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A data-parallelism approach for PSO-ANN based medical image reconstruction on a multi-core system

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ABSTRACT

This paper presents the sequential and parallel data decomposition strategies implemented on a Particle Swarm Optimization (PSO) algorithm based Artificial Neural Network (PSO-ANN) weights optimization for image reconstruction. The application system is developed for the reconstruction of two-dimensional spatial standard Computed Tomography (CT) phantom images. It is running on a multi-core computer by varying the number of cores. The feed forward ANN initializes the weight between the 'ideal' images that are reconstructed using filtered back projection (FBP) technique and the corresponding projection data of CT phantom. In an earlier work, ANN training time is too long. Hence, we propose that the ANN exemplar datasets are decomposed into subsets. Using these subsets, artificial sub neural nets (subnets) are initialized and each subnet initial weights are optimized using PSO. Consequently, it was observed that the sequential approach of the proposed method consumes more training time. Hence the parallel strategy is attempted to reduce the computational training time. The parallel approach is further explored for image reconstruction from 'noisy' and 'limited-angle' datasets also.

1. Introduction

The complexity of image reconstruction has acquired much concentration in the medical imaging literature. This is due to the continuous search for developments of imaging modalities, varying from X-ray computerized tomography and emission tomography up to acoustic and optical techniques. They all bring different approaches in the human body either morphological or functional. The classic mathematical model of X-ray computerized tomography (CT) assumes that the sensing device evaluates the line integrals of the object attenuation coefficient at some known orientations [1]. As a typical inverse problem, tomography image reconstruction is usually considered as an ill-posed problem [2]. The tomography image reconstruction of an image is formed of deciding an image object $f(x, y)$ from a collection of projections [3]$p_\theta(r)$ given by Eq. (1).

$$p_\theta(r) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y)\delta(r - x\cos\theta - y\sin\theta)dxdy. \tag{1}$$

Where r is taken on the x–y plane such that $r = x\cos\theta - y\sin\theta$. The discrete inverse radon transform is carried out with the Filtered Back Projection (FBP) algorithm. FBP is established on the basis of Fourier slice theorem [4], Fast Fourier summation algorithm for image reconstruction [5]. The excellence of reconstruction from entire projections with FBP is widely acceptable, based on the number of angles and sampling points.

The projections$p_\theta(r)$, accumulated along a group of static field-gradient orientations in polar grid, are utilized to acquire the sample spin density $f(x, y)$ by Eq. (2) FBP,

$$f(x, y)\int_0^\pi p_\theta^*(r)d\theta = \int_0^\pi [\int_{-\infty}^{\infty} P_\theta(k) \mid k \mid e^{-2\pi ikr}dk]d\theta, \tag{2}$$

Here $p_\theta^*(r)$ is the projection $P_\theta(k)$ filtered by the expression inside the square brackets.

The important reconstruction methods such as FBP [6] is convincingly effective and fast, but their quality is low when the projection data are noisy [7,8] and limited [1,9]. An Algebraic Reconstruction Technique (ART) [10–12], Simultaneous ART (SART) [13], Simultaneous Iterative Reconstruction Technique (SIRT) [14] are shows better resolution for medical imaging in real time [9]. However, these techniques are suffered with enormous computational complexity [15], that is corresponding to the square of the image size multiplied by the number of projections [10]. In the framework of soft computing strategies to image reconstruction from projections, artificial neural networks have been utilized as a very popular and important

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tool [16]. In an earlier study recurrent neural network algorithm has been utilized for image reconstruction [17], fast tomography reconstruction from limited data has been reported using ANN [14] and the reconstruction technique using BP-ANN has been implemented on a sequential computer [9], which require ANN very long training time.

BP-ANN uses the gradient based approach which either trains slowly or get struck with local minimum. Instead of using gradient-based learning techniques, one may apply the commonly used optimization methods such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO) to optimize the network initial weights. The PSO algorithm with artificial neural network (PSO-ANN) has offered fine answers to many problems in biomedical science. PSO is to regulate the weight of a BP-ANN has a better performance than random search. The particle swarm optimization algorithm is shows to converge global optimum. So in this paper, a hybrid algorithm combining particle swarm optimization (PSO) with back-propagation (BP) algorithm is utilized. PSO has been used with BP-ANN for optimizing the various parameters such as number of hidden nodes, hidden layer sizes, feature subsets, learning rate, momentum, and optimize the network connection weights. This paper presents the application of hybrid model that integrates PSO and BP-ANN (PSO-ANN) for reconstruction of shepp-logan head phantom image by optimizing the connection weights, which require PSO-ANN very long training time.

The parallel approach to ANN has been explored in a variety of manner, specifically, training session parallelism, exemplar parallelism, node parallelism, and weight parallelism [18]. Parallel approach of BP-ANN has been exposed to be an efficient resolution to all cases of long training times in sequential ANN training on a cluster computer [19–22]. The training datasets are decomposed into a number of subsets and the subsets are allocated to different computing nodes for parallel processing [23] on a cluster computer [24]. As an extension of the recent work carried out on a sequential computer [9], the present work deals with parallel approach of PSO-ANN decomposition principle. The next section describes standard dataset for the sequential and parallel PSO-ANN. The Section 3 deals with the methodology of the parallel approach of the PSO-ANN. The Section 4 explains the design and implementation details. The results are discussed in Section 5 and concluded in Section 6.

2. Exemplar datasets

Initially, the Shepp–Logan head phantom [4,25] has been utilized for testing purposes like CT, MRI, fMRI, PET and SPECT [26]. It is widely used in medical imaging and is the sum of 10 ellipses of varying size and orientation. [27]. The standard shepp-logan head images 64 x 64 (Fig. 1a) and 128 x 128 (Fig. 1b) are bring into play for the present work. FBP is most commonly used algorithm for medical image reconstruction crisis. In fact, the image produced by filtered back projection is identical to the correct image when there are an infinite number of views and an infinite number of points per view. Fig. .2b and d shows reconstruction of phantom head model by FBP with 18

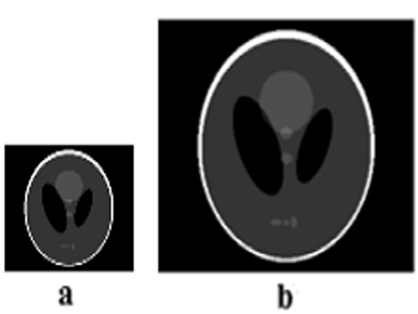

Fig. 1. The 2-dimensional standard shepp-logan head phantom images of size 64 x 64 (a), 128 x 128 (b).

projections, coverage angle ranging from 0 to 180º with an incremental value of 10º. The number of projection is proportional to the quality of FBP image. The head image (Fig. 2a) 64 x 64, (Fig. 2c) 128 x 128 reconstructed by FBP with 180 projections are utilized for PSO-ANN. The projections of phantom related to the size of 64 x 64 (Fig. 3a), and 128 x 128 (Fig. 3b).

FBP has been realistically useful, but the quality is low when the projection data are noisy and limited [9]. Projection noise crucially limits the capability of a radiologist to categorize between two regions of special spin density and hence to find the talent of the presence of attributes of interest in medical images. Such random noise is simulated either as additive signal reliant noise. Such noise is simulated and added either as additive signal reliant noise, given by $p_\theta(r)$ =s + n or multiplicative noise is, specified by $p_\theta(r)$ =s ∗ n. Various levels of random noises are added to the projection of the phantom to resemble the noise-added projection data. The noise-added projections (Fig. 3c and d) with FBP based reconstruction data produce distorted images shown in Fig. 4a and b. Many training exemplars are constructed with 'noise-added' projection dataset (Fig. 3c, d) and 'ideal' target images (Fig. 2a, c). The noise-added projection data and the FBP images are used to construct (Fig. 5) an exemplar dataset. The input training data set comprised 95 sample points of 18 projections. The Shepp-Logan image [64 * 64 pixels] reconstructed by FBP method using these 180 projections are presented to the network as the 'ideal' target output. Exemplars are constructed with 'noise-free', and 'noise-added' projection dataset. The PSO-ANN has topology with 1710 nodes in the input layer, representing the 18 'noise-added' projections, each with 95 samples scaled uniformly between 0 and 1. The output layer has 4096 nodes, representing FBP image of size 64 ∗ 64 pixels. The FBP images with 180 projections are used as output to exemplar dataset needed for the present work. On the whole of an exemplar creation (Fig. 5), input layer (1710 neurons) represent the 18 projections and output layer (4096 neurons) represent the FBP with 180 projections based reconstructed (64x 64 pixels) spatial image. similarly another type of an exemplar creation for 128 x 128 phantom, input layer (3330 neurons) represents the 18 projections each with 185 samples and output layer (16384 neurons) represents the image of size 128 x 128.

Biomedical imaging with long acquisition time and large number of projection data are not chosen for instantaneous studies, because the system under testing has to expend a long time within the imager. Moreover, it can't be feasible to obtain such a large amount of projection data due to the biological clearance of the imaging agent. In addition, the PSO-ANN training system is constructed with limited-angle projection datasets and the 'ideal' target images reconstructed by FBP. The dataset for reconstruction from limited number of projections consisted of nine projections collected at 20◦ apart each. Hence, the structure of the neural network has only 855 nodes in the input layer representing the nine projections each with 95 samples, scaled uniformly between 0 and 1 and 4096 nodes in the output layer forming the two-dimensional spatial image of size 64 x 64 pixels. The reconstruction by FBP images with limited angle projection produces highly distorted and unknown information of image shows in Fig. 4c and d. The next section deals with the sequential and parallel PSO-ANN methodology of the present work.

3. Methodology

3.1. Sequential PSO-ANN training for phantom image reconstruction

The phantom image reconstruction system is based on a supervised, feed-forward, fully connected artificial neural network which already exists [28–30].

$$net = \sum_i w_v Nd_v = w^T Nd \tag{3}$$

Here Nd_1, Nd_2, ... Nd_n are ANN's inputs. The w_1, w_2, ...w_n are