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ORIGINAL PAPER

Image improvement method for positron emission mammography

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ABSTRACT

Purpose: To evaluate in clinical use a rapidly converging, efficient iterative deconvolution algorithm (RSEMD) for improving the quantitative accuracy of previously reconstructed breast images by a commercial positron emission mammography (PEM) scanner.

Materials and methods: The RSEMD method was tested on imaging data from clinical Naviscan Flex Solo II PEM scanner. This method was applied to anthropomorphic like breast phantom data and patient breast images previously reconstructed with Naviscan software to determine improvements in image resolution, signal to noise ratio (SNR) and contrast to noise ratio (CNR).

Results: In all of the patients' breast studies the improved images proved to have higher resolution, contrast and lower noise as compared with images reconstructed by conventional methods. In general, the values of CNR reached a plateau at an average of 6 iterations with an average improvement factor of about 2 for post-reconstructed Flex Solo II PEM images. Improvements in image resolution after the application of RSEMD have also been demonstrated.

Conclusions: A rapidly converging, iterative deconvolution algorithm with a resolution subsets-based approach (RSEMD) that operates on patient DICOM images has been used for quantitative improvement in breast imaging. The RSEMD method can be applied to PEM images to enhance the resolution and contrast in cancer diagnosis to monitor the tumor progression at the earliest stages.

1. Introduction

Positron Emission Tomography (PET) [1] has been widely used as an imaging modality in oncology [2]. Its applications include tumor detection, tumor staging [3], radiation planning [4], optimizing individual treatment planning [5], and probing tumor metabolism [6]. While whole-body (WB) PET has shown some utility in applications to breast cancer, the intrinsic spatial resolution of WB PET has limited its ability to detect smaller cancers (usually below 1 cm) [7,8]. A variety of dedicated breast PET scanners often referred to as Positron Emission Mammography (PEM) systems have been developed to provide higher resolution, higher sensitivity, and faster imaging than WB PET [9,10]. PEM [11] is potentially the most attractive modality for breast cancer imaging using positron emitting radiotracers since it offers a much higher spatial resolution (~2 mm) [12] than clinical WB PET devices (5–7 mm) [12,13]. In practice, however, WB PET reconstructed resolution is 10–15 mm due to added smoothing. Ideally, cancer is treated in the early stage of the disease. The idea of dedicated PEM systems is to reduce the size threshold for accurate breast cancer imaging and assist earlier intervention.

In this report, we focus on the FDA-cleared, commercially available Flex Solo II PEM Scanner (Naviscan PET Systems, Inc. CA) although many of the conclusions can apply to other PEM systems [14]. The Flex Solo II is a limited-angle (not full 360° coverage) tomosynthesis imaging system requiring image reconstruction at several rotating angles with attendant overlap or blurring. The scanner has two opposite gamma-ray imaging detectors (6 cm × 16.4 cm × 6 cm in imaging area) mounted on an articular arm (allows different imaging views) inside compression paddles used to immobilize the breast. The detectors are constructed from 2 mm × 2 mm × 13 mm lutetium yttrium orthosilicate scintillation crystals coupled to a position-sensitive photomultiplier tube [15]. This compact geometry with a restricted field of view (FOV) PEM camera was employed because it exhibits the highest resolution performance compared to commercially available breast imaging scanners. Many of the imaging characteristics of the PEM Solo II scanner were effectively analyzed in detail by MacDonald, et al. [15]. The main conclusion of their study is that this

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system has a reconstructed spatial resolution for in-plane image slices of 2.4 ± 0.3 mm (8 ± 1 mm in the cross-plane) in FWHM (Full-Width at Half-Maximum) representing a significant improvement over conventional WB PET scanners. This results in a reduced lower threshold on lesion size and tracer uptake for the PEM SOLO II system as compared to WB PET. The causes of performance limitation in positron emission mammography systems were analyzed in Ref. [16].

Quantitative accuracy in PET reconstruction is particularly poor for small tumors because of partial volume errors and a limited number of photons resulting in noisy images that require a regularization procedure. PET imaging requires fast image reconstruction software that can take into account the majority of finite resolution effects [1] that could affect quantitation: resolution [17], photon attenuation and scattering, random coincidence rate, positron range [18], depth-of-interaction [14], detector normalization, detector performance with low activity range [19], dead time and noise level.

The reconstruction algorithm is a very important component of PET scanners. The most common methods employed for PET image reconstruction are the fast-filtered back projection (FBP) method [20], iterative image reconstruction methods such as Maximum Likelihood-Expectation Maximization (MLEM) [21], its improvement, One-Pass List-Mode high resolution algorithm with System Matrix modeling (OPLEM) [22], Algorithm with Resolution Deconvolution (EMD) [23] and Ordered-Subsets EM iterative algorithm (OSEM) [24] and modifications [17,25]. According to existing procedures, PEM images are reconstructed from projection data [26]. The Solo II PEM image reconstruction technique is based on the simple iterative back projection MLEM method [21]. The current FLEX Solo II version of MLEM reconstruction converges very slowly. In clinical practice, only 5 MLEM iterations [15] are used and therefore the resulting image has low quality. Reconstruction algorithm with finite resolution corrections (scattered or accidental coincidence detections) and user-selectable image smoothing filters are not included in the FLEX Solo II software package.

Iterative algorithms have become integral methods for PET/PEM image recovery because they can provide reduced image noise, lower artifacts as compared with FBP and can be optimized for specific clinical needs. The advantages and disadvantages of using iterative reconstruction methods to produce good quality PET/PEM images have been described in the literature [14,20–26]. Note technological improvements in computational speed have reduced iterative image reconstruction times to clinically acceptable levels. There are a few groups who contributed to the development of a fast iterative image reconstruction algorithm for PEM and its clinical application [14,23,25,27]. Dedicated breast WB PET and PEM scanners are still an active area of research, development and implementation.

As proposed in this study, a fast converging iterative deconvolution method with the resolution subsets-based approach (RSEMD) can be employed retrospectively to de-noise and enhance image resolution and contrast by using only a few additional iterations. The RSEMD operates on DICOM (Digital Imaging and Communications in Medicine) breast images previously reconstructed with commercially used variants of MLEM or other EM methods and can be used to improve image quality leading to faster acquisition time for PEM imaging, better lesion conspicuity, and possibly impacting the dose of the radiotracer.

2. Materials and methods

The performance of RSEMD was evaluated in anthropomorphic like breast phantoms and clinical imaging studies (16 patient cases) acquired and reconstructed on a PEM Flex Solo II scanner. The field of view was subdivided into 200 × 136 × 12 voxels with an in-plane pixel size 1.2 mm × 1.2 mm and thickness about 7.16582 mm. The RSEMD algorithm is employed in PEM image space (the original input is pixels, not lines) after conventional MLEM reconstruction (5 iterations) completed and post-filtering is done. Several imaging characteristics used in the PEM clinical community for describing the image quality are included for consideration. As an additional metric related to the convergence speed of the algorithm, we considered the minimal number of iterations to achieve final results. Naviscan has created different versions of image quality breast phantoms, some of them more or less consistent with the NEMA standard. We used the Naviscan phantom data for a sponge with FDG warm background to simulate the breast and implant a point or line-with-a-point source in the middle as the lesion (breast phantom). The point-like source is about 1 mm in internal diameter and about 1.5 mm thick (embedded in a plastic disk). The line source has an active element diameter 1 mm and the stainless steel tubing of diameter about 2.7 mm diameter. The length of the line source is about 22 cm. The active element is about 6 mm ± 2 mm shorter. We used image-processing tools available with Flex Solo II software in a clinical environment for the RSEMD imaging tests and evaluation. The clinical reading workflow MIM (MIM Software Inc., OH) is used for image interpretation and analysis. The RSEMD algorithm was developed using MATLAB® and a LINUX platform within a multi-modality image handling environment.

2.1. MLEM based iterative reconstruction

The simple list-mode MLEM algorithm iterates the unknown activity value f_j^k of voxel j (image is assumed to be discretized into J voxels) for each iteration step k:

$$f_j^{k+1} = \frac{f_j^k}{\sum_{i=1}^{I} a_{ij}} \sum_{i=1}^{M} a_{ij} \frac{1}{q_i^k}, \quad \text{where} \quad q_i^k = \sum_{j=1}^{J} a_{ij} f_j^k \tag{1}$$

where f_j^{k+1} and f_j^k are the voxel values for the new and old image estimates, q_i^k is the expected count in line of response (LOR) i for the intensity estimate f_j^k, I is the number of all possible system LORs and a_{ij} represents the probability that an emission from voxel j will be detected along LOR i. The measured data consist of a list of M LOR definitions with implicitly equal to 1 for each acquired LOR. The normalization factor $\sum_{i=1}^{I} a_{ij}$ includes all possible measurable *LORs.*

Without the implementation of corrections for the resolution improvement, the resulting MLEM image is noisy and has poor resolution. In order to take into account the most finite resolution effects, the matrix of probabilities $A = (a_{ij})_{I \times J}$ in Eq. (1) has to be decomposed into a product of three matrices A = WXH [22,23], where W is the diagonal matrix of weighted factors for geometric sensitivity correction accounting for detector rotation, X is a matrix whose elements correspond to the intersection length of *LOR i* with the voxel j and H is a square matrix which accounts for resolution effects. To neglect the scattering effects (the PEM case) the blurring component H of the system matrix can be represented as a set of shift-invariant kernels $\rho_{\sigma^{EM}}$ then resolution blurring will be invariant across the image. The resolution kernel $\rho_{\sigma^{EM}}$ can be chosen [22] as a Gaussian function with standard deviation σ^{EM} as the parameter. So, the EM algorithm with resolution system modeling in the nonnegative space using the convolution technique can be written in vector form:

$$f^{k+1} = f^k \times s \times (c^k \otimes \rho_{\sigma^{EM}}) \tag{2}$$