International Journal of Electronics Communication and Computer Engineering
Volume 5, Issue (4) July, Technovision-2014, ISSN 2249–071X

Technovision-2014: 1st International Conference at SITS, Narhe, Pune on April 5-6, 2014

Threshold Selection using Segmentation Inconsistency Minimization Technique in Tomographic Reconstructions

Ms. Komal D. Yamgar
Dept. of Electronics and Telecommunication
PVPIT, Pune University, Pune, India
Email: komyam@yahoo.com

Prof. B. V. Pawar
Dept. of Electronics and Telecommunication
PVPIT, Pune University, Pune, India
Email: bvpawar1@gmail.com

Abstract **– Tomographic reconstructions are often segmented to extract valuable quantitative information. In this paper, we consider the problem of segmenting a dense object of constant density within a continuous tomogram, by means of global thresholding. Selecting the proper threshold is a nontrivial problem. Segmentation Inconsistency Minimization is used for segmentation of dense, homogeneous objects in a tomographic reconstruction. The propose a new method exploits the available projection data to accurately determine the optimal global threshold.**

Keywords **– Threshold, Reconstruction, Segmentation, Simultaneous Iterative Reconstruction Technique (SIRT).**

I. Introduction

Tomography is a technique for obtaining images of the interior of an object from projection data, acquired along a range of angles. Quantitative information about objects, such as their shape or volume, is often extracted as a postprocessing step. To obtain such information from the greylevel tomogram, segmentation has to be performed. If the scanned object consists of a small set of materials, each corresponding to an approximately constant grey level in the reconstruction, it is sometimes possible to combine reconstruction and segmentation in a single step, using techniques from discrete tomography [4].In some cases, this can lead to a dramatic reduction in the number of projections required for an accurate reconstruction.

Basically, image segmentation is to partition an image into meaningful regions with respect to an application.The segmentation is based on measurements taken from the image that might be grey level, colour, texture, depth or motion. Applications of image segmentation includes identifying objects in a scene for object-based measurements such as size and shape .The segmentation is to simplify change the representation of an image into something which is more meaningful and easier to analyze. Image segmentation is used to locate objects and boundaries in images. Dense objects are not clearly seen in images i.e. they are blurred images. We can process these objects using segmentation.

II. Related Work

For dense object segmentation, it is a common choice to set a global threshold somewhere between the grey level of the pixels belonging to the object and those of the maximum value of the other pixels. Typically, this threshold is selected based on the histogram of the tomogram. If only a few materials are present and each of these correspond to a distinct grey level peak in the histogram. Accurate determination of appropriate thresholds is possible. This can be done by analyzing the concavity points on the convex hull of the histogram or by modeling the histogram as a mixture of a series of Gaussian distributions. The most popular global threshold selection method is the clustering method of Otsu [1].It minimizes the weighted sum of intra-class variances of the different segmentation partitions.

Histogram-based methods in the context of segmenting a homogeneous object in a continuous grey level image does not guarantee peaks that will be representing the continuous background. Histogram-based methods are particularly inadequate if the object of interest is only slightly more dense than the surrounding materials.

There are different approaches to segmentation of dense objects like region-based algorithms such as region growing and watershed segmentation .These methods are also solely based on the reconstructed image and are therefore very susceptible to reconstruction artefacts. Recently, a new method was proposed for global and local threshold selection in tomograms, called projection distance minimization (PDM) [2][3].This approach is based on the assumption that the scanned object contains a small number of different densities and each corresponds to a constant grey level in the reconstruction. By segmenting the reconstructed image, tomogram is restored. Projections of the segmentation are computed and compared to the measured projection data so that we can measure the quality of this segmentation. An optimal segmentation will result in maximal correspondence between the simulated projections and the measured dataset. The preliminary work on this topic was published and an algorithm called segmentation consistency maximization (SCM) was introduced in [4]. The basic strategy behind the newly proposed SICM is similar to that of SCM, but there are significant differences as well, such as the addition of automatic grey level estimation and a more elaborate optimization technique.

III. SICM ALGORITHM

Using scanner, intensity projection images are acquired for a set of projection angles. After the projection data is acquired, a preprocessing step is applied to prepare the data for use in a reconstruction algorithm. In the next phase the reconstruction is performed. Often, the reconstructed images contain pixels whose values do not correspond to the attenuation factors of the original object. They are referred to as reconstruction errors or reconstruction artefacts and can arise due to a variety of reasons. Given the collection of possible reconstruction artefacts, the reconstructed image may not be suitable for analysis without segmentation step. All common segmentation techniques are effectively postprocessing steps. They are solely based on the finished reconstructed image. At the final step in the flow diagram the data is ready for analysis shown in Fig 1.

Segmentation Inconsistency Minimization SICM algorithm will be used. This SICM algorithm combines grey level estimation with segmentation inconsistency computation. It uses the segmentation inconsistency found after a fixed number of SIRT iterations as a quantitative measure for the quality of the selected threshold. The overall system is shown in Fig 2.

The set of all valid continuous Sinograms describe a set of conditions that must be satisfied by all sinograms, known as consistency conditions. In a discretized setting, where projection data is available only for a limited set of angles a measured sinogram is called consistent. In practice, a sinogram will rarely be consistent due to noise, discretization, and partial volume effects.

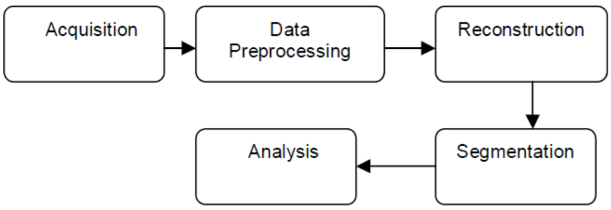


Fig.1. Tomographic Segmentation

The inconsistency of a sinogram given by

$$min_{x \in R_n} \| Wx - p \| \quad (1)$$

Where ||•|| operator denotes distance between p and the nearest consistent sinogram.
p is the measured projection data.

The segmentation inconsistency (SIC) of any segmentation image is defined as

$$SIC(\hat{s}) = IC(p_{\tilde{A}}) := \| WS_{\tilde{A}} (p - W_{\hat{s}}) - (p - W_{\hat{s}}) \|_R \quad (2)$$

Where p Ā is residual sinogram of the region Ã.
p is the measured projection data.
W is the projection operator that maps the image v to the projection data q.
S is the linear operator that creates a SIRT reconstruction of p.
ŝ denotes segmentation of the dense object.

This SICM method is used for dense object segmentation. For each segmentation, the projections of the segmented object are subtracted from the measured projection data, and then remaining part of the image is reconstructed and checked for consistency with the residual projections. The threshold for which minimal inconsistency is obtained is selected for the segmentation. Here the assumption is that, the density of the object is constant and that it is higher than all remaining densities in the scanned object.

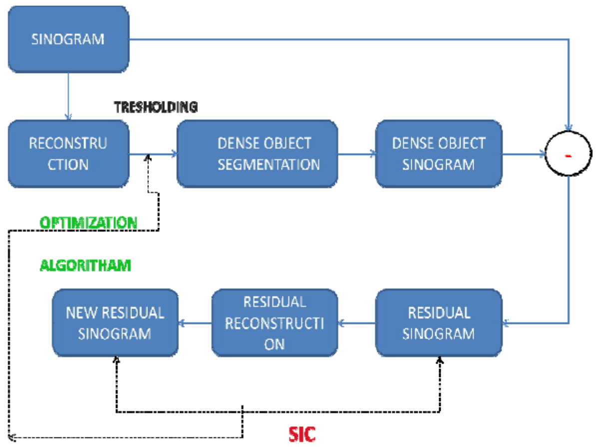
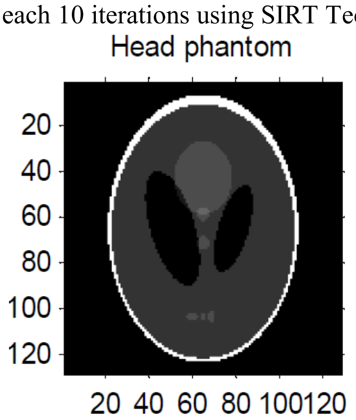


Fig.2. Schematic overview of the SICM algorithm.

IV. RESULTS

Simulation was performed using head phantom image. Fig 3(a) shows head phantom image, Fig 3(b) shows sinogarm of Fig 3(a). Fig 3(c) to 3(l) shows reconstructed images after each 10 iterations using SIRT Technique.



(a)

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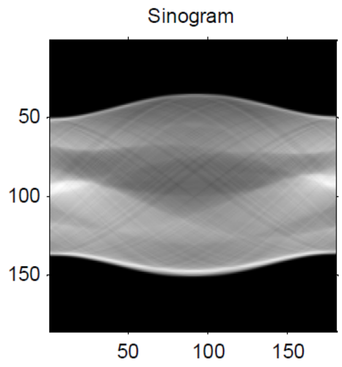
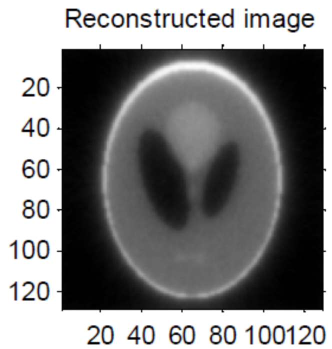
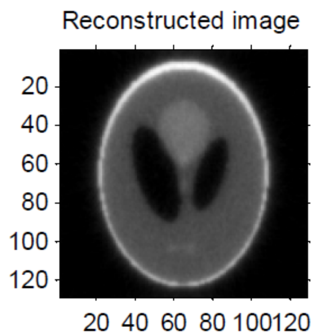


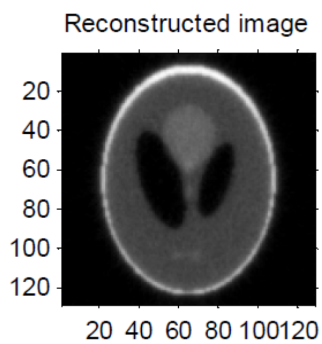
(b)



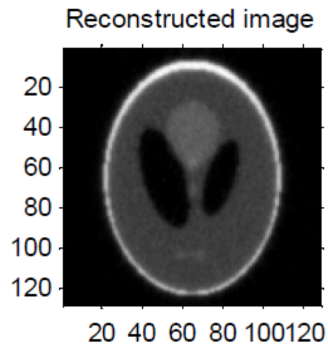
(c) After 10 Iterations



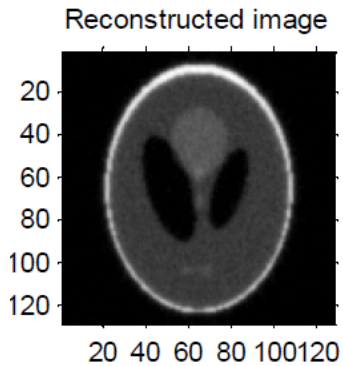
(d) After 20 Iterations



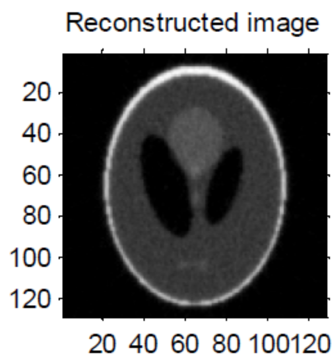
(e) After 30 Iterations



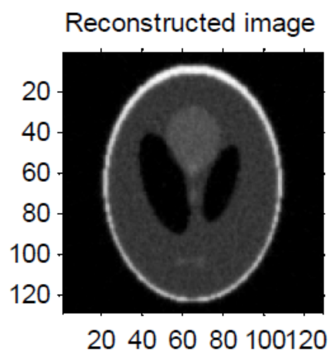
(f) After 40 Iterations



(g) After 50 Iterations



(h) After 60 Iterations



(i) After 70 Iterations

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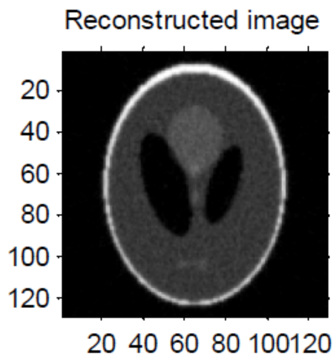
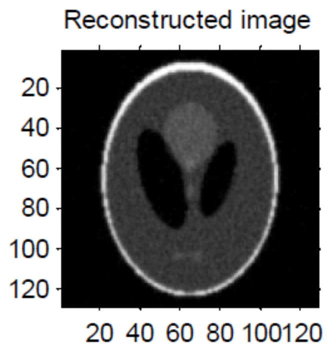
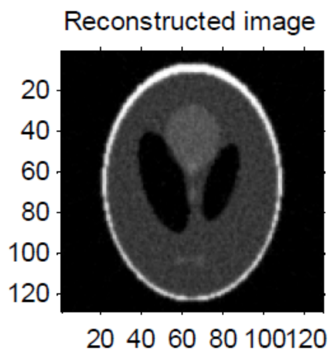


(j) After 80 Iterations



(k) After 90 Iterations



(l) After 100 Iterations

V. Conclusion

In this paper, we have presented a novel method for finding a global threshold to accurately locate dense objects in a continuous surrounding in a tomographic reconstruction. The SICM method is not only based on the reconstructed image, but also on the available projection data.

Acknowledgment

I am extremely thankful to Prof .B.V.PAWAR for giving me helpful guideline. He always supported and guided me.

References

[1] N. Otsu, "A threshold selection method from gray level histograms,"*IEEE Syst., Man, Cybern. C*, vol. 9, no. 1, pp. 62–66, Mar. 1979.
[2] K. J. Batenburg and J. Sijbers, "Optimal threshold selection for tomogram segmentation by projection distance minimization," *IEEE Trans. Med. Imag.*, vol. 28, no. 5, pp. 676–686, May 2009.
[3] K. J. Batenburg and J. Sijbers, "Adaptive thresholding of tomograms by projection distance minimization," *Patt. Recognit.*, vol. 42, no. 10, pp. 2297–2305, 2009.
[4] W. van Aarle, J. Batenburg, and J. Sijbers, "Threshold selection for segmentation of dense objects in tomograms," in *Int. Symp. Visual Computing, Ser. Lecture Notes Comput. Sci.*, G. Bebis, Ed., Berlin, Germany, Dec. 2008, vol. 5358, pp. 700–709.
[5] *Integral geometry and Radon transforms*, by Sigurdur Helgason, Springer, New York, 2010, xiv+301 pp., ISBN 978-1-4419-6054-2, hardcover