Fast Tomographic Reconstruction from Highly Limited Data Using Artificial Neural Networks

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ABSTRACT

Obtaining accurate reconstructions from a small number of projections is important in many tomographic applications. Current advanced reconstruction methods are able to produce accurate reconstructions in some cases, but they are usually computationally expensive. Here, we present a reconstruction method based on artificial neural networks, which can be viewed as a combination of fast filtered backprojection reconstructions. Since the method learns characteristics of scanned objects during the training phase, it is able to reconstruct images accurately from limited data. Results from experimental µCT data show that the new method is able to produce more accurate reconstructions than both regular filtered backprojection and the slower iterative SIRT method, while having a relatively low computational cost.

1.   INTRODUCTION

Fast and accurate reconstruction from limited data is one of the major problems in current tomographic research. In limited-data problems, projection data is only available for a small number of projection angles (Mudde, 2010) or for limited angular range (Moore et al., 2002). Practical considerations can limit the number of angles for which data can be acquired in real world applications. In electron tomography, for example, the electron beam damages the sample, imposing a strong limitation on the number of angles. In industrial tomography, cost considerations impose constraints on the total scan duration, limiting the number of angles as well.

Analytical reconstruction methods, of which filtered backprojection (FBP) is the most widely used example, are based on a continuous representation of the problem (Kak and Slaney, 2001). This representation assumes that projection data is available for *all* angles, which is clearly not feasible in practice. When data is available for a sufficient number of angles however, this assumption is approximately satisfied, and resulting reconstructions are usually accurate. For limited-data problems, the assumption is clearly not satisfied, and the reconstruction quality of analytical methods is often unacceptable.

Advanced reconstructions methods are sometimes able to produce accurate results for limited-data problems, by exploiting prior knowledge of the scanned object. If it is known, for example, that the object has a sparse gradient, one can use total variation minimization techniques, such as FISTA (Beck and Teboulle, 2009), to create a significantly better reconstruction than analytical methods. Or, if the object consists of only a small number of different materials, methods from the field of discrete tomography, such as DART (Batenburg and Sijbers, 2011), can usually solve the reconstruction problem accurately. However, methods that exploit prior knowledge are generally very slow, since they are often iterative methods for which a substantial number of costly iterations must be performed. Furthermore, the specific prior knowledge that is needed for each method can limit the types of images that can be reconstructed.

Figure 1: *In (a), a multilayer perceptron with three input nodes, two hidden nodes and one output node is shown. The input nodes are connected to the hidden nodes with weights w, and the hidden nodes are connected to the output node with weight q. In (b) the corresponding NN-FBP method is shown, which consists of two FBPs, with custom filters w_0 and w_1.*

Here, we present a reconstruction method for limited-data problems designed to avoid both problems of existing advanced methods. The method is computationally similar to FBP, sharing its low computational cost. Furthermore, the method automatically learns specific knowledge about scanned objects, improving the reconstruction quality. This learning is accomplished by using an artificial neural network (ANN). Since the prior knowledge is only modelled implicitly by the selection of training examples, it can be applied to any type of image.

Several neural networks for tomographic reconstruction have been proposed in the literature (Batenburg and Kosters, 2006; Cierniak, 2008), yet the connection to the filters in FBP has never been made. By exploiting the equivalence between the ANN model and a composition of FBP operations, our approach is capable of reconstructing large datasets with similar efficiency as FBP, and far more accurately. The approach used in this paper is similar to the single pixel network of (Batenburg and Kosters, 2006). In that paper however, the neural network was used as a black box, resulting in an accurate, but slow method. Here, we make a small modification to the method, such that the network can be viewed as an analytical reconstruction method instead of a black box. Although the method can, in theory, be applied to fan-beam or three-dimensional cone-beam reconstruction problems, we will focus on the two-dimensional parallel beam case in this paper.

2. METHOD

Our reconstruction method, called NN-FBP, can be viewed as a nonlinear weighted sum of N_h FBP reconstructions. Each FBP uses a custom filter kernel, different from the usual Ram-Lak filter. The nonlinear logistic function is applied to each pixel of every reconstruction. Afterwards, a weighted sum is created from the FBP reconstructions, where the weights can be negative, and the logistic function is applied to each pixel of the sum. The result is the output of the NN-FBP method.

The custom filters and weights are trained by an artificial neural network, using a multilayer perceptron. A multilayer perceptron consists of three distinct layers: the *input* layer, the *hidden* layer, and the *output* layer. In the case of NN-FBP, the input layer has as many nodes as there are elements in a custom filter, the hidden layer consists of N_h nodes, and the output layer has only one node. The number of hidden nodes can be chosen freely, where more hidden nodes will usually lead to a more accurate, but slower method. Each input node is connected to all hidden nodes, and each hidden node is connected to the output node. Every connection between nodes has a certain weight associated with it. The structure of such a multilayer perceptron is shown in Figure 1a.

To perform the training, we used a supervised learning approach, where we need a set of training images, which will be used by the network to learn which filters and weights should be used for this particular type of data. During the learning phase, the method minimizes the squared error of the reconstructions with the training images. Therefore, the choice of training images will be important for the behaviour of the resulting NN-FBP method: the method learns image characteristics during training. After learning, the method will be good at reconstructing images similar to the training images, but, in general, it will perform worse on completely different images.
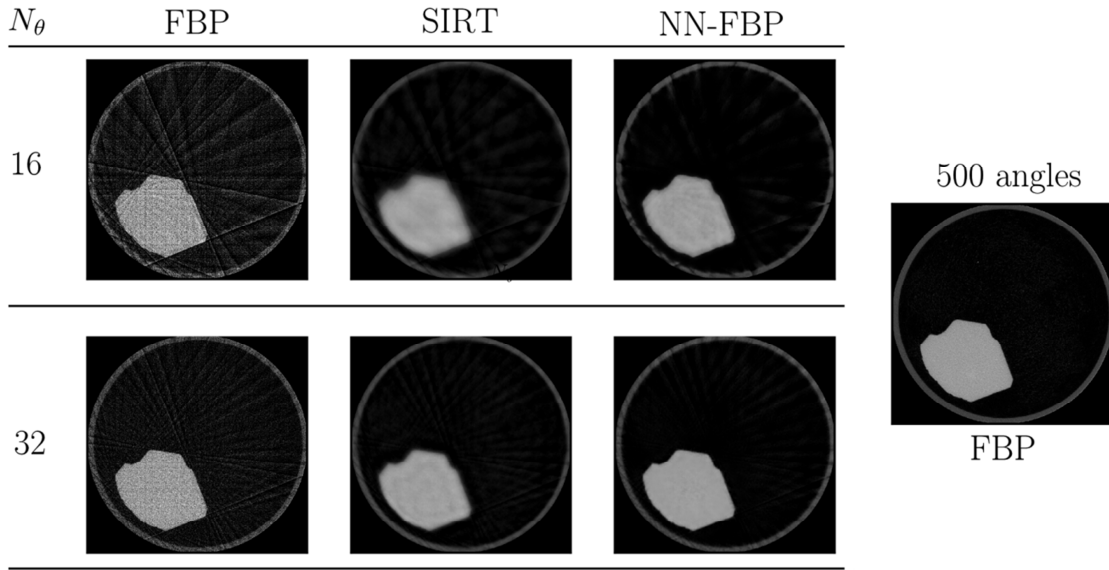
Figure 2. *Reconstructions of a single slice of a diamond dataset, acquired by a µCT scanner. The reconstruction on the right was obtained by the regular FBP method, using all 500 available angles. The other reconstructions were obtained using only 16 or 32 out of the available angles. The mean absolute pixel error for FBP, SIRT and NN-FBP with 16 angles is 0.163, 0.044 and 0.037, respectively, while the reconstruction time was equal to 0.02, 35.4 and 0.23 seconds. For 32 angles, the errors are 0.107, 0.036 and 0.032, with reconstruction times 0.02, 48.4 and 0.25 seconds.*

3.   EXPERIMENTS AND RESULTS

We implemented NN-FBP using Python and NumPy. For the training phase, minimization of the supervised learning error was performed by the Levenberg-Marquardt algorithm, which can be efficiently applied to neural networks (Hagan and Menhaj, 1994). In addition to the training images, we also used a set of validation images to improve the generalizability of our results, as explained in (Fine, 1999).

To test the reconstruction quality of the new method for limited-data problems, we performed experiments on three datasets of different raw diamonds, scanned using a Scanco µCT 40 X-ray scanner. The dataset consists of 629, 375 and 358 slices, respectively, and for each slice, 1024 line projections were acquired for 500 angles in $[0, \pi)$ range. FBP reconstructions of the first and second diamond were used as training and validation images. We trained the NN-FBP method to reconstruct using only N_θ out of all available angles. The selected angles were chosen such that they were still in $[0, \pi)$ range. All reconstructions were calculated on a 1024x1024 pixel grid. We chose to use eight FBPs to use in the NN-FBP method, resulting in a neural network with eight hidden nodes, which was experimentally verified to be a good compromise between reconstruction quality and computation time.

Results of NN-FBP for a single slice of the third diamond are given in Figure 2. The results show that NN-FBP is able to produce more accurate reconstructions than FBP using the Ram-Lak filter. Compared to SIRT, an algebraic reconstruction method (Kak and Slaney, 2001), the reconstructions of NN-FBP are slightly better. Furthermore, reconstructing the images using NN-FBP took almost a factor of 20 less time compared to SIRT. Training the neural network took roughly 1000 seconds. Note however, that we only have to perform this training once; afterwards, we can use the trained network to produce accurate limited-data reconstructions very fast.

4.   CONCLUSIONS

In this paper, we presented a reconstruction method, NN-FBP, which consists of several FBPs with custom filters. The custom filters can be efficiently optimized using artificial neural network techniques.

During this optimization, the method learns characteristics of the training images, which helps it to create accurate reconstructions for limited-data problems. Since the method is not iterative in nature, its computation time is much better than existing algorithms for reconstruction from limited data.

The results given in this paper seem to confirm these advantages of the NN-FBP method. When presented with data acquired over only a small number of angles, NN-FBP produced more accurate reconstructions than regular FBP, while being much faster than SIRT, which produced less accurate images as well. The data for which results are given was not used during training, which shows that the trained NN-FBP method can be applied in practice to reduce the number of projections or which data has to be acquired when scanning similar objects, or the same object at different time steps.

5.   ACKNOWLEDGEMENTS

6.   REFERENCES

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