Dynamic Angle Selection in X-ray Computed Tomography

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ABSTRACT

In X-ray tomography, a number of radiographs (projections) are recorded from which a tomogram is then reconstructed. Conventionally, these projections are acquired equiangularly, which intrinsically assumes that the information added by each projection does not depend on the angular spacing. However, especially in case when only a limited number of projections can be acquired, the selection of the angles has a large impact on the quality of the reconstructed image. In this paper, a dynamic algorithm is proposed, in which the new projection angle is selected by maximizing the information gain about the object, over the set of possible new angles. Experiments show that this approach can select projection angles for which the accuracy of the reconstructed image is significantly higher compared to the standard angle selection scheme.

1. INTRODUCTION

Tomography has a wide range of application areas, ranging from transmission electron tomography to seismic and astro-tomography. In many of these applications, it is highly desirable to reduce the number of projections taken, or it is even impossible to acquire many projections. In image-guided surgery, for example, a patient is being imaged for several times posing a serious radiation safety concern. In astro-tomography, only a few satellites are capable of imaging the corona of the sun, leading to long acquisition times. In electron tomography, the electron beam gradually damages the object, also imposing a restriction on the number of projections that can be acquired.

When an image is being reconstructed from a small set of projections, the set of projection angles used can significantly influence the reconstruction quality. In (Varga *et al.* 2011), it was shown that the quality of the reconstructions can be highly dependent on the projection angles in binary tomography. In that paper, an algorithm was proposed for identifying optimal projection angles based on a blueprint image known to be similar to the scanned object, which can be readily applied in the field of non-destructive testing. For the more general case of greyscale tomography, a framework was proposed in (Zheng and Mueller 2011), which allows to optimize the set of projection angles based on certain prior knowledge about the object. In (Batenburg *et al.* In press), a new strategy was recently proposed for angle selection in binary tomography, which does not require specifying prior knowledge about the object.

In present paper, this algorithm is adapted for use in greyscale tomography. It is a dynamic algorithm, which selects a new angle based on the currently available projection data and incorporates two major concepts: 1) sampling of the set of images that are consistent with the already acquired projection data and 2) determining the amount of information that can be gained by acquiring a projection from a particular angle.

2. APPROACH

The principle of the proposed approach is to select an angle for which a projection will be measured that gains as much knowledge about the object as possible. In (Batenburg *et al.* In press), a measure of such knowledge is proposed for binary images based on the diameter of the set of solutions that are consistent with all currently measured projections. In this paper, a similar idea is adopted and extended to grey level images.

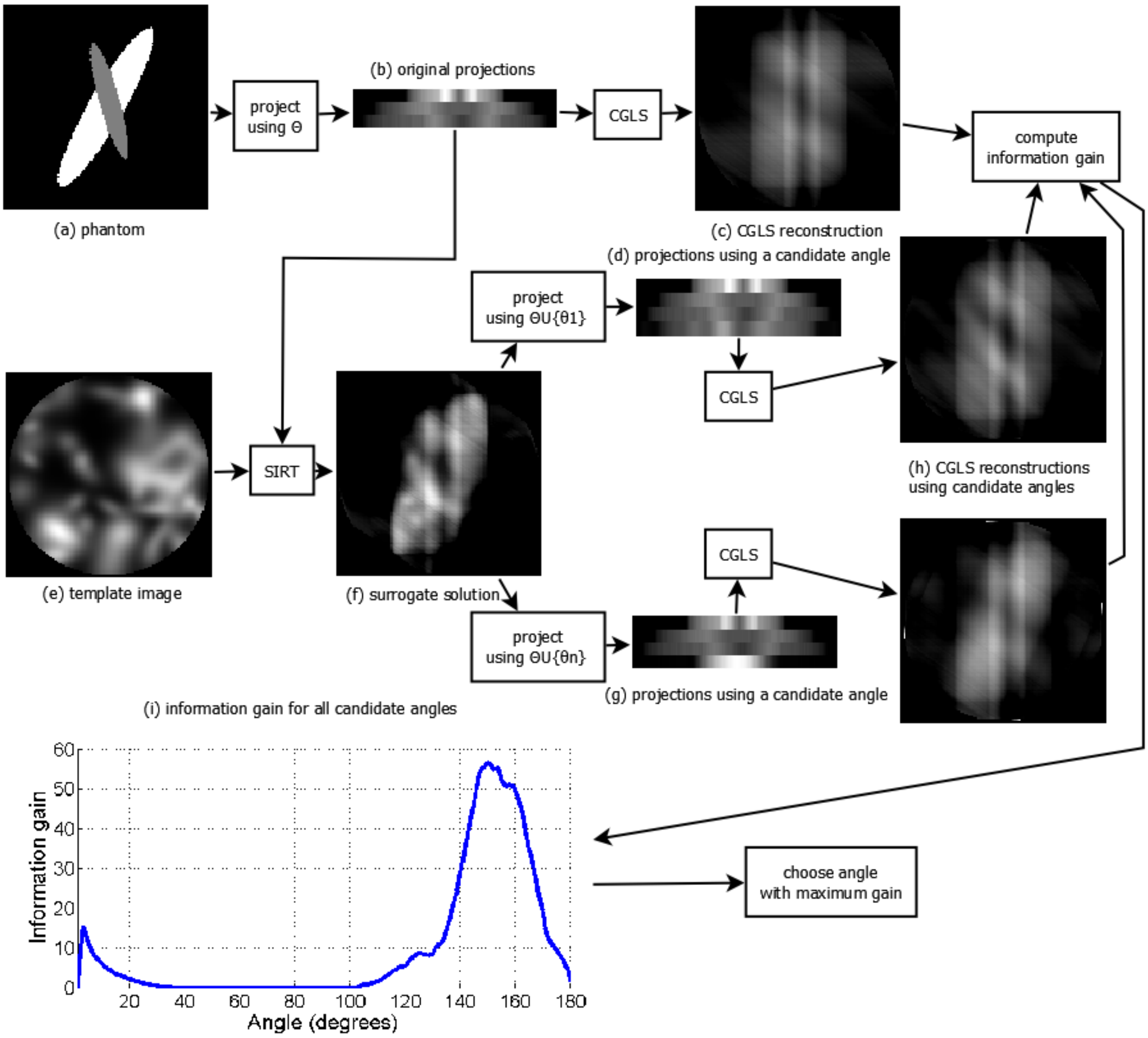

Figure 1: *Schematic overview of the proposed angle selection algorithm*

Consider projection data *p* (Figure 1(b)), which have already been measured for the unknown image (Figure 1(a)) using the current angle set *Θ*. A number of so-called *surrogate solutions* (Figure 1(f)) that are consistent with projection data *p* are calculated using randomly generated template images (Figure 1(e)) as the starting points for an iterative reconstruction algorithm. These template images belong to a parameterized family of grey level images and control the approximation of the solution set by the surrogate solutions, as some of the features of the template images are preserved in the corresponding surrogate solutions. Projections are then computed for the surrogate solutions along the set of candidate angles (the ones which can be selected next). The set of available projections, extended with one of the candidate angles, (Figure 1(d, g)) is then reconstructed using the Conjugate Gradient Least Squares (CGLS) method (Saad 2003), which produces the shortest real-valued solution (in the Euclidean sense) for a given system (Figure 1(h)). This operation is performed for each candidate angle. Next, the approximation of the information gain for the given surrogate solution and the given candidate angle is calculated as the difference of the upper bounds for the diameters of the solution sets using the CGLS reconstructions for the surrogate solution (Figure 1(h)) and for the original projection data (Figure 1(c)) (Batenburg *et al.* 2011). Finally, the average information gain for the candidate angles is calculated over all surrogate solutions and a candidate angle with the maximum information gain (Figure 1(i)) is chosen as the next projection angle for which a projection should be measured.

3. EXPERIMENTS

Simulation experiments were run using the phantom (Figure 2(a)) to assess the ability of the proposed algorithm to select favourable projection angles. The phantom was of size 128×128 pixels. The reconstructions were restricted to a disk of radius 64 pixels. Ideally, a quantitative evaluation of the proposed algorithm should include an experiment showing how well the information gain computed by the algorithm represents the actual information gain defined as the difference of the solution set diameters. However, due to the computational complexity of such evaluation, another evaluation procedure is used, based on the assumption that a good angle selection scheme will lead to a more accurate reconstruction from fewer angles compared to a reconstruction from angles chosen by a standard selection scheme.

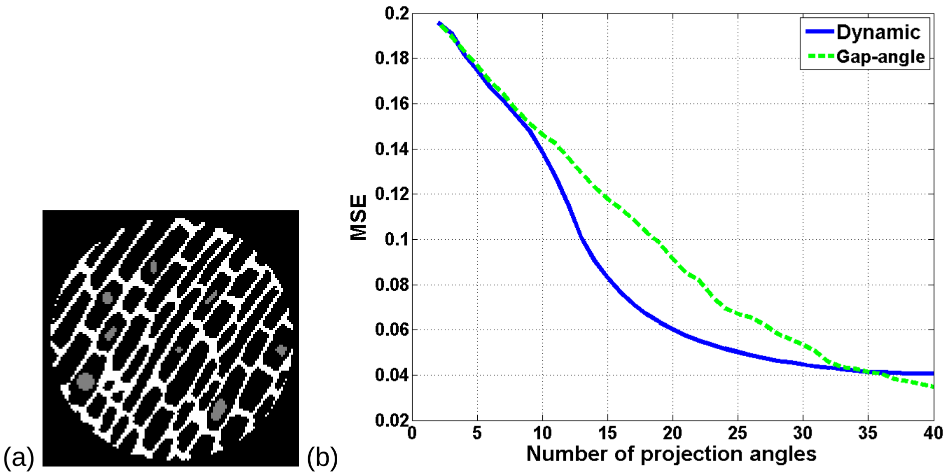

Figure 2: *The phantom used for the experiments (a) and MSE as a function of the number of projection angles (b)*

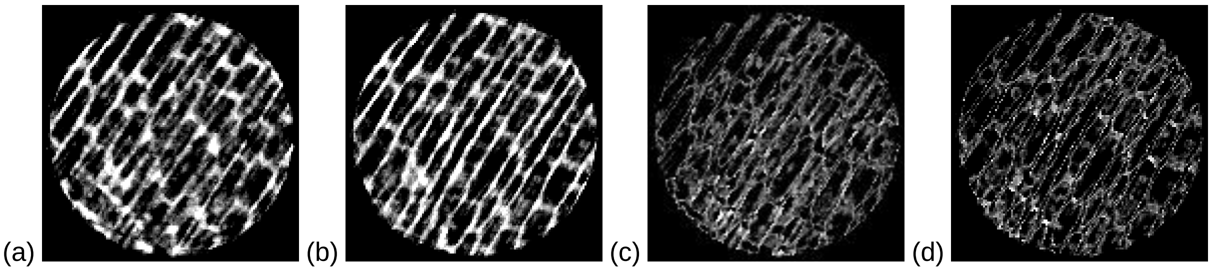

Figure 3: *The reconstructions of the phantom using 20 projection angles selected by the gap-angle algorithm (a) and the proposed algorithm (b) and the corresponding absolute difference images (c, d)*

For the presented experiment, the template images used for the generation of the surrogate solutions were generated as a superposition of 50 2D Gaussian blobs with randomly chosen orientation and standard deviation along both axes between 3 and 10 pixels. For the selection of each angle, $K = 10$ surrogate solutions were generated.

A so-called gap-angle scheme was chosen as an antagonist for the proposed algorithm. In the gap-angle scheme, a new angle is selected as the midpoint between the two consecutive angles with the largest angular gap between them. If several pairs of angles have equal gaps, one of them is chosen randomly. For the proposed algorithm, an angular step of 1° was chosen for the discretization of the angular domain. Nine angle sets were used as a starting point for both algorithms, containing two perpendicular angles and having an angular shift of 10° with respect to the previous initial angle set. As both selection schemes depend on a random seed, five seeds were used for each initial angle set, giving 45 starting configurations. For each of the starting configurations, angles were selected with both schemes under consideration and the selected angles were then used to compute reconstructions using 250 iterations of the Simultaneous Iterative Reconstruction Technique (SIRT) (Gregor and Benson 2008). The mean values of the mean squared errors (MSEs) of the reconstructions for all starting configurations were then calculated and plotted in Figure 2(b). Figure 3 shows the reconstructions of the phantom using 20 projection angles generated by the gap-angle and the proposed algorithm along with absolute difference images.

For the phantom used in the experiments, the proposed algorithm shows significantly better results for a number of projections ranging between 10 and 30, allowing to greatly reduce the number of projections required to obtain a reconstruction with the quality comparable to a reconstruction from a much larger number of angles provided by the gap-angle algorithm. Results of the preliminary experiments suggest that the performance of the algorithm depends significantly on the object under concern, and a full study of its properties is currently being performed.

4. CONCLUSION

In this paper, a dynamic algorithm for angle selection in greyscale computed tomography was proposed, which is based on a formal model involving a concept of information gain over a set of solutions of the reconstruction problem. Several approximation steps were introduced in order to transform this model to a practical algorithm. Simulations show that this approach can provide the projection angle sets leading to the more accurate reconstructions compared to the standard gap-angle approach. However, the computational complexity of the proposed algorithm is not feasible for large experimental datasets, leaving room for further investigation. Another important open question is the influence of the template images on the results. In future work, these issues will be investigated.

5. ACKNOWLEDGEMENTS

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