RECONSTRUCTION OF PET IMAGE BASED ON KERNELIZED EXPECTATION-MAXIMIZATION METHOD

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Abstract - *Positron emission tomography (PET) image reconstruction is challenging for low count frame. The reconstruction is important method to retrieve information that has been lost in the images. To improve image quality, prior information are used. Based on kernel method, PET image intensity in each pixel is obtained from prior information and the coefficients can be estimated by the maximum likelihood (ML).This paper proposes a kernelized expectation maximization (EM) algorithm to obtain the ML estimate. It has simplicity as ML EM reconstruction. PET image is constructed as kernel matrix. In dynamic PET image reconstruction, proper numbers of composite frames is important for reconstructing high quality images and reduce noise. Comparing with other methods, existing method is done by iterations, but the proposed method is done by matrix form and it provides better image quality. This experimental result shows improved reconstructed image and also reduce noise.*

Key Words: **Positron Emission Tomography (PET), Expectation maximization (EM), maximum likelihood (ML), image reconstruction, kernel method.**

1. INTRODUCTION

Image reconstruction from low-count frames is challenging because it is ill-posed and the image is very noisy. To improve the quality of reconstructed images, incorporate the prior information in PET image reconstruction.

Incorporating information from co-registered anatomical images into PET image reconstruction based on information theoretic similarity measures through priors [1]. For defining the *a* priori distribution use the anatomical image in a maximum-a-posteriori (MAP) reconstruction algorithm [2].For statistical iterative reconstruction the prior-image induced nonlocal (PINL) regularization via the penalized weighted least-squares (PWLS) criteria [3]. In magnetic resonance imaging (MRI) images do not provide a patient-specific attenuation map directly. So the proposed work generating synthetic CTs and attenuation maps to improve attenuation correction [4].For fully simultaneous pre-clinical PET/MR studies PET performance evaluation of a silicon photo-multiplier (SiPM) based PET scanner designed [5]. To simulate realistic SPECT\PET brain database, Brain-VISET (Voxel-based Iterative Simulation for Emission Tomography) is a method which includes anatomical and functional information [6]. To improve PET images MRI information can be used by using Maximum A Posteriori (MAP) reconstruction algorithms [7]. Evaluation of the HighlY constrained back-PRojection (HYPR) de-noising in conjunction with the maximum a posteriori (MAP) reconstruction for the micro PET- Inveon scanner [8,9,10]. The HYPR technique involves the creation of a composite image from the entire duration of the dynamic scan. The image model can be incorporated into the forward projection model of PET to perform maximum likelihood (ML) image reconstruction without an explicit regularization function. The expectation-maximization (EM) algorithm with and without ordered subsets can be directly applied to obtain the ML estimate. The various algorithms [11, 12] have been used to extract the features from an image.

The proposed kernelized EM method has the same simplicity as the conventional ML EM reconstruction followed by post-reconstruction denoising. We expect the former method to result in better performance than the latter for low-count data because it models noise in the projection domain where PET data are well modeled by independent Poisson random variables.

1.1 IMAGE RECONSTRUCTION

Image reconstruction is the creation of a two or three dimensional image from scattered or incomplete data such as the radiation readings acquired during a medical imaging study. Most strategies have focused on post processing algorithms with time series data reconstructed with filtered back projection (FBP) or ordered-subset expectation maximization.
Filtered Back Propagation (FBP) has been frequently used to reconstruct images from the projections. This algorithm has the advantage of being simple while having a low requirement for computing resources.

1.2 POSITRON EMISSION TOMOGRAPHY

Positron Emission Tomography is an imaging method in nuclear medicine based on the use of a weak radioactively marked pharmaceutical in order to image certain features of a human or animal body. PET images display the spatial distribution of the radiopharmaceutical, also called tracer, thus allowing to draw conclusions about metabolic activities or blood flow. Therefore, PET is a functional imaging technique which has applications in oncology, cardiology and neurology, e.g. for monitoring tumors or visualizing coronary artery disease. One of the most commonly used tracers is 18F-fluordesoxyglucose (18F-FDG).

2. EXISTING SYSTEM

The expectation-maximization (EM) algorithm with and without ordered subsets can be directly applied to obtain the ML estimate. The EM algorithm is used to find (locally) maximum likelihood parameters of a statistical model in cases where the equations cannot be solved directly. Typically these models involve latent variables in addition to unknown parameters and known data observations. That is, either there are missing values among the data, or the model can be formulated more simply by assuming the existence of additional unobserved data points.

Given a statistical model which generates a set X of observed data, a set of unobserved latent data or missing values Z, and a vector of unknown parameters θ, along with alikelihood function $L(\theta;X,Z) = P(X,Z|\theta)$ the maximum likelihood estimate (MLE) of the unknown parameters is determined by the marginal likelihood of the observed data, where $P(X|\theta)$ is the probability function of X and θ.

$$L(\theta;X)=P(X|\theta)=\sum_Z P(X,Z|\theta) \quad (2.1)$$

However, this quantity is often intractable (e.g. if Z is a sequence of events, so that the number of values grows exponentially with the sequence length, making the exact calculation of the sum extremely difficult).

The EM algorithm seeks to find the MLE of the marginal likelihood by iteratively applying the following two steps:

Step 1:

Expectation step (E step): Calculate the expected value of the log likelihood function, with respect to the conditional distribution of Z given X under the current estimate of the parameters $\theta^{(t)}$:

$$Q(\theta|\theta^{(t)}) = E_{Z|X,\theta^{(t)}}[\log L(\theta;X,Z)] \quad (2.2)$$

Step 2:

Maximization step (M step): Find the parameter that maximizes this quantity:

$$\theta^{(t+1)} = \underset{\theta}{\arg\max}\, Q(\theta|\theta^{(t)}) \quad (2.3)$$

3. PROPOSED METHOD

The proposed kernelized EM method has the same simplicity as the conventional ML EM reconstruction followed by post-reconstruction denoising. The former method to result in better performance than the latter for low-count data because it models noise in the projection domain where PET data are well modeled by independent Poisson random variables. The latter method requires a noise model in the image domain where noise is highly correlated and the covariance matrix is very difficult to estimate. The benefit of modeling noise in the projection domain over that in the image domain can become significant when the count level of PET data is low. Compared to regularization-based methods, the advantage of the proposed kernel-based EM reconstruction is its simplicity in implementation.

The proposed kernel method applies spatial-adaptive smoothing based on prior images and has applications in both anatomical-prior guided PET image reconstruction and dynamic PET reconstruction. Here we apply the method to frame-by-frame image reconstruction of dynamic PET data.

3.1 KERNEL METHOD

Kernel Methods are a new class of pattern analysis algorithms which can operate on very general types of data and can detect very general types of relations. Correlation, factor, cluster and discriminant analysis are just some of the types of pattern analysis tasks that can be performed on data as diverse as sequences, text, images, graphs and of course vectors. The method provides also a natural way to merge and integrate different types of data.

Computationally most kernel-based learning algorithms reduce to optimizing convex cost functions to computing generalized eigenvectors of large matrices. Kernel design is based on various methods. For discrete data (e.g: sequences) often use methods like dynamic programming, branch and bound, discrete continuous optimization. Combination is very efficient but still computationally challenging, for our ambitions.

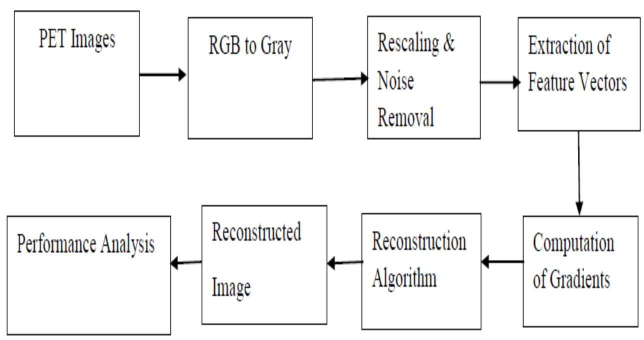


Fig-1 Block diagram of proposed system

As shown in the block diagram Fig-1, the first step in the process is RGB to gray scale conversion. The next step is rescaling and noise removal where the PET image is rescaled and removing noise. Extraction of feature vectors to features that represent some object and Computation of Gradients used to extract information from images. The next step is reconstruction algorithm, here kernel method is used. Then the image is reconstructed and performance is analyzed by existing and proposed method.

PET IMAGE

A positron emission tomography (PET) scan is an imaging test that helps reveal how your tissues and organs are functioning. A PET scan uses a radioactive drug (tracer) to show this activity. The tracer may be injected, swallowed or inhaled, depending on which organ or tissue is being studied by the PET scan. The tracer collects in areas of your body that have higher levels of chemical activity, which often correspond to areas of disease.
Steps in proposed system are given below:

STEP 1: RGB to gray image

In RGB color model, each colour appears in its primary spectral components of red, green and blue. The colour of a pixel is made up of three components: red, green, and blue (RGB), described by their corresponding intensities. Colour components are also known as colour channels or colour planes (components).
Gray scale is also known as an intensity, or gray level image. Array of class uint8, uint16, int16, single, or double whose pixel values specify intensity values. For single or double arrays, values range from [0, 1]. For uint8, values range from [0,255].For uint16, values range from [0, 65535]. For int16, values range from [-32768, 32767].

STEP 2: Image rescaling and noise removal

Image scaling is the process of resizing a digital image. Scaling is a non-trivial process that involves a trade-off between efficiency, smoothness and sharpness. The reversible process of scaling is called rescaling. Removing the noise from the input images. It is commonly used to denoise the audio sound. This is the most important technique for removal of blur in images.

STEP 3: Extraction of feature vectors

In pattern recognition and machine learning, a feature vector is an n-dimensional vector of numerical features that represent some object. Many algorithms in machine learning require a numerical representation of objects, since such representations facilitate processing and statistical analysis. When representing images, the feature values might correspond to the pixels of an image, when representing texts perhaps term occurrence frequencies. Feature vectors are equivalent to the vectors of explanatory variables used in statistical procedures such as linear regression. Feature vectors are often combined with weights using a dot product in order to construct a linear predictor function that is used to determine a score for making a prediction.

STEP 4: Computation of gradients

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Color gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Another name for this is color progression.

STEP 5: Reconstruction algorithm

Reconstruction algorithms have been developed to implement the process of reconstruction of a 3-dimensional object from its projections. These algorithms are designed largely based on the mathematics of the Radon transform, statistical knowledge of the data acquisition process and geometry of the data imaging system.

STEP 6: Reconstructed image

Iterative reconstruction refers to iterative algorithms used to reconstruct 2D and 3D images in certain imaging techniques. For example, in computed tomography an image must be reconstructed from projections of an object.

STEP 7: Performance analysis

The set of basic quantitative relationships between performance quantities. The analysis of EM algorithm and KEM algorithm performance is evaluated. The proposed algorithm gives better performance than EM algorithm.

4. DYNAMIC PET SIMULATION SETUP

Dynamic PET scans were simulated for a GE DST whole body PET scanner using a Zubal head phantom. The Zubal brain phantom is shown below in Fig-2. The proposed kernelized EM (KEM) algorithm with the conventional ML-EM reconstruction, ML-EM followed by post-reconstruction denoising methods (HYPR [9] and NLM [10]).

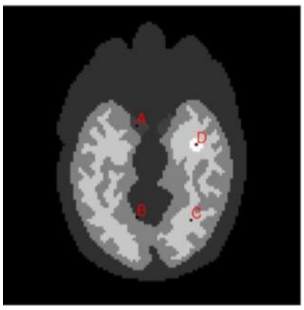
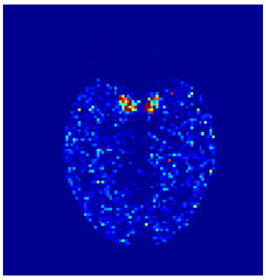


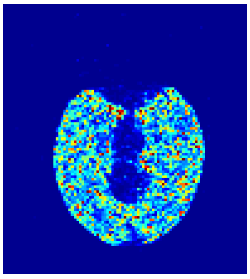
Fig-2 Zubal brain phantom

To construct the kernel matrix, we have to obtain the priori mages from composite frames in dynamic PET. Multiple short time frames are summed together to improve the counting statistics and reduce noise. Choosing a proper number of composite frames for reconstructing high-quality images. A small number of composite frames reduce noise in composite images, but the risk of losing important spatial information in the kernel matrix. A large number of composite frames can preserve spatial information but may be ineffective in suppressing noise. Using three composite frames provided a good balance between preserving spatial information and reducing noise in the composite images. The rebinned sinograms, each with 20 min, were reconstructed using the conventional ML EM algorithm with100 iterations. For the proposed KEM method, the reconstructed activities of the three rebinned frames were used to form the feature points.

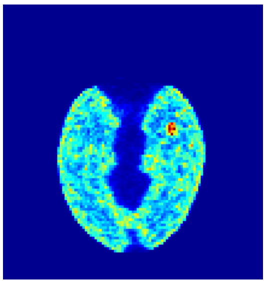
5. COMPARING EM AND KEM METHODS



(a)

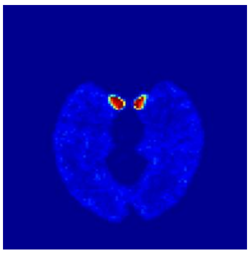


(b)

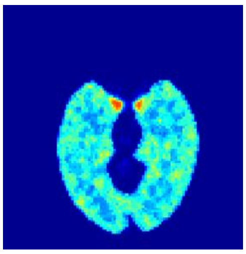


(c)

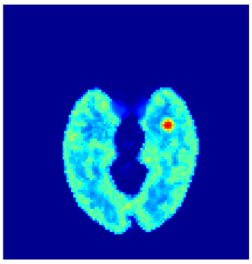
Fig-3 (a) Reconstructed image of Frame 2, (b) Reconstructed image of Frame 12, (c) Reconstructed image of Frame 22 using Expectation-Maximization



(a)



(b)



(c)

Fig-4 (a) Reconstructed image of Frame 2, (b) Reconstructed image of Frame 12, (c) Reconstructed image of Frame 22 using Kernelized expectation-maximization

Comparing fig 3 and 4 , EM has the high mean squared error (MSE) and more noise. It doesn't have good image quality whereas KEM has lowest mean squared error (MSE) and less noise. It also has better image quality.

6. CONCLUSIONS

The proposed kernel method to model PET image intensity as a function of feature points obtained from prior knowledge. The kernelized image model can incorporate prior information in the forward projection model. The maximum likelihood estimate can be easily obtained using the popular EM algorithm. Dynamic PET simulation results shown that the proposed reconstruction method can achieve better performance than the conventional ML-EM reconstruction for low-count frames. Comparing with EM method, KEM has better image quality and less noise and minimum MSE. The proposed kernelized EM algorithm has been applied to reconstruct the dynamic PET images of a breast cancer patient and has achieved promising results. In addition, patient motion, if not corrected, may result in mismatches between the composite images and the dynamic images to be reconstructed, which will affect performance of the kernel method.

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