CH9700405

IMAGE RECONSTRUCTION USING MONTE CARLO SIMULATION AND ARTIFICIAL NEURAL NETWORKS

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PET data sets are subject to two types of distortions during acquisition: the imperfect response of the scanner and attenuation and scattering in the activity distribution. In addition, the reconstruction of voxel images from the line projections composing a data set can introduce artifacts. Monte Carlo simulation provides a means for modeling the distortions and artificial neural networks a method for correcting for them as well as minimizing artifacts.

Improved resolution and definition of PET activity distributions would contribute to studies of glioblastoma or multiple sclerosis, which affect white matter where activity is masked by the higher activity of the surrounding gray matter. They would also contribute to studies of aging and degenerative brain diseases where enlarged sulci resulting from cerebral atrophy aggravate underestimates of gray matter activity due to partial volume effect.

Accurate reconstruction of PET data sets requires that the known physical characteristics of the scanner and the subject be incorporated as an integral part of reconstruction. The characteristics of the scanner include the geometry of the cylindrical array of crystal detectors constituting the scanner, the saw cuts defining the crystals and the design of the crystal readout. Conventional reconstruction algorithms using the analytic inverse Radon transform are inadequate because the discreteness and inhomogenity of the scanner sampling do not fulfill the requirements of the transform, resulting in artifacts. The relevant characteristic of the subject is its mass distribution, which determines the attenuation and scattering of the photon pairs arising from annihilation of the positron emitted by the PET tracer. Since scatter, contributing as much as 40% to data acquired in brain studies with modern 3D scanners, distorts the tracer activity distribution, correction is essential.

Three data sets: blank, transmission and emission data, are required for each reconstruction. Blank and transmission scans are made with a source of activity external to the subject. The blank scan, in which the scanner is empty, serves to normalize the transmission scan, made with the subject in the scanner before activity is injected or inhaled, required to measure mass distribution. For the emission scan, which reflects the physiological processing of the tracer, the external source is removed and the tracer incorporated by the subject.

The proposed reconstruction process can be decomposed into three stages. In the first stage, the sinograms, an ordered set of line projections measured by the coincidences in opposing crystal pairs for each type of scan, will be corrected for the scanner response. The purpose of this correction is to improve the resolution of the images to the limit imposed by the crystal size of the scanner (~3 mm in-plane in the newest devices) while increasing the signal-to-noise ratio. In the second stage, the emission and transmission sinograms are corrected for scattering; the scattering correction for transmission is distinct from that for emission due to the differing locations of the activity. Then the emission sinograms are corrected for absorption by dividing each line projection by the ratio of counts in the corresponding transmission projection relative to the blank projection. Correcting for scattering before the correction for absorption is essential in order to assure that both transmission and emission sinograms contain only true line projections. The last stage of the reconstruction process is the transfomation of the set of absorption corrected emission sinograms, i.e. the line projections, to an image volume.

In order to simulate the response of the scanner as well as the attenuation and absorption in the subject, we model scanner and subject using GEANT. This Monte Carlo program module incorporates the design of the scanner and mass distribution of the subject and computes the relevant scattering processes in the detectors and subject: photoeffect, Rayleigh and Compton scattering. Moreover, an interactive interface permits the properties of the scanner and subject to be altered with ease. The program traces each photon from its source in an activity distribution to its registration in a BGO detector, recording type and position of each interaction and the direction and energy of the resultant photon.

The capability of discriminating scattered from unscattered events using Monte Carlo simulation makes it possible, for example, to compute sinograms of unscattered coincidences registered by a realistic scanner with the inhomogenities described above as well as sinograms of unscattered coincidences detected by an analogous ideal scanner. The simulated sinograms serve as input and output data sets to teach an artificial neural network to correct for scanner response in the reconstruction process.The capability of generating sinograms containing only unscattered or scattered coincidences should similarly permit the development of neural networks to correct for scatter in transmission and emission scans.

Artificial neural networks represent nonlinear transformations between input and output arrays. In supervised networks, the matrices determining the transfomation are computed by presenting the network with sample input and output arrays. For each sample, a learning rule instructs the network how to change the matrices. When they converge, the transformation matrices are fixed and used to compute an output array from a given input array. Whereas training can be time consuming, computation of an output array is a fast, single step procedure. Neural networks are adaptive systems which have proven themselves capable of yielding optimal solutions to similar inverse problems with noisy and incomplete input data.

Four neural networks are envisaged for the processing of PET data: one to correct for scanner response, one each to correct for scattering in transmission and emission scans and one to reconstruct the image volumes. The inputs and outputs of the first three networks are sinograms as are the inputs to the reconstruction network; the output of the reconstruction network is the image volume. The network correcting for scanner response, and possibly that perfoming reconstruction, will share the design of the network proposed to restore astronomical images in the case of the Hubble telescope [1,2]. Since the functions of these networks depend only on the characteristics of the scanner, the networks must only be trained once, in principle, for each scanner; therefore, they might be installed as hardware when the scanner is constructed. For scattering, feed-forward, backpropagation networks with a single hidden layer are being explored; since scattering is determined by the mass distribution, the networks may be able to correct only for classes of objects.

Due to the size of 3D data sets, a typical data set is of order 10 Mbyte in size, processing and reconstructing them requires substantial computing capacity and time. The speed of neural networks could reduce computing time substantially; Moreover, the linearity of the reconstruction process suggests that training and operation of the network might benefit from parallel processing. This aspect of reconstruction with neural networks remains to be explored.

During the past year, numerous Monte Carlo simulations of simple geometrical objects, including an extensive simulation of a granite phantom [3] have been performed. This simulation was consistent with the data acquired; it was used to train a prototype neural network for scattering correction. Simulations of blank and transmission scans of a water phantom are currently being made in conjunction with a scanner manufacturer to trace anomalies in the reconstruction process. Finally, variance reduction techniques have been introduced to accelerate the Monte Carlo simulations. In addition to the prototype neural network trained for scattering correction, an image reconstruction network is now being tested to verify that it performs well indepently of the image object.

REFERENCES

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