4D ($MSE = 4.85$).

For comparison, in Figure 3 (b) we show the MSE results obtained by the NLM-S filter. In these results, the smoothing window size was set as $3 \times 3 \times 3$, $5 \times 5 \times 5$, or $7 \times 7 \times 7$. As can be seen, the best $MSE = 11.36$ was achieved with $h = 0.1$ and window size of $5 \times 5 \times 5$, which is notably higher than that of NLM-ST in Figure 3 (a).

These results indicate that, due to the use of temporal smoothing, NLM-ST is much more effective for noise reduction than NLM-S. Interestingly, this is noted to be also consistent with 4D reconstruction wherein temporal smoothing is demonstrated to be more effective than spatial smoothing [3,4]. Furthermore, for NLM-ST the optimal MSE was obtained with window size $3 \times 3 \times 3$ whereas for NLM-S it was with window $5 \times 5 \times 5$. We believe this is due to the fact that the image voxels from the neighboring gates (the 2nd term in (4)) could offer added smoothing for noise suppression in NLM-ST, thereby reducing the extent of spatial smoothing.

Finally, we note that in these results the patch size was fixed at $5 \times 5 \times 5$ in the similarity measure. In the experiments we also varied this parameter and found that the optimal MSE

was somewhat insensitive to the patch size. For example, for NLM-ST (with 4 neighboring gates and smoothing window size of $3 \times 3 \times 3$), the optimal MSE obtained was 5.19 and 5.10 when the patch size was set as $3 \times 3 \times 3$ and $7 \times 7 \times 7$, respectively. Therefore, unless specified explicitly otherwise, in the rest of the results the patch size of $5 \times 5 \times 5$ was used and the smoothing window was set as $3 \times 3 \times 3$ for NLM-ST and $5 \times 5 \times 5$ for NLM-S (based on their optimal MSE results).

(2) LV regional accuracy—In Figure 4, we show a plot of the results of bias-standard deviation analysis obtained by the NLM-ST filter for an ROI on the LV (Figure 1). In the plot, each curve was obtained by varying the smoothing parameter h incrementally from 0 to 1.5 under a given setting of the number of neighboring gates at 2, 4, or 6. For example, the curve “NLM-ST2” represents the results obtained with 2 neighboring gates, and similarly for “NLM-ST4” and “NLM-ST6”. On each curve, the top-left end corresponds to $h = 0$ while the bottom-right end corresponds to $h = 1.5$. For comparison, the bias-std results are also shown for the NLM-S filter in Figure 4; moreover, the bias-std results obtained by 4D reconstruction (at optimal MSE) are also shown.

It is observed from Figure 4 that, with the increase in smoothing parameter h , the noise level (measured by std) is notably reduced in NLM-ST while the bias level is increased. A similar decrease in noise is also observed in NLM-S, but the bias level is much higher. In particular, with the std level at 10%, the corresponding bias level is 22.66%, 12.29%, and 20.24% for “NLM-ST2”, “NLM-ST4”, and “NLM-ST6”, respectively, compared to 35.87% for NLM-S. At the same noise level, “NLM-ST4” yields the least bias; the bias level is noted to be close to that of 4D reconstruction. Interestingly, this is also consistent with the MSE results earlier in Figure 3, where “NLM-ST4” yielded the smallest MSE (which is also close to 4D reconstruction).

It is noted that the bias in NLM-ST6 (with more neighboring gates included) is larger than NLM-ST4 at the same level of std. We believe that this is likely caused by the partial volume effect in gated images; because the wall intensity and resolution vary across neighboring gates, especially for those that are further away from the target gate, the improvement becomes limited as more gates are included.

Finally, we note that the bias-variance plots may vary with the location of the ROI within the myocardium. In our experiments, we also tested for the ROI at a different location and obtained similar trade-off between bias and std for NLM-S and NLM-ST.

(3) Intensity profiles—To demonstrate the potential blurring effect on the LV wall, we show in Figure 5 the intensity profiles obtained by NLM-ST for a cross-section through the LV wall (indicated in Figure 2). The results are given for two extreme phases of the cardiac cycle, namely, the end-systole (ES) phase in Figure 5(a) and the end-diastole (ED) phase in Figure 5(b). For comparison, the results are also shown for the NLM-S filter and 4D reconstruction in Figure 5. These results were averaged over 30 noise realizations. For each method, the parameters were set according to the optimal MSE results (i.e., $h = 0.2$ for NLM-ST, and $h = 0.1$ for NLM-S). As reference, the intensity profiles from the ideal reconstruction are also shown in Figure 5.

It is observed that in the ES gate the intensity profile obtained by NLM-ST closely follows the Ideal; the bias level at the peak intensity is similar to that of 4D reconstruction. In the ED gate, this bias level is slightly increased compared to 4D reconstruction. By comparison, the bias level in NLM-S is notably larger in both ES and ED gates.

To quantify the effect on wall resolution, we further computed the FWHM of the intensity profiles obtained by the different methods. The results are summarized in Table 1. As can be seen, for both ED and ES gates, the FWHM values obtained by NLM-ST are only slightly higher than that of 4D. By comparison, the FWHM values of NLM-S are notably larger in the two gates, which indicate more blurring of the LV wall (as to be seen in the reconstructed images shown below).

(4) Lesion detectability—To demonstrate the smoothing effect on perfusion defect detection, we also quantified the detectability of a perfusion defect (indicated in Figure 2) in the reconstructed images. In Figure 6 we show the CHO detection results from the images obtained by the NLM-ST filter. To illustrate the effect of smoothing, the parameter h was varied incrementally from 0 to 1.5 in these results. For comparison, the CHO results are also given in Figure 6 for the NLM-S filter and 4D reconstruction (at optimal MSE). These results were obtained from a total of 60 noise realizations (30 lesion-present and 30 lesion-absent).

It is observed from Figure 6 that use of NLM filtering (NLM-ST or NLM-S) can notably increase the detectability of the defect in the reconstructed images when compared to no filtering (i.e., $h = 0$), and that the improvement is much higher in NLM-ST than in NLM-S thanks to added temporal smoothing in NLM-ST. For NLM-ST the best $A_z = 0.775$ was obtained with $h = 0.2$, whereas for NLM-S the best $A_z = 0.646$ was obtained with $h = 0.1$. Interestingly, these optimal settings of NLM-ST and NLM-S in A_z also yielded the best MSE results earlier in Figure 3. Moreover, the optimal A_z value obtained by NLM-ST is also very close to that of 4D reconstruction ($A_z = 0.7859$).

(5) Reconstructed NCAT images—In Figure 7, we show a set of reconstructed images by the different methods from one typical noise realization of the NCAT phantom. For brevity, only one short-axis slice and one long-axis of the reconstructed LV are shown for every fourth gate. For each method, the parameters were set according to the optimal MSE results above (i.e., $h = 0.2$ for NLM-ST, and $h = 0.1$ for NLM-S). As can be seen, the LV is notably more uniform and exhibits less blur in NLM-ST than in NLM-S. The appearance of the LV wall among the different gates in NLM-ST is very similar to that of 4D reconstruction. While the noise level is somewhat suppressed in NLM-S, the LV heart wall suffers from noisy distortion (e.g., gate#13).

4.2 Reconstruction of clinical imaging data at standard dose

In Figs. 8–10 we show the reconstructed images for three example subjects obtained by the following different methods: NLM-ST, NLM-S, 4D, and ST121; in addition, the results from OSEM without any smoothing are also included for comparison. For each patient, one short-axis slice and one long-axis slice of the reconstructed LV are shown for every other gate. Specifically, Figure 8 is from a normal male subject, Figure 9 is from a normal female

subject, and Figure 10 is from a female subject interpreted as having a perfusion defect in the left anterior descending (LAD) and left coronary artery (LCX) territory.

It can be observed among the different subjects that the wall resolution of the LV is markedly improved in NLM-ST over NLM-S. The LV also exhibits a higher contrast relative to its surrounding background in NLM-ST than in NLM-S in each of the subjects. Moreover, the NLM-ST images are noted to be comparable to the 4D images in all these subjects. In particular, in Figure 10 the extent and contrast of the perfusion defect (in short-axis view) among the different gates are consistently better defined in both NLM-ST and 4D. This indicates that the use of temporal smoothing in NLM-ST has not resulted in noticeable motion blur of the defect. In comparison, the ST121 images suffer from some noticeable artifacts, including attenuation effect (e.g. Figure 9) and blurring of the LV wall.

We note that similar reconstruction results were also obtained for the other five subjects in the clinical data. Their images are omitted here for brevity.

We also quantified the wall resolution in the eight subjects by computing the FWHM of the intensity profile for a cross-section of the LV wall (as indicated in Figure 2). The results are summarized in Table 2, wherein the mean and standard deviation values among the subjects are given for both ED and ES gates. For example, for the ED gate, the mean FWHM values are 2.46 cm and 2.42 cm for NLM-ST and 4D, respectively, compared to 2.87 cm and 2.81 cm for NLM-S and ST121, respectively. These results are consistent with the observed improvement in image resolution in the NLM-ST and 4D reconstructed images in Figs. 8–10.

In these clinical results, due to the difference in the number of cardiac gates (8 vs. 16) and the detector spatial resolution (128×128 vs. 64×64), the parameters in the NLM filters were adjusted accordingly from the optimal setting for the NCAT data. Specifically, for NLM-ST, the number of neighboring gates was set to 2 (i.e., $k' = k \pm 1$), the smoothing window and patch were enlarged to $5 \times 5 \times 5$ and $9 \times 9 \times 9$, respectively, and the smoothing parameter $h = 0.3$. Similarly, for NLM-S, the smoothing window and patch were set as $7 \times 7 \times 7$ and $9 \times 9 \times 9$, respectively, and $h = 0.15$; this was to keep the physical size of resulting patches and windows to be similar between NCAT simulation and clinical studies, and the parameter h was set such that the std is the same for an ROI on the LV between NLM-S and NLM-ST.

4.3 Reconstruction of clinical imaging data at half dose

In Figs. 11–13, we show the reconstructed images from the half dose data by the different methods. For comparison, the same three subjects are shown as earlier in the standard dose data in Figs. 8–10. It can be seen that the NLM-ST images at half dose are almost indistinguishable from their respective counterparts at full dose for these subjects. In particular, the contrast and extent of the perfusion defect in subject #3 (Figure 13) also appear similar at half dose compared to the standard dose. At half dose, the NLM-ST images also remain similar to the 4D images in all the subjects. In addition, the ST121 images at half dose are noted to suffer from reduced uniformity of the LV wall due to increased noise.

We also quantified the wall resolution in the eight subjects at half dose as in the standard dose data above. The obtained FWHM results of both ED and ES gates are summarized in Table 3 for the different reconstruction methods. As in the standard dose (Table 2), NLM-ST and 4D achieved the best wall resolution at half dose. There was only a slight increase in the mean FWHM values of ED and ES gates at half dose compared to standard dose.

In these results, the bandwidth parameter was set as $h = 0.4$ for NLM-ST and $h=0.2$ for NLM-S in order to accommodate the increase noise level at half dose.

Finally, in the experiments the 4D NLM filter was implemented in MATLAB on a Mac computer (32 GB memory, 3.2 GHz CPU). It took 1 min on average for NLM-ST to reconstruct one subject (all the gated images), compared to 30 min on average for motion-compensated 4D.

5. Conclusions

We investigated an NLM filtering approach for suppressing the noise level in cardiac gated SPECT images. In the NLM filter the smoothing neighborhood was extended along the temporal dimension in order to exploit the similarity of the cardiac image signal among neighboring gates. The filter coefficients at a given location were adjusted automatically according to the local image pattern both spatially and temporally. This enables the filter to effectively achieve adaptive smoothing in the myocardium by following the motion trajectories throughout the cardiac cycle. By varying the bandwidth parameter in the filter, one can easily control the tradeoff between the noise level and regional bias on the heart wall in the reconstruction. Our evaluation results prove that, compared to spatial filtering alone, 4D NLM filtering can lead to a more accurate reconstruction of the myocardium in gated images in terms of overall accuracy of the myocardium, regional bias-variance level of the LV wall, resolution of the LV, and detectability of perfusion defects. Such improvement was also demonstrated with eight clinical acquisitions both at standard dose level and when the imaging dose is reduced by 50%. The 4D NLM could also yield results that are comparable to that obtained with a motion-compensated 4D joint reconstruction approach. Finally, the two SPECT systems were different in simulated and clinical acquisitions, but the results showed consistent improvement in 4D NLM over 3D NLM. This indicates that 4D NLM processing can be beneficial for both systems. Encouraged by these promising results, we plan to further explore the use of 4D NLM filtering for reducing the imaging dose in clinical acquisitions.

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Appendix A

DEFINITION OF QUANTITATIVE METRICS

A.1 Mean squared error (MSE)

The mean squared error (MSE) of the reconstructed myocardium region is computed as:

$$MSE = \frac{1}{N} \|\mathbf{f} - \hat{\mathbf{f}}\|_{VOI}^2 \quad (\text{A.1})$$

where $\mathbf{f}$ and $\hat{\mathbf{f}}$ denote the reference and reconstructed images, respectively, VOI denotes the volumetric region, and N is the number of voxels in the region.

A.2 Bias-standard deviation (std) analysis

Consider an ROI consisting of M voxels. Let $\bar{f}_{ROI}$ denote the mean intensity of the reference image $\mathbf{f}^*$ in the ROI, i.e.,

$$\bar{f}_{ROI} = \frac{1}{M} \sum_{i \in ROI} f^*(i) \quad (\text{A.2})$$

Our goal is to quantify the statistical accuracy of an estimate of this quantify from different noisy reconstructions.

Let $\hat{f}_{ROI}^{(q)}$, $q = 1, \dots, Q$, denote the estimate of $\bar{f}_{ROI}$ obtained from Q different noise realizations. The mean estimate is computed as:

$$\hat{u} = \frac{1}{Q} \sum_{q=1}^Q \hat{f}_{ROI}^{(q)} \quad (\text{A.3})$$

Then the bias and standard deviation (std) of this estimator are respectively estimated as:

$$\text{bias} = \frac{|\bar{f}_{ROI} - \hat{u}|}{\bar{f}_{ROI}} \times 100\% \quad (\text{A.4})$$

$$\text{std} = \frac{\sqrt{\frac{1}{Q-1} \sum_{q=1}^Q (\hat{f}_{ROI}^{(q)} - \hat{u})^2}}{\bar{f}_{ROI}} \times 100\% \quad (\text{A.5})$$

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Figure 1.
A 2D slice of a volumetric region containing the entire myocardium and an ROI on the LV used for regional bias-variance analysis.

Figure 2.

(a) A cross section of the LV used for intensity profile analysis; (b) The center position of the perfusion defect used in CHO analysis.

Figure 3.

Mean square error (MSE) results of the myocardium obtained with (a) NLM-ST filter, and (b) NLM-S filter. The bandwidth parameter h was used to control of the level of smoothing. The curve labelled by “NLM-ST2 w3” corresponds to the setting of 2 neighboring gates and neighborhood window size of $3 \times 3 \times 3$; similarly, “NLM-ST4 w5” corresponds to the setting of 4 neighboring gates and neighborhood window size of $5 \times 5 \times 5$, and so on. These results were averaged from 30 noise realizations. The error bars represent the standard deviation values.

Figure 4.

Bias-std plots of the LV reconstructed with different methods. Each curve was obtained by varying the bandwidth parameter, with the upper-left endpoint corresponding to no smoothing.

Figure 5. Cross-sectional intensity profile of the reconstructed LV with different methods: a) ED gate, and (b) ES gate. These plots were averaged from 30 noise realizations.

Figure 6.
Lesion detectability measured by CHO with different reconstruction methods.

Figure 7.
Reconstructed short axis and long axis slices of NCAT by different methods.

Figure 8. Short axis and long axis slices of subject #1 (male) reconstructed by different methods at standard dose. The subject is interpreted as being normal.

Figure 9. Short axis and long axis slices of subject #2 (female) reconstructed by different methods at standard dose. The subject is interpreted as being normal.

Figure 10.

Short axis and long axis slices of subject #3 (female) by different methods at standard dose. The subject is interpreted as having a perfusion defect in the LAD and LCX territory.

Figure 11. Short axis and long axis slices of subject #1 (male) reconstructed by different methods at half dose. The subject is interpreted as being normal.

Figure 12.

Short axis and long axis slices of subject #2 (female) reconstructed by different methods at half dose. The subject is interpreted as being normal.

Figure 13.

Short axis and long axis slices of subject #3 (female) by different methods at half dose. The subject is interpreted as having a perfusion defect in the LAD and LCX territory.

Table 1

FWHM values obtained by different reconstruction methods for a cross-section of the LV in simulated NCAT data.

Reconstruction method	ED gate (cm)	ES gate (cm)
NLM-ST	2.25±0.10	2.40±0.11
NLM-S	2.81±0.25	2.97±0.26
4D	2.10±0.10	2.36±0.11
Ideal	1.83	1.97

Table 2

FWHM values obtained by different reconstruction methods for a cross-section of the LV in clinical data with standard dose.

Reconstruction method	ED gate (cm)	ES gate (cm)
NLM-ST	2.46±0.23	2.76±0.24
NLM-S	2.87±0.34	3.25±0.35
4D	2.42±0.22	2.70±0.23
ST121	2.81±0.23	3.22±0.24

Table 3

FWHM values obtained by different reconstruction methods for a cross-section of the LV in clinical data with standard dose.

Reconstruction method	ED gate (cm)	ES gate (cm)
NLM-ST	2.47±0.25	2.80±0.27
NLM-S	2.93±0.35	3.27±0.37
4D	2.45±0.23	2.78±0.24
ST121	2.79±0.26	3.10±0.28