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Tomographic image reconstruction using Artificial Neural Networks

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Abstract

A new image reconstruction technique based on the usage of an Artificial Neural Network (ANN) is presented. The most crucial factor in designing such a reconstruction system is the network architecture and the number of the input projections needed to reconstruct the image. Although the training phase requires a large amount of input samples and a considerable CPU time, the trained network is characterized by simplicity and quick response. The performance of this ANN is tested using several image patterns. It is intended to be used together with a phantom rotating table and the γ-camera of IASA for SPECT image reconstruction.

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Keywords: SPECT; PSPMT; γ-camera; Artificial Neural Networks (ANN); Image reconstruction

1. Introduction

Three-dimensional (3D) reconstruction techniques from projections have been used for many years in medical imaging. The most usual algorithms are based on a Fourier Transformation which has the disadvantage that a very large number of projections with uniformly distributed angles are required.

In this project, a new image reconstruction technique based on the usage of an Artificial Neural Network (ANN) is presented. The most crucial factor in designing such a reconstruction system is the network architecture and the number of the input projections needed to reconstruct the image. The CPU time needed to train the network is often equivalent or even more time consuming to that of the conventional techniques. However, once the ANN has completed the learning phase, it could be applied to any relevant set of input data of the same type to produce fast

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results from the trained network without any iterative process.

This reconstruction technique is intended to be used with an automated phantom rotating system, which is being developed at IASA together with an existing γ-camera for SPECT imaging. In the next sections we describe briefly the development of the rotary positioning table and the specifications of the γ-camera followed by the detailed presentation of the image reconstruction procedure based on ANN.

2. Description of the experimental setup

The final automated system consists of a phantom rotating system which allows us to take the projections at any selected set of angles, the γ-camera [1,2] with its data acquisition system and a master computer (PC) which drives and controls the whole system. The schematic diagram in Fig. 1 shows how all these hardware parts are connected together. The reconstruction procedure for a given type of input data, mainly defined by the number of the planar records from the γ-camera, and for a given network architecture can be easily implemented in the master computer.

2.1. The rotating system

The rotating system consists of a computer-controlled rotating table manufactured by the Arrick Robotics [3]. The table rotation around an axis perpendicular to the γ-camera axis is provided by a stepping motor which consists of a rotor and four coils. The coils are supplied with current through the MD-2 controller which is attached to the rotating table by a standard 9-pin cable. The MD-2 controller is further connected to the parallel port of the master computer.

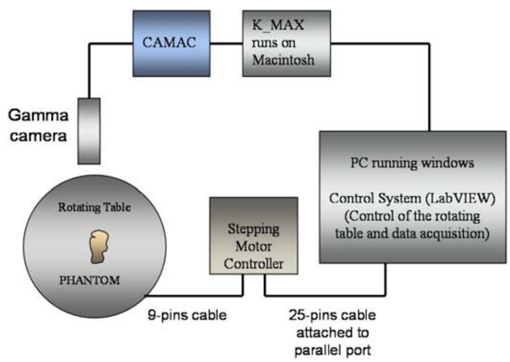

Fig. 1. Schematic diagram of the experimental setup.

The motion of the rotating table to a desired set of angles is programmed in the LabVIEW environment running in the master computer. Several drivers (VIs) have been developed in order to control the stepping motor. A fine programming of the bit register sequence for the four coils allows a clockwise control of the motor in half, single or double steps, resulting to a final angle resolution of 0.2° [4].

2.2. The γ-camera

The γ-camera consists of an R2486 Position Sensitive PMT equipped with 8×8 crossed-wire anode pairs, a 4.5 cm in diameter CsI(Tl) pixelized crystal and a collimator. The anode signals after pre-amplification are transferred to a CAMAC system for digitization and data acquisition [1,2]. The CAMAC is controlled and read out by a program written in *K*max (Sparrow Corporation) which runs on a Macintosh G3 processor.

In the final design all the *K*max functions needed to start or stop the data acquisition system, as well as to transfer the recorded data for projection analysis, are steered by a procedure running in the master computer (PC). This computer will also process the data in order to reconstruct the image. In the full automated system the user will place the phantom on the centre of the rotating table and will activate the acquisition procedure. The system is then responsible for taking all the planar images at the predefined angles and for transferring the data to the master host, where the ANN reconstruction procedure occurs. The reconstructed image will appear on a screen ready for any further manipulation.

3. Methodology—neural network architecture

In this section, the reconstruction problem is defined in mathematical terms and the methodology used to define the ANN architecture is explained in detail.

3.1. Problem definition

By using mechanical collimation, which only allows nearly perpendicular incident photons, the camera takes planar images of the activity distribution in the phantom. These planar images can be regarded as projection images of the activity distribution. For simplicity reasons only the two-dimensional version of the problem is here regarded; any extension to a higher dimension requires only recurrence of the method. The simple reconstruction problem is then described in Fig. 2.

The image to be reconstructed is represented by a square matrix $\mathbf{n} \times \mathbf{n}$. The schematic diagram in Fig. 2 shows the matrix projection at a given angle, which normally corresponds to a strip of the camera planar image taken for this angle. As a simplification we suppose that at each angle there is a constant number of strips, equal to $\mathbf{n}$. By totally recording $\mathbf{m}$ projections at different angles the number of the known variables equals to $\mathbf{m} \times \mathbf{n}$, while a solution for the $\mathbf{n} \times \mathbf{n}$ elements of the matrix is required. Although in the usual tomographic problems an infinite number of projections can be taken, restricted only by the camera resolution, in our method the number of the recorded planar images is kept small. Consequently, this reduces the total number of the fit parameters (weights) in the Neural Network to the minimum possible, as it will be explained below. Usually, $\mathbf{n}$ is of the order of 100 and $\mathbf{m}$ of the order of 10; thus the procedure has to reconstruct the 100×100 unknown matrix elements from the 100×10 measured projection data.

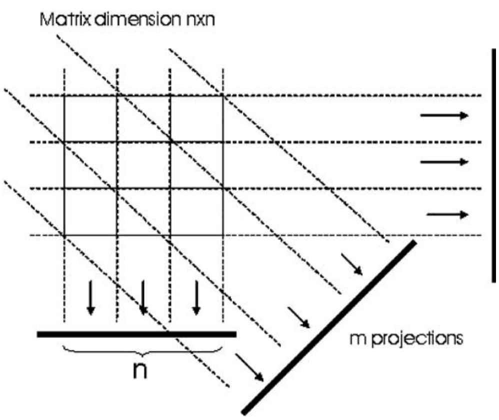

Fig. 2. Definition of the reconstruction procedure: The image (square matrix $\mathbf{n} \times \mathbf{n}$) has to be reconstructed from the $\mathbf{m}$-measured projections, each one with length $\mathbf{n}$.

3.2. ANN architecture—training

In this project, a reconstruction technique based on ANN is introduced and tested. The software package JETNET [5] has been used for the network definition and training. This package consists of FORTRAN (F77) subroutines with a large number of adjustable parameters for performance and error control of the network.

The ANN Architecture is schematically shown in Fig. 3. The Input Layer comprises $\mathbf{m} \times \mathbf{n}$ nodes supplied with the projection data. The reconstructed image ($\mathbf{n} \times \mathbf{n}$) is represented by the Output Layer. The number of the hidden layers in our study is varied from zero [6] to one or two hidden layers. It has been proved out that more hidden layers do not contribute to a better solution and due to the increasing number of the free fit parameters (more weights in the network) the convergence of the procedure becomes unstable. In all these variants the back-propagation (standard gradient descent) updating procedure has been applied.

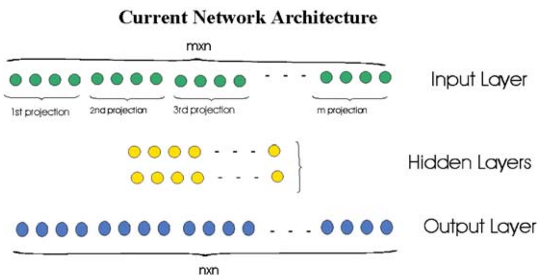

Fig. 3. Network Architecture: The Input Layer comprises $\mathbf{m} \times \mathbf{n}$ nodes supplied with the projection data. The reconstructed image ($\mathbf{n} \times \mathbf{n}$) is represented by the Output Layer.

4. Image reconstruction results

In the following, image reconstruction results based in the above described ANN technique will be presented. These results are based on a reconstruction of a 27×27 matrix with 3 or 8 projections by varying the number of the hidden layers. In Fig. 4 results are shown for a Network Architecture with one hidden layer. To the left is shown the original matrix for direct comparison with the reconstructed one at the right of the Figure. The network training has been performed with a large number of 3D ellipsoids with variable densities and widths randomly distributed in the square matrix. This training sample is kept constant until the network reaches a reasonable learning level.

Similar results for a Network Architecture with two hidden layers are presented in Fig. 5. It has been shown that the network learning convergence with two hidden layers is slower than in the previous case. For more than two hidden layers the training procedure becomes unstable. It is clearly seen that the increasing number of the projections improve the reconstruction result.

For small matrix dimensions there is a strong relation between the optimum number of projections needed to reconstruct the image [6]. Exceeding this number of projections the procedure does not any more significantly contribute to better results.

A crucial parameter for the usage of this technique is the CPU time consumed in the training phase. Running on a Pentium-4 processor at 2.4 GHz and using the two hidden layer architecture (27×27 matrix with 8 projections) the time needed to train the network with 2000 patterns is about 10 s for each epoch. The estimated time for a full training is about 2 h.

Although the learning phase requires a large amount of input samples and a considerable CPU time, the trained network is able to give immediate

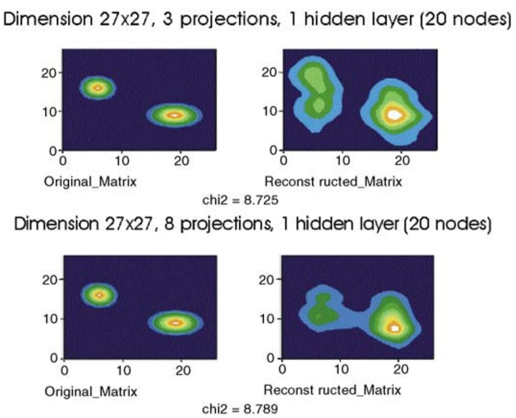

Fig. 4. Reconstruction results using a Neural Network Architecture with one hidden layer. Left is the original matrix, right the reconstructed matrix after network training.

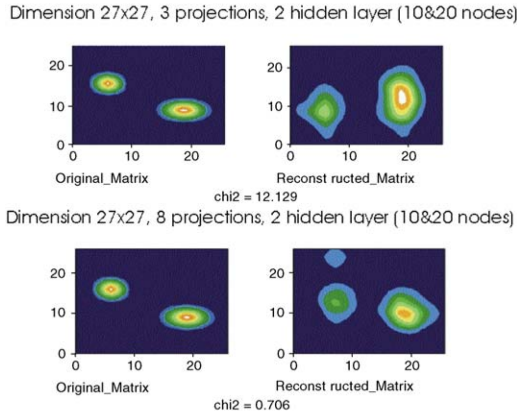

Fig. 5. Reconstruction results using a Neural Network Architecture with two hidden layers. As in the previews Figure, left is the original matrix for direct comparison.

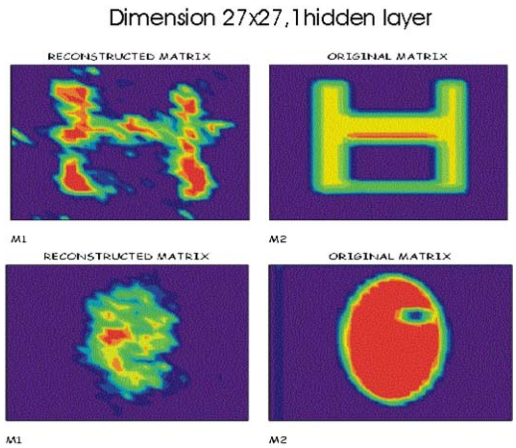

Fig. 6. Reconstruction results for more complicated test patterns using the parameters of the trained network.

results. In order to test the relevance of the described method, we require from the network to reconstruct more complicated patterns. Fig. 6 shows such a typical network response to an input matrix totally different from the ellipsoid pattern sample used for training.

Future work of this project is focused on extending and establishing the same procedure on higher matrix dimension problems and training with real SPECT data from the γ-camera and the phantom rotation system.

References

[1] N.D. Giokaris, et al., Nucl. Instr. and Meth. A 497 (2003) 141.
[2] G.K. Loudos, et al., Comput. Med. Imaging Graphics 27 (2003) 307.
[3] RT-12 Rotary Positioning Table, Arrick Robotics, Texas, USA: http://www.robotics.com.
[4] P. Paschalis, M.Sc. Thesis, Physics Department, University of Athens, in preparation.
[5] C. Peterson, et al., Comput. Phys. Commun. 81 (1994) 185.
[6] Ch. Tsoumpas, Diploma Thesis, Physics Department, University of Athens, 2002, unpublished.