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New neural network algorithm for image reconstruction from fan-beam projections

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ABSTRACT

Neural networks have some applications in computerized tomography, in particular to reconstruct an image from projections. The presented paper describes a new practical approach to the reconstruction problem using a Hopfield-type neural network. The methodology of this reconstruction algorithm resembles a transformation formula—the so-called ρ-filtered layergram method. The method proposed in this work is adapted for discrete fan beam projections, already used in practice. Performed computer simulations show that the neural network reconstruction algorithm designed to work in this way outperforms conventional methods in obtained image quality, and in perspective of hardware implementation in the speed of the reconstruction process.

1. Introduction

Although there are several tomograph methods used in medicine (for example PET, NMR etc.), the most popular and the most widespread one is X-ray computerized tomography (CT). The possibility to acquire three-dimensional images of the investigated object, using this type of medical diagnostic device, is realized by applying an appropriate method of projections acquisition and an image reconstruction algorithm. In diagnostics the knowledge of the distribution of the attenuation of the X-rays in the investigated object gives very useful information about both the body tissues and any pathological changes.

The key problem arising in computerized tomography is *image reconstruction from projections* obtained from the X-ray scanner of a given geometry. There are several reconstruction methods to solve this problem, for example the most popular reconstruction algorithms using convolution and back-projection [10,14] and the algebraic reconstruction technique (ART) [1,4,7].

Considering the increasing amount of soft computing algorithms used in different science disciplines, it is possible that in the foreseeable future they will occupy an important place in computerized tomography as well. The applications of neural networks in computerized tomography were presented in the past for example in [8,9,12,18]. The reconstruction algorithms based on the supervised neural networks presented in those publications cannot lead to a good performance because these kinds of neural nets have a limitation in the number of types of reconstructed images. Other structures representing the so-called algebraic approach to image reconstruction from projections were studied in papers [15,17]. The main disadvantage of that approach to image reconstruction from projections problem is the extremely large number of variables which are used during calculations. The computational complexity of the reconstruction process is proportional in that case to the square of the image size multiplied by the number of performed projections. Unfortunately, it leads to a huge number of connections between neurons in the neural networks presented there.

In this paper a new approach to the reconstruction problem will be developed based on transformation methodology. It resembles the traditional ρ-filtered layergram reconstruction method where the two-dimensional filtering is the crucial point of that approach (see e.g. [10]). Unfortunately, two-dimensional filtering is computationally complex. Therefore, in our approach a Hopfield-type neural network [5] is proposed to design the reconstruction algorithm. Some authors [2,6,11] applied similar neural network structures to solve another problem, namely unidimensional signal reconstruction. Our approach significantly decreases the complexity of the tomographic reconstruction problem. It means that the number of neurons in the proposed network is proportional only to the square of the image size and is independent of the resolution of the performed earlier projections. As a result of this fact we have a drastic decrease in the number of connections in the designed neural network. The reconstruction method presented herein, originally formulated by

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the author, can be applied to the fan-beam scanner geometry of the tomography device. Moreover, it can be easily extended to employ in spiral tomography. The weights of the neural network arising in our reconstruction method will be determined in a novel way. The calculations of these weights will be carried out only once before the principal part of the reconstruction process is started. It should be emphasized that our concept appears to be very convenient for hardware implementation of the neural network realizing image reconstruction from projections.

The paper is organized as follows. The reconstruction method is presented in Section 2. In consequent subsections the acquisition of the fan-beam projections (Section 2.1), the rebinning procedure (Section 2.2) and the neural network reconstruction algorithm (Section 2.3) will be depicted. Section 3 describes the performance of the computer simulations and presents the most important results. Section 4 gives some conclusions.

2. Fan-beam reconstruction method

As we mentioned in the introduction our reconstruction algorithm resembles the ρ-filtered layergram method [10]. The main difference between these two methods is the realization of the filtering. In our case a Hopfield-type neural network is implemented instead of the two-dimensional filtering of the blurred image obtained after the back-projection operation. The idea of the presented reconstruction method using the neural network is shown in Fig. 1, where the fan-beam geometry of collected projections is taken into consideration.

2.1. The acquisition of the projections

In the first step of the reconstruction algorithm a set of all fan-beams projections is collected using a scanner whose geometry is depicted in Fig. 2. A value of projection depends on the depth of the shadow cast by the object onto a certain place on the screen positioned opposite the radiation source. A given ray from a fan-beam is involved in obtaining a particular projection value $p^f(\beta,\alpha^f)$,

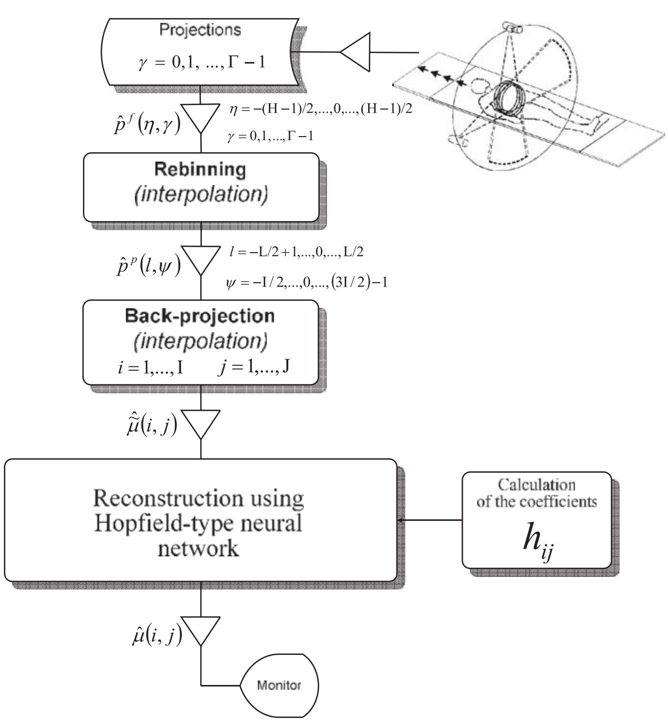

Fig. 1. Neural network image reconstruction algorithm using fan-beams.

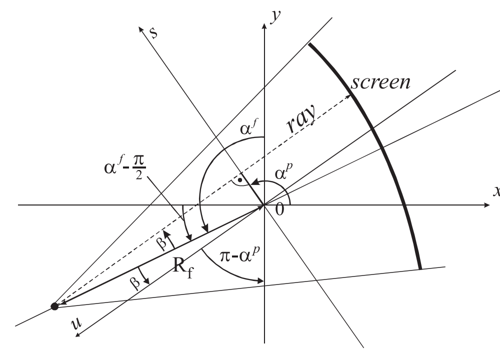

Fig. 2. Geometric relation between parallel and fan X-ray beams.

where the projection value is obtained at angle α^f and β is the angle of divergence of the ray from the symmetry-line of the fan-beam. In practice only samples $p^f(\beta_\eta,\alpha^f_\gamma)$ of the projections are measured, where $\beta_\eta = \eta\cdot\Delta$ are equiangular rays, $\eta = -(H-1)/2,\ldots,0,\ldots,(H-1)/2$ are indexes of these rays, $\alpha^f_\gamma = \gamma\cdot\Delta^f_\alpha$ are particular angles of the X-ray source from which projections are obtained, and $\gamma = 0, 1, \ldots, \Gamma-1$ are the indexes of these angles. For simplicity we can define the discrete projections $\hat{p}^f(\eta,\gamma) = p^f(\eta\cdot\Delta_\beta, \gamma\cdot\Delta^f_\alpha)$.

2.2. Rebinning

After getting a set of fan-beam projections we can proceed with the image reconstruction. One of the most widespread algorithms for image reconstruction from fan-beam projections is a method, which consists of rebinning (re-sorting). After this operation it is possible to use any algorithm destined to reconstruct an image from parallel projections. In our case it is a method using a Hopfield-type neural network.

Before we start the rebinning operation it is convenient to determine a set of parallel projections, which are needed for further signal processing. In the case of the parallel geometry of the scanner, the projection is called Radon's transformation [13]. In continuous domain it can be expressed as follows:

$$p^p(s,\alpha^p) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mu(x,y)\cdot\delta(x\cos\alpha^p + y\sin\alpha^p - s)\,dx\,dy, \qquad (1)$$

where α^p is the angle of rotation of the parallel geometry scanner, x, y are the co-ordinates of the examined object, $s = x\cos\alpha^p + y\sin\alpha^p$ is the distance from the centre of rotation to the axis of the ray falling on the projection screen, $\mu(x,y)$ is the distribution of the attenuation of X-rays in the analysed cross-section, $\delta(\cdot)$ is the Dirac delta function.

Referring to Fig. 2 we can find relations between parameters in both considered geometries of scanners as

$$\begin{aligned} p^p(s,\alpha^p) &= p^f(\beta,\alpha^f) \\ &= p^f\left(\arcsin\left(\frac{s}{R_f}\right), \alpha^p - \arcsin\left(\frac{s}{R_f}\right)\right). \end{aligned} \qquad (2)$$

Only a limited number of parallel projection values $p^p(s,\alpha^p)$ are chosen for further processing. Let $\hat{p}^p(l,\psi)$ denote discrete values of parallel projections taken at angles indexed by variable ψ, where $\psi = 0, 1, \ldots, \Psi-1$, where Ψ is a number of projections (integer value).

Now we determine a uniform sampling on the screen at points $l = -L/2+1, \ldots, 0, \ldots, L/2$, where L is an even number of virtual detectors from the projection obtained at angle α^p_ψ. It is easy to calculate the distance between each parallel ray from the origin in space (x, y) as follows:

$$s(i,j) = l\cdot\Delta_s, \qquad (3)$$

where Δ_s is a sample interval on the screen.