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Noise-Weighted FBP Algorithm for Uniformly Attenuated SPECT Projections

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Abstract

Noise-weighted FBP (filtered backprojection) algorithm and Bayesian FBP algorithm were developed recently for un-attenuated Radon transform, which have applications in x-ray CT (computed tomography). This paper extends the noise-weighted FBP algorithm to the case of uniformly attenuated Radon transform, and this extended FBP algorithm can be applied in uniformly attenuated SPECT (single photon emission computed tomography). Computer simulations and experimental data demonstrate that the proposed FBP algorithm has similar noise control capability as the iterative ML-EM (maximum likelihood expectation maximization) algorithm. In practice, the attenuator is rarely uniform. A stable FBP algorithm must be developed for non-uniform attenuators before the FBP algorithm can be applied in clinics when attenuation correction is required.

Keywords

Attenuated Radon transform; exponential Radon transform; analytical algorithm; Poisson noise; filtered backprojection algorithm; SPECT

I. Introduction

USING analytical algorithm to reconstruct images with attenuated Radon transform data is not new. Back in 1917 Radon solved the inverse problem of tomography [1]. Many other people made significant early contribution to tomography [2]–[6] in various fields. Their works are independent from Radon's pioneer formula. Some others actually applied Radon's formula to their research [7], [8]. Shepp and Logan recognized that the filtered backprojection algorithm can be viewed as an implementation of Radon's inversion formula [9].

In SPECT (single photo emission computed tomography), attenuation correction may be required. If the attenuator can be assumed to be uniform, the attenuated SPECT projections can be converted into the exponential Radon transform, for which some FBP algorithms were developed in the 1970's and 1989's [10]–[12]. Hawkins developed a circular harmonic reconstruction algorithm for the exponential Radon transform [13]. In 2001, Noo and Wagner observed that the inversion of the exponential Radon transform can be done with 180° measurements, instead of 360° [14]. In 1995, Metz and Pan revisited the algorithms developed in [11], and proposed a family of algorithms based on the different combinations of the redundant 360° measurements [15].

Our group extended Metz and Pan's algorithm [15] to the fan-beam, skew-slit, cone-beam, and 180° acquisition geometries [16]–[19]. One drawback of the above mentioned FBP algorithms is that the projection noise is not considered; they may produce noisy images. As a result, in most SPECT applications, the iterative ML-EM algorithm [20], instead of an FBP algorithm, is commonly used when attenuation compensation is required.

Recently we developed noise-weighted FBP and Bayesian FBP algorithms for the Radon transform for parallel-beam, fan-beam, and cone-beam imaging geometries [21]–[25]. We showed that the noise-weighted FBP algorithms in some cases can outperform the iterative ML-EM algorithm.

The main purpose of this paper is to combine the above two technologies so that the noise-weighted FBP algorithm can properly handle uniform attenuation in line-integral measurements. Computer simulations and real data experiment are used to verify that this new method can have almost the same performance as the iterative ML-EM algorithm. In many cases, it can even outperform the ML-EM algorithm.

II. Methods

A. Proposed FBP Algorithm

As stated in Metz and Pan's 1995 paper [15], there are two types of exact FBP algorithms that can process uniformly attenuated projections. The first type uses the regular unweighted backprojector, while the second type uses the back-projector that contains an exponential weighting function. We chose the first type, due to its superior noise control property.

The FBP algorithm is not unique within the first type. One has the freedom to select a "combination weighting factor." The original purpose of this factor is for noise control adjustment. We arbitrarily chose such a "combination weighting factor" for the sake of implementation convenience. The mathematical expression of this factor will be given in the implementation procedure. We will use a different window function method to control noise on the ray-by-ray base, as will be explained a little later in this section.

Ray-by-ray noise control [25] is achieved by applying a noise-variance-dependent window function in the Fourier domain of the measurements. Ten filtered measurements are generated with ten different window functions, according to ten pre-set noise variance levels. For a given data set, the maximum value of the measurements is used to set the largest noise variance level. Nine other noise levels are determined by uniformly dividing this largest value. A parameter K is used and chosen by the user in forming the window functions. The effect of this parameter K is similar to the number of iterations in a typical iterative algorithm.

After the application of the window functions in the Fourier domain, the total count in the measurements may get altered. If it happens, the filtered measurements should be normalized to its original total count.

Before the conventional FBP algorithm is applied, a final sinogram is formed from these 10 versions of filtered measurements. If an original projection value is in the n th interval, then

the associated projection value in the final sinogram is extracted from the m th version of the filtered measurements. Finally, the conventional FBP algorithm is applied, that consists of a ramp filter and an un-weighted backprojector.

The implementation procedure is as follows.

Step 1: Transform measurements as if they were measured by a virtual detector passing through the center of rotation. This transformation is achieved by pre-scaling. We pre-scale the measurements by an exponential function $\exp(b\mu)$, where μ is the linear attenuation coefficient for the uniform attenuation and b is the line-length along the projection ray from the virtual detector to the boundary of the attenuator in the direction towards the actual detector.

Step 2: Take the two-dimensional fast Fourier transform (2D FFT) of the pre-scaled SPECT measurements (which are also known as the sinogram). Let the pre-scaled measurements be $m(s, \theta)$. Let the 2D FFT of $m(s, \theta)$ be $M(\nu, k)$. Since $m(s, \theta)$ is periodic with respect to the second variable θ and the period is 2π , in the Fourier domain k is discrete. It is a good idea to zero pad $m(s, \theta)$ in the s dimension before taking the Fourier transform. For example, if the detector size is 128, s -size can be zero-padded to, for example, 1024. After zero-padding, let the s -size be L . One reason to choose the (after zero padding) array size to be 1024 is to increase the frequency resolution so that an accurate low-frequency cutoff ($\mu(2\pi)$) can be implemented. The second reason is to reduce error that is introduced by the inaccurate-DC-gain introduced (see Table II of [28]). According to Table II of [28], the DC gain introduced error is 4.95×10^{-5} for the array size of 1024. Do not zero-pad in the θ dimension, because it is assumed to be periodic already.

Step 3: Transform the attenuated sinogram to the un-attenuated sinogram in the Fourier domain, by performing frequency shifting. Let $P(\nu, k)$ be the 2D Fourier transform of the un-attenuated sinogram (i.e., the Radon transform) $p(s, \theta)$. Then $P(\nu, k)$ can be obtained from $M(\nu, k)$ by using the following relationship according to [15], [16] with some simplifications:

$$P(\nu, k) = \gamma^k M\left(\sqrt{\nu^2 + \left(\frac{\mu}{2\pi}\right)^2}, k\right), \quad (1)$$

with

$$\gamma = \frac{|\nu|}{\sqrt{\nu^2 + \left(\frac{\mu}{2\pi}\right)^2} + \frac{\mu}{2\pi}}. \quad (2)$$

In [15], Metz and Pan presented a fundamental relationship, which is Eq. (27) in [15] and is Eq. (1) in this paper. Metz and Pan used the Hermitian symmetry property of the 2D Fourier transform to combine the Fourier transform value with its Hermitian value, hoping that the combined value is less noisy. A family of combination schemes was proposed in [15]. Tang

et al in [16] extended the parallel-beam methods of [15] into a method that can be applied for the fan-beam and cone-beam with a new combination scheme was developed in [16]. This paper argues that the backprojection weighting effect is much more significant in terms of noise amplification than using the combination schemes. The Hermitian combination scheme is not used in this current paper.

Step 4: Apply 10 window functions for noise modeling. The ramp filter $|\nu|$ is discretized as

$0, 1/L, 2/L, \dots, 1/2$. Let $m_{10} = m_{\max} = \max\{m(s, \theta)\}$ and $m_n = n \times \frac{m_{10}}{10}$ for $n = 1, 2, \dots, 10$. Without loss of generality, one can set $m_{10} = 1$ in forming the window functions, and the algorithm should work just fine. By assuming a Poisson noise model, let $w_n = 0.1/m_n$ for $n = 1, 2, \dots, 10$, where the factor 0.1 is a relaxation parameter. The 10 Fourier-domain window functions are defined as

$$\text{Window}_n(|\nu|) = \begin{cases} 1, & \nu=0 \\ 1 - \left(1 - \frac{w_n}{L|\nu|}\right)^K, & \nu \neq 0. \end{cases} \quad (3)$$

The window function (3) is referred to as the Landweber window [26] and as been extended to super sampling applications [27]. These 10 window functions in (3) are actually 10 lowpass filters with different cut off frequencies. After Step 4, 10 versions of filtered $P(\nu, k)$ are generated from $P(\nu, k)$ using the 10 filters expressed in (3) for $n = 1, 2, \dots, 10$.

Step 5: Apply the 2D inverse Fourier transform to the 10 filtered $P(\nu, k)$, obtaining 10 filtered sinograms. Let the 10 filtered sinograms be $p_n(s, \theta)$ for $n = 1, 2, \dots, 10$.

Step 6: A final sinogram $p(s, \theta)$ is formed as

$$\begin{aligned} p(s, \theta) &= p_n(s, \theta) \text{ if } (n-1) \times \frac{m_{\max}}{10} < m(s, \theta) \leq n \times \frac{m_{\max}}{10}; \\ p(s, \theta) &= 0 \text{ if } m(s, \theta) = 0. \end{aligned} \quad (4)$$

Step 7: Finally, the conventional FBP algorithm is applied to sinogram $p(s, \theta)$.

1) Data Preparation—The computer simulations used a modified Shepp-Logan head phantom to simulate the SPECT application. The skull of the head phantom was removed and a circular, uniform attenuator was assumed. The linear attenuation coefficient of water is $\mu = 0.12 \text{ cm}^{-1}$ (tends to be lower), and this value is at 140 keV. The detector had 128 detection bins and rotated 360° with 120 uniformly distributed stops. The detector bin size was 0.39 cm. After zero-padding, the detector size was increased to 1024. The attenuated line-integral data were calculated analytically. A Poisson noise model was used, and the total number of photons was approximately 8 million. Neither scattering nor system blurring were included in data generation. The reconstructed image size was 128×128 .

In computer simulations, the number of iterations in the ML-EM algorithm was determined when the reconstruction reached the minimum MSE (mean squared error) with respect to the true image. The MSE is defined as

$$MSE = \frac{\sum [reconstructed_image(n) - true(n)]^2}{\sum [true(n)]^2}. \quad (5)$$

Similarly, the parameter K in the proposed FBP algorithm was selected when the reconstructed image reached the minimum MSE with respect to the true image. Line profiles along the central horizontal line are shown to compare the image resolution. The noise variance in a constant region within the phantom is calculated for each image for the purpose of noise comparison.

In the real SPECT data acquisition, a Hoffman brain phantom was used. The phantom was filled with Tc-99m using a clinical dose (10 mCi). The Siemens Signature e.Cam was used for data acquisition, using a set of low-energy high-resolution, parallel-hole collimators, with a 128×128 acquisition matrix size. Projections of 120 views were acquired over 360° . Projections from one 2D slice were used for image reconstruction.

III. Results

For comparison purposes, the iterative ML-EM reconstructions are provided in this section. For the computer simulations, the number of iterations is determined when the reconstructed image reaches the minimal mean-squared-error (MSE) with respect to the true image.

In the reconstruction with the proposed FBP algorithm, the parameter K is selected as the reconstructed image reaches the minimal MSE with respect to the true image. The new FBP algorithm has the flexibility to use a weighting function that is not the reciprocal of the noise variance. For this particular computer simulated data set, a better result can be obtained by using a weighting function that is the reciprocal of the square-root of the noise variance. All computer simulation results are shown in Fig. 1.

For the real phantom experiment, only visual evaluation is considered. The number of iterations for the ML-EM algorithm and the parameter K for the proposed FBP algorithm are selected to produce similar images, as shown in Fig. 2. However, they have some different noise textures. Each image in Figs. 1 and 2 is displayed from its minimum value (corresponding to gray scale value 0) to its maximum value (corresponding to gray scale value 255).

IV. Discussion

The classic FBP algorithms for exponential Radon transform use a backprojector that contains an exponential factor [11], [15], [29], [30]. It is believed that the theory for the exponential transform is fairly complete [29]. In [30], the classic Tretiak-Metz FBP algorithm [11] is considered mathematically well established and no more work needs to be done. However, in practice, the classic Tretiak-Metz FBP algorithm produces extremely

noisy images as shown in Fig. 3, in which the projection data sets are identical to those in the previous section. Therefore, FBP algorithm is never used in clinics when attenuation correction is required to perform. Iterative algorithms are used whenever SPECT image reconstruction is required to compensate for attenuation.

The author of [15] realized that when exponential Radon transform data are acquired over 360° , the measurements are redundant. Properly weigh the redundant data can reduce the image noise variance. They thus suggested a family of algorithms with various weighting schemes for the redundant data. Unfortunately the properly weighted data still produce very noisy images.

We believe that the large noise produced by FBP algorithms when compensating for the attenuation is primarily from the exponential factor in the backprojector. The weighting of the redundant data only plays a minor role. If no special weighting is introduced, normally the doubly measured measurements have the equal weight.

The exponential backprojection weighting factor is in the form of $e^{\mu t}$, and this gives a noise variance amplification factor of $e^{2\mu t}$. In other words, if the noise variance in the filtered sinogram is σ^2 , the noise will propagate into the reconstructed image with a variance approximately $e^{2\mu t}\sigma^2$. For example, let $\mu = 0.15$ /cm and $t = 10$ cm; this results in $e^{2\mu t} = 20$. A 20-fold noise amplification is huge! From Fig. 3, we observe that in the regions farther away from the center (i.e., t is larger) the image noise dramatically becomes larger.

Among available FBP algorithms that can correct for uniform attenuation, our strategy is to choose the one that does not have an exponential weighting factor in the backprojector. In [12] and [15], a relationship between the exponential Radon transform and the regular (without attenuation) Radon transform is given in the Fourier domain, and this relationship is adopted in this paper as (1) and (2). We make it clear that (1) is not implemented in Inouye's method [12], and not in the quasi-optimal generalized Tretiak-Metz method [15] either.

In both [15] and [16], the uniform attenuators in all examples were circular. When a non-circular attenuator was implemented, we found some distortion in the reconstructions. In the pre-processing step of the attenuated FBP algorithm, an exponential function is used to scale the measured attenuated Radon transform of an emission object, so that the measured projections are transformed into the projections with a virtual detector at the center of rotation. The resulting projections should contain no information about the shape of the uniform attenuator. Two-dimensional (2D) Fourier transform of a real object satisfies the Hermitian symmetry property. This symmetry property is theoretically exact; however, this property is sensitive to practical errors. In computer implementations, the pre-scaling function contains errors so that the boundary information is not completely removed from the scaled projections. The errors make the Hermitian symmetry relationship invalid for the Fourier-domain image function. We must point out that this Fourier-domain image function is not formed by taking the 2D Fourier transform of a real image, but is synthesized from different projections with different pre-scaling functions. When the uniform attenuator is non-circular, the combination of the Hermitian terms can produce artifacts that are severe

enough to be visualized by human eye. In [15] and [16] all reconstruction studies used circular attenuators. In this paper, the scheme of combining Hermitian terms is not used, and good results are obtained with non-circular attenuators. It is better to reconstruct the image without using the Hermitian property to re-arrange the data. The use of the Hermitian symmetry property does not create more information about the object.

One important aspect of this paper is to point out that we should avoid the FBP algorithms that contain a large weighting factor in the backprojector. A good strategy is to convert the attenuated SPECT data to un-attenuated SPECT data, and to use an FBP algorithm without a large weighting factor in the backprojector to reconstruct the image.

Another contribution of this paper is to further improve the FBP reconstruction by introducing noise weighting. The noise weighting is inversely proportional to a function of the data noise variance. This function may not be unique, and can be object and/or noise level dependent.

The third aspect is that the development of a stable (meaning robust to noise) FBP algorithm for the uniform attenuator is an essential step towards the development of a stable (i.e., robust to noise) FBP algorithm for the non-uniform attenuator.

A FBP algorithm exists for the attenuated Radon transform with a non-uniform attenuator [31]–[35]. Unfortunately, this FBP algorithm has a backprojector contains an exponential weighting factor. This exponential weighting factor amplifies the noise and produce very noisy images. This is a very challenging obstacle that we must overcome before a stable FBP algorithm for the non-uniform attenuator can be developed.

V. Conclusions

Since the early 1980's, the FBP algorithm has a bad reputation for producing very noisy images, such as those shown in Figure 3, when it is used to reconstruct SPECT images with attenuation compensation. We believe that the exponential weighting function (with a positive exponent) in the backprojector is the main degradation factor to cause significant noise propagation. If the attenuated data are first transformed into un-attenuated data [15], the regular FBP algorithm can be used for image reconstruction. Because the backprojector in the regular FBP algorithm does not contain an exponential weighting function, the noise propagation is not as severe.

In order to further reduce noise in the reconstruction, the Poisson noise model is considered in forming the window functions. The proposed FBP algorithm has two features: (i) it uses a non-weighted backprojector; (ii) it uses a ray-by-ray noise model. The results of the proposed FBP algorithm are comparable with those obtained with the iterative ML-EM algorithm. In some cases, the proposed FBP algorithm can even outperform the iterative ML-EM algorithm. The proposed FBP algorithm also has freedom to change the noise weighting function.

Our future investigation will include extending the proposed FBP algorithm to the situation where the attenuation is non-uniform [31]–[35].

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True emission image (*The square indicates the ROI)	ML-EM Reconstruction	Proposed FBP Reconstruction $w = 1/\text{var}$	Proposed FBP Reconstruction $w = 1/\sqrt{\text{var}}$

MSE = 0 ROI mean = 4.2 ROI var = 0	MSE=0.0575 ROI mean = 4.12 ROI var = 0.39 Iter. # = 16	MSE = 0.0555 ROI mean = 4.16 ROI var = 0.25 $K = 2140$	MSE = 0.0519 ROI mean = 4.11 ROI var = 0.23 $K = 1180$

Fig. 1.

Computer simulation results from the iterative ML-EM algorithm and the proposed FBP algorithm, using noisy uniformly attenuated line-integral data. The line profiles are drawn along the central horizontal line of the images.

ML-EM Reconstruction Iter. # = 14	Proposed FBP Reconstruction $w = 1/\text{var}$ $K = 3500$

Fig. 2.
Experimental Hoffman brain phantom SPECT study.

Fig. 3. Reconstructions by Tretiak-Metz's FBP algorithm. First row: Display from min to max. Second row: Display in a narrow window for better visualization.