Advanced Image Processing Using Feature Images Extracted from Different Iterations

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Abstract: In iterative image reconstruction, different structures may reconstruct or evolve at different rates with iterations. From the difference between the images at different iterations, we extract feature images based on the evolution characteristics of different structures. We then use the feature images for advanced image processing. A TOF list-mode OSEM algorithm was used for iterative image reconstruction. A methodology was established to calculate feature images which distinguish regions of fast evolution (presumably associated with large and uniform structures) and slow evolution (associated with small structures such as lesions and cold regions). The feature images were then used to guide the in-reconstruction noise-suppression approaches (such as regularized reconstruction) and post-reconstruction noise-suppression approaches. Phantom and patient studies were used to demonstrate the proposed technique and its advantages. Results showed that with the feature images even very simple image domain techniques could achieve superior performance for the intended applications.

Key words: PET, iterative image reconstruction, evolution, feature image, TOF, filtering

1. Introduction

Suppressing noise while preserving lesion/organ quality (edge-preserving) and quantification is critical for quantitative PET. Unfortunately, these two goals generally work in the opposite directions and compete against each other. For example, post-reconstruction filtering is a popular approach for noise suppression in medical imaging. Careful choice of filter types and filter parameters can in general provide an acceptable, even if not optimal, solution to the clinical needs. Such filters include low-pass filters, bi-lateral filters, and advanced adaptive filters, etc. Low-pass filters tend to smooth the image uniformly, thus, lesion contrast may be compromised. Bi-lateral filters [1] try to use the local image information to determine if an edge exists; the filters only smooth the regions to the sides of the edge and leave the edge untouched (not crossing the edge) or minimally smoothed. In this way, the edge is preserved, so lesion/organ quantitation can be preserved. The challenge, however, is that depending upon the filter parameters, edges may not be detected around some small/weak lesions/organs. Consequently, such small/weak lesions/organs will be filtered and the quantitative accuracy may be compromised. Other advanced adaptive filters, such as partitioned image filtering [2], guided filter [3], etc., also share similar challenges as the bi-lateral filters.

Advanced image processing approaches aim at finding the best compromise between noise suppression and edge preservation. However, such approaches rely on image-based intensity difference between voxels. For small/weak lesions/organs, the intensity difference between them and the background may be small, the approaches might “think” there are no edges and smooth (over-smooth) such lesions/organs.

Additionally, when count level is low and noise level is high, the edge detection can be significantly challenged by the noise. If the parameters for edge detection are chosen to enable the detection of weak edges (weak lesions/organs), then some bright noise spots can be “falsely” deemed as containing edges and be preserved as “lesion” rather than being smoothed out. On the other hand, if the parameters are chosen to enable sufficient noise suppression, then some weak/small lesions/organs may be smoothed when the difference between the lesions/organs and the background are too small to be deemed as edges.

A non-local mean filter [4] may be able to filter images based on spatial similarity of different regions in the image. Different regions with high similarity levels can be averaged so that a voxel in one region can be averaged with the corresponding voxel in another region. The filtering of the pixel does not have to be with its own neighboring voxels. This approach can be very effective if the similarity based on the intensity distribution in the regions can be reliably computed, and if the image does contain many regions with high level similarity. For nuclear medicine, such as SPECT and PET, due to the relatively high noise level and the complexity of patient updates, the effectiveness of non-local mean filtering may not be guaranteed.

In this work, we describe a unique approach based the following observations in iterative PET reconstruction:

- Large structures (low frequency signals) converge faster than small structures (high frequency signals), i.e., it takes fewer number of iterations for large structures to converge
- Cold regions may converge more slowly than hot regions
- Small lesions and edges are high frequency signals,

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thus converge slowly in general

- Noise (high frequency signals) is typically slow to converge
- Specific to PET image reconstruction, reconstruction from data with time-of-flight (TOF) information converges faster in general than without TOF information

With these observations, we first use the difference image between two iterations of iterative processing to generate a feature image. The feature image carries the "evolution" information of each object/organ between the iterations. The values of the same voxel in the images at different iterations are compared directly to each other, but not compared to its neighboring voxels in the individual images. Therefore, the voxel in the feature image carries the evolution information (similar to the "temporal" concept in dynamic studies). In contrast, conventional approaches use the difference of the voxel and its neighboring voxels in the same image for noise suppression purpose. Such difference is in the space domain, but not in the "temporal" domain. The feature image provides additional and complementary information to what can be obtained from the individual image in space domain, thus, it can be used to guide and improve advanced processing using the latter [5].

2 Methods

To demonstrate how the proposed approach works and to evaluate its effectiveness, we used the data acquired on a digital PET system with TOF resolution of 325ps. NEMA IEC image quality phantom data were acquired using the standard NEMA image quality study protocol. Patient studies were acquired using standard whole body PET/CT protocols with clinically relevant count level.

2.1 Feature Extraction Methodology

We first reconstructed the image using iterative TOF list-mode OSEM reconstruction with one iteration and four subsets (Image1), then with two iterations and four subsets (Image2). Then we subtracted Image1 from Image2 and took the absolute value of each voxel of the difference image to generate the absolute difference image followed by calculating the ratio of the absolute difference image to Image1 voxel-by-voxel to generate the ratio image Ratio12. Finally, for the resulted ratio image Ratio12, we clamped the voxel values to 0.15 and then divided the image by 0.15 to obtain the feature image. Note that the clamping value of 0.15 is just for example. One can use a smaller or larger value to gauge the level of changes in the images from different reconstructions. One will also adjust the value based on how the iterative reconstruction is performed, e.g., when TOF is used, image converges faster than non-TOF, one may need a larger clamping value for TOF reconstruction; when more subsets are used in each iteration, one may also need a larger clamping value.

The feature image generated in this way has the following characteristics:

a. Any voxel that has value change of 15% or more from Image1 to Image2 has value 1.0;
b. Any voxel that has value change between 0 to 15% is linearly scaled to 0-1.0; and
c. Small structures (e.g., lesions), cold regions and edges tend to have large percentage change between iterations, the corresponding voxels in the feature image have relative large values.

The steps above can be shown in Equation (1), in which F_i is the value of voxel i in the feature image, I_{1i} and I_{2i} are the values of the same voxel in Image1 and Image2, and α is the clamping value, which is 0.15 in the description above.

$$F_i = \begin{cases} 1.0, \ if \ \frac{|I_{2i}-I_{1i}|}{I_{1i}} \geq \alpha \\ \frac{|I_{2i}-I_{1i}|}{\alpha \cdot I_{1i}}, \ if \ \frac{|I_{2i}-I_{1i}|}{I_{1i}} < \alpha \end{cases}. \quad (1)$$

Note that we use linear scaling in step b above. One may also use nonlinear scaling for intended applications. This remains as an open area for performance optimization.

2.2 Using Feature Image for Image Filtering

For post-reconstruction filtering, voxels that have value 1.0 in the feature image will not be filtered or will only be filtered slightly, in contrast, voxels with value 0 will be filtered heavily. For values between 0 and 1.0, the values will be used to generate a weight to determine how much the voxel will be filtered. The resulted image will preserve the quantitation of the lesions and organ boundaries while smoothing out the noise in the background/uniform regions.

The NEMA IEC phantom study was used for evaluation. We first generated a feature image (*IEC_Feature*) using the feature extraction methodology above. Then we reconstructed the image using a standard reconstruction protocol (*IEC0*) with three iterations and seventeen subsets per iteration.

For the filtering scheme, the reconstructed image *IEC0* was first heavily filtered (*IEC_Heavy*), i.e., filtered three times using a 3x3 filter with equal kernel weight (box filter). The reconstructed image IEC0 was then slightly filtered using a 3x3 filter with kernel weight of 19 at the center and 1 at the other elements (*IEC_Slight*). The two filtered images were then combined voxel by voxel using the feature image as the weighting factor image to obtain the final image (*IEC_Joint*), as shown in Equation 2:

$$IEC\_Joint = (1.0 - IEC\_Feature) * IEC\_Heavy + IEC\_Feature * IEC\_Slight. \quad (2)$$

2.3 Using Feature Image to Synthesize Two Differently Reconstructed Images

In regularized reconstruction, different regularization schemes will lead to different image quality. For example, when using quadratic priors, regularized reconstruction leads to more smoothed images with the price that some small structures may be over smoothed; when using edge-preserving priors, on the other hand, the edges in the image will be preserved, but some areas may not be sufficiently smoothed if the noise level is relatively high in those areas.

Using the extracted feature image, we can reconstruct the images using two different schemes to obtain a smooth image and an edge-preserved image. Then we use Equation 2 to synthesize the two images into one joint image, i.e., using the smooth image to replace the heavily filtered image and the edge-preserving image to replace the lightly filtered image. The final image has the edge preserving advantage of the edge-preserved image and smoothing advantage of the smooth image since the feature image provides extra information for different handling of different regions.

Note that this same synthesis approach can also be applied to two different images obtained from two different advanced post-reconstruction processing. For example, one can use the anisotropic diffusion filter (ADF) [6] with two different parameter settings to obtain an edge-preserving image and a smooth image, then synthesize the two images using the feature image to obtain the final image.

2.4 Using Feature Image for Advanced Reconstruction

One can use the feature images for advanced iterative reconstruction such as selective convergence acceleration/deceleration, relaxation and regularization for different regions. For example, in regularized reconstruction, for voxels corresponding to values 1.0 in the feature image (voxels with large relative change between different iterations), one can use an edge preserving prior to guide the regularization; for voxels with small values in the feature image, one can use a quadratic prior to guide the regularization. The resulted reconstruction applies selective regularization using the extra information from the feature image, leading to optimized regularization in one reconstruction.

For evaluation, we generated a hybrid simulation/patient dataset by simulating multiple small lesions and adding them into a real patient data set. This was done by (a) modeling the same PET system in GATE simulation, (b) using the attenuation map of the patient study and simulating multiple lesions in the body, assuming no activity in other regions, (c) generating list-mode data of the lesions; and finally (d) adding the list-mode data from the lesions to the list-mode data of the patient study.

3 Results

Figure 1 displays Image1, Image2, the Absolute Difference image, and the feature image obtained for a NEMA IEC phantom study with 30 million counts. Figure 2 illustrates a simple filtering scheme of the NEMA IEC phantom image using the obtained feature image.

According to Equation (1), a voxel in the final image is a weighted sum of the value of the same voxel in the heavily filtered image and that in the slightly filtered image, using the voxel value in the feature image to calculate the weight. For lesions, the voxel value is 1.0 in the feature image, the weight is 1.0 for the slightly filtered image and 0 for the heavily filtered image. Thus the lesions have the values from the slightly filtered image. In contrast, the background regions have small value in the feature image, therefore, the weight for the heavily filtered image is large. Consequently, the obtained image showed preserved spheres and significantly filtered background. The jointly filtered image had significantly

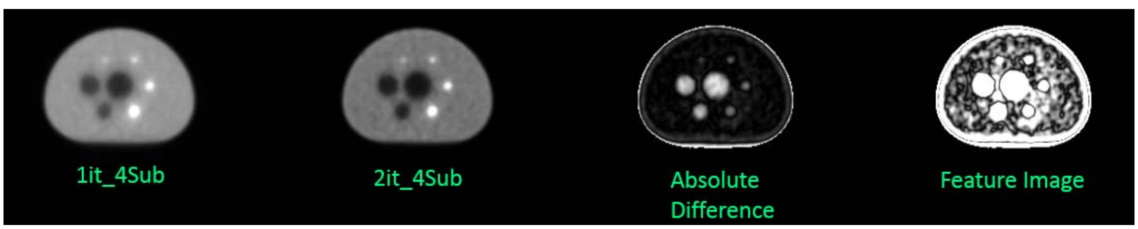

Figure 1. Example of extracting a feature image from images at two different OSEM iterations. Images were displayed using linear gray scale and each image was scaled to its own maximum. From left to right: Image1 (one iteration, four subsets), Image2 (two iterations, four subsets), the absolute difference, and the feature image. The small hot spheres and big cold spheres as well as the lung insert in the center (cold) had large changes between Image1 and Image2. The corresponding voxels of such objects in the feature image had large values. The uniform background (low frequency components) of the phantom had small values in the feature image (more black area in the gray scale display), indicating relatively small change from Image1 to Image2 due to faster convergence than the spheres (higher frequency or cold activity components).

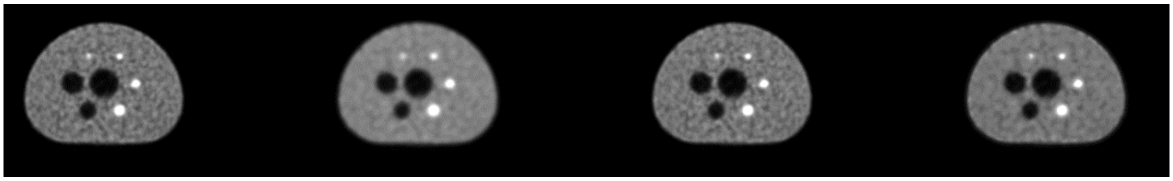

Figure 2. Example of using the feature image (from Figure 1) to post-filter the NEMA image reconstructed using the standard reconstruction protocol (three iterations, 17 subsets). From left to right: the NEMA image to be filtered, a heavily filtered image (box filter with window size 3, filter three times sequentially), a slightly filtered image (a 3x3 filter with element weight of 19 at center and 1 for the rest), and the jointly filtered image using the feature image.

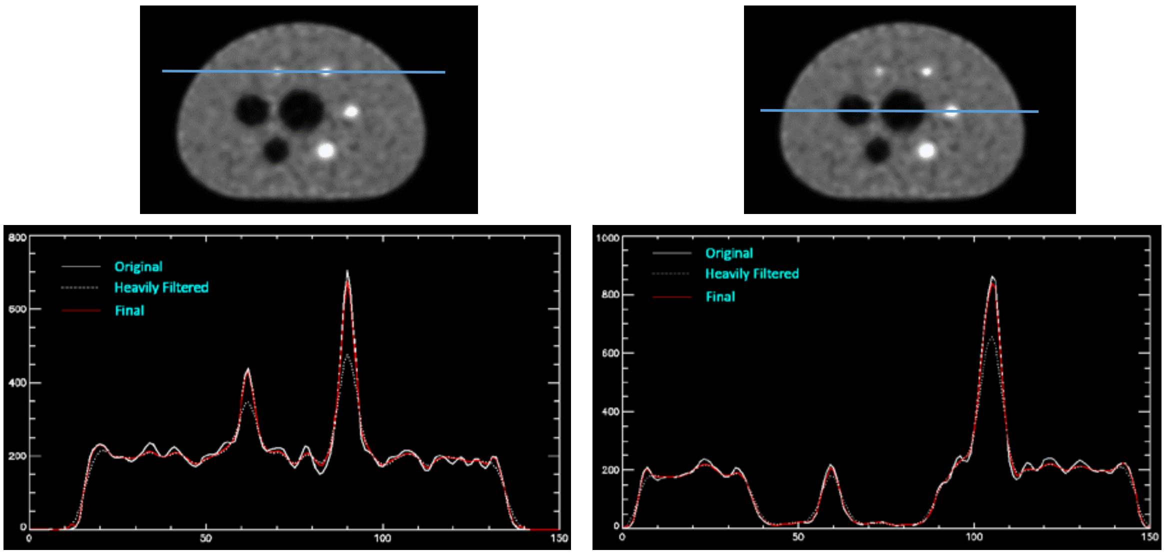

Figure 3. Line profiles (bottom) along the lines shown in the images (top) illustrate the effective sphere preservation and background noise suppression in the NEMA IEC phantom using the feature image in a simple weighted summation of a heavily filtered image and a lightly filtered image.

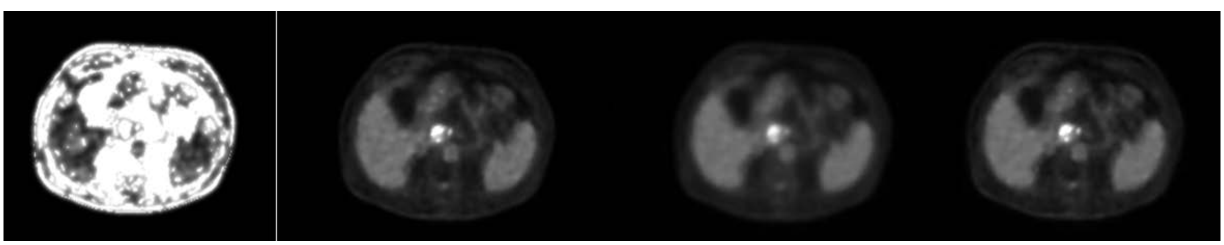

Figure 4. Transaxial slices of the patient image illustrating the effectiveness of using the feature image (left) to synthesize an MAP reconstructed image using an edge-preserving prior (second) and an MAP reconstruction using a (non-edge-preserving) quadratic prior (third, smooth image). The last image was the synthesized image that showed preservation of the small structures in the image and filtering of the soft tissue (indicated by the black regions in the feature image). The final image was better than both of the MAP images.

suppressed noise in the background and well preserved sphere quantitation, as shown in the profile plots in Figure 3. The profiles of the final image followed that of the original image at the spheres, indicating nearly perfect edge preservation; and followed that of the heavily filtered image at the background, indicating effective filtering of the background region.

Figure 4 are transaxial slices of the images of a patient study that illustrate the effectiveness of the synthesis application using the feature image. Figure 5 illustrates the effect of the same patient study using coronal slices. The liver region was significantly filtered in the synthesized image as compared to the edge-preserving image, but the small structures, such as the hot spot in the center, were preserved as compared to the smooth image using a quadratic prior.

Figure 6 illustrates the effectiveness of using the feature image to guide what priors to use in regularized reconstruction [7]. With this approach, the final images showed superior lesion preservation and noise reduction in the background.

4 Discussion

In conventional image processing for optimized compromise of noise suppression and edge preservation, small/weak lesions/organs are more likely to be smoothed out because they have small intensity difference from the surround tissues. In this work, we use the feature images extracted from images at different iterations to optimize the advanced processing. The voxels of the lesions/organs in one image are compared to the same voxels in the image from a different iteration, rather than being compared to the voxels of their surrounding tissues in the same image. Although the intensity difference from their surround tissues may be small in each image, small/weak lesions/organs may have large relative changes between images at different iterations, and hence be identified in the feature images.

The conventional approach can be understood as using the local spatial information of an image to identify lesions/organs. The proposed approach can be understood as using the "temporal" change from an earlier iteration to a later iteration to identify lesions/organs. The feature image, therefore, provides a conceptually new dimension of information for advanced processing (the evolution information, or temporal information) in addition to the information from the local images. Such temporal information potentially eases the challenges to traditional image domain processing, as was shown in the results that simply image domain processing could achieve superior performance when the feature images were used.

The feature extraction performance is closely related to the clamping value. A smaller clamping value means more voxels will be deemed as features, hence more voxels will be untouched by the filtering, leading to more edge preservation and less noise suppression. The clamping value of 0.15 in the feature extraction methodology in this work was first determined empirically based on the NEMA IEC phantom study. It was then applied to all the patient studies. In general, PET image reconstruction convergence rate is higher for higher TOF timing resolution and lower for lower TOF timing resolution. The clamping value has to be re-established accordingly for optimal performance for data with different TOF resolution.

In the Methods section, we use images from different iterations to simplify the description. In iterative image reconstruction with multiple number of subsets, the image is updated at each subset. For the application of this approach, we are not limited to the use of the images from two iterations. In fact, we can in general use the images from any desired two different updates.

There are two general considerations when choosing which updates/iterations to generate the feature images.

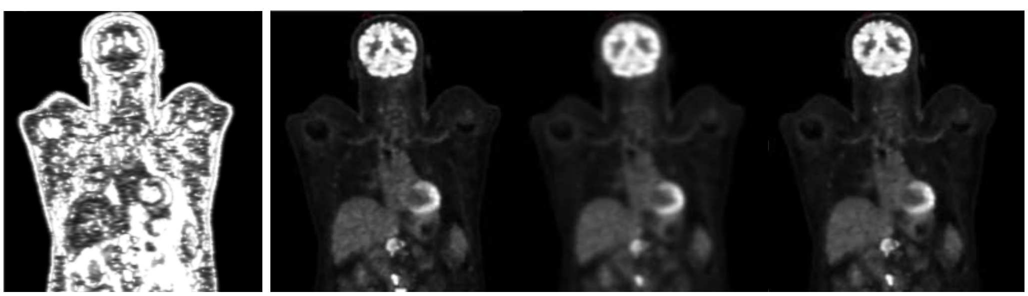

Figure 5. Coronal slices of the same patient as in Figure 4, illustrating the effectiveness of using the feature image (left) to obtain the final image (right) that has both the advantage of edge-preservation of small features in the edge-preserving image (second, using edge-preserving prior for reconstruction) and the advantage of smoothness of the liver and mediastinum of the smooth image (third, using quadratic prior for reconstruction).

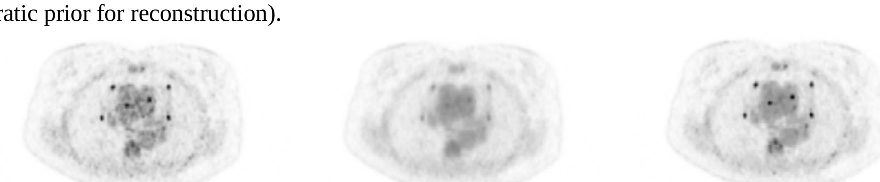

Figure 6. Using the feature image for selective regularization in regularized reconstruction obtained excellent lesion preservation and noise reduction in the background through visual assessment. Left: Conventional OSEM reconstruction (no regularization). Lesions were sharp but background was noisy. Middle: regularized reconstruction using a quadratic prior for much suppressed noise in the background, but the small lesions were also smoothed and the contrast was decreased significantly. Right: using the feature image to guide the selective regularization voxel-by-voxel. Background noise was much suppressed while lesion sharpness and contrast were preserved.

One is to minimize the impact of noise and the other is to maximize the evolution contrast between different regions. In relatively early iterations/updates, image noise is relatively low as compared to late iterations/updates. Therefore, when we choose relatively earlier iterations for feature image extraction, we largely avoid the noise complication, hence minimizing the impact of noise in feature extraction. Also, in such updates/iterations, low frequency components have largely, if not fully, converged, hence they have small changes between the updates/iterations; while high frequency components have not converged yet, hence they have large changes. Consequently, the feature image will have small values for large/uniform regions and large values for small objects or cold regions, maximizing the contrast between different objects/regions as compared to using late updates/iterations.

5 Conclusion

A feature image extracted from images at different iterations provides voxel evolution information that can be used to design and guide advanced image processing, such as regularized reconstruction and image filtering. The voxel evolution information (can be understood as information in time domain) is complementary to the local density information in image domain, allowing simple image domain techniques to achieve superior performance that may not be achievable without the feature images.

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