17th World Conference on Nondestructive Testing, 25-28 Oct 2008, Shanghai, China

3D Image Reconstruction from Low Energy and Noisy X-Ray Projection Data

Valery VENGRINOVICH, **Sergei ZOLOTAREV**, **Iliya RESHETOUSKI**, **IAPH, Minsk**, **Belarus Tel:**
+375-17-2842344, Fax: +375-17-2842344 E-mail: veng@iaph.bas-net.by Web: http://iaph.bas-net.by
Oleg TROFIMOV, **Alexej LIKHACHEV, Institute of Automation and Electrometry SB RAS, Novosibirsk, Russia. E-mail: ipm1@iae.nsk.su Web: http://www.iae.nsk.su**

Abstract

Conventional tomography offers an effective tool for medical diagnostics, non-destructive testing of engineering constructions and checking the quality of industrial products. The tomographic imaging of objects in case of a restricted angle for observation, limited number of projections, and/or restricted x-ray source power becomes strongly ill conditioned. The article deals with the last case, within which the linear attenuation for a partial set of views does not valid any more: thus for them the beam hardening effect introduces substantial uncertainty to reconstruction results. Two kind of approaches are considered: 1) beam hardening effect influence compensation with some kind of linearization procedure in CAD description; 2) introducing 2D and 3D hull deformation algorithms, which are highly effective for tomographic reconstruction of binary object.

Keywords: X-ray tomography, limited data, hull approach, low energy, beam hardening

1. Background

Recently industrial X-ray tomography accelerated very quickly: the production of shaped castings, complex automotive parts, turbine blades, precise mechanisms, multi layer electronic boards, biological structures, etc. is inconceivable without this technology. It allows to observe the hidden cavities, provide non destructive testing, measure linear dimensions, approve complex structures and so on.

Tomographic visualization helps to recover the three-dimensional digital images of manufacturing workpieces and processes. Usually applied Radon transformation (the fundamentals are available in [1]) and its 3D version named filtered back projections (FBP) (fundamentals are available, for example, in [2]) yield excellent results for the complete set of projections, the case defined by the entirely filled Radon space. However, in case of a restricted angle for observation and small number of projections the acquisition data are limited and noisy, thus the reconstruction problem becomes strongly ill conditioned. Bayesian iteration methods are sometimes very advantageous to improve the quality of final image (look, for example, [3-6]).

Limited and noisy data conditions are appear also in case of restricted x-ray source power. That means that within entire set of observation angles there are a limited set for which the x-ray linear absorption rule does not valid any more. For them the beam hardening effect introduces substantial uncertainty to reconstruction results, which are finally corrupted by this effect. The image then can be reconstructed with the help of conventional iterative algorithms only by neglecting corrupted data and worsening thus the final image quality [7,8,9]. Use of prior information in the form of image statistical properties is sometimes very helpfull [10-14].

The situation like limited x-ray source power is very typical for industrial tomography. It takes place when the part is very large or extended in one or several directions, or the material has too large absorption coefficient, also in all cases demanding decreasing of the radiation dose. It should be noted that the decreasing of utilized x-ray source energy is motivated by both decreasing of the radiation dose and focal spot dimension respectively. Thus it is important to develop reconstruction tools able to overcome data deficit typical for this kind of restrictions: limited observation angle and corrupted x-ray projections.

Two kind of approaches are considered in the article as used here: 1) beam hardening effect influence compensation with some kind of linearization procedure in CAD description illustrated by the image reconstruction of turbine blades; 2) introducing 2D and 3D hull deformation algorithms, which are highly effective for tomographic reconstruction of binary objects, illustrated by the engine cylinder head image reconstruction.

2. Iterative reconstruction of turbine blades images

Turbine blades are widely used in conventional engines. They have numerous types and shapes of cooling cavities, which should be done with high precision. One of them is shown in the fig.1, which cross section image, restored with FBP algorithm from projections acquired with the help of 420 kV tube, is shown in the fig. 3. There is no way to observe the blade internal structure non destructively except of tomographic imaging. It is usual that the ratio of linear dimensions in self perpendicular directions could be by factor 5 or more . Thus the x-ray source power should be sufficient to penetrate linearly through longer distance what requires 420 kV x-ray tube available to penetrate through a small blade with only 70 mm size in longer direction (Fig. 3).

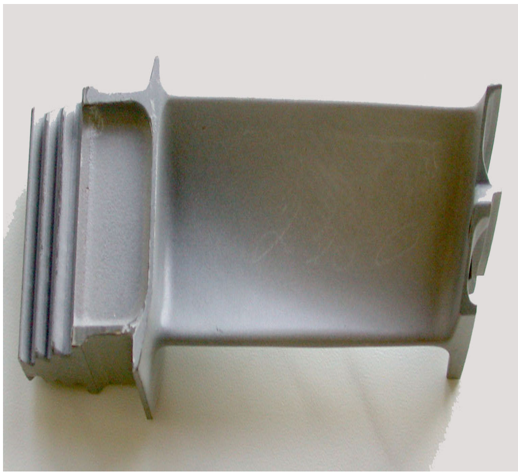

Fig. 1. Turbine blade used for experiments.

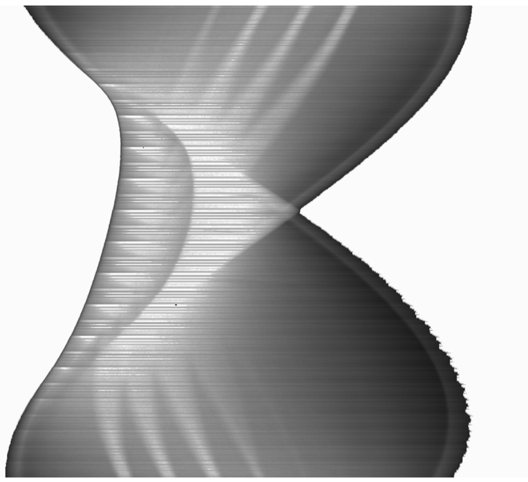

Fig. 2. 480 blade projections made with 125 kV x-ray source by prof. E.Vainberg

Further in the figure 2 the linear 480 projections of the blade's cross sections are pictured (so called synogram), containing 1024x480 16 digit values. In this case the X-ray shooting was done at a tube voltage 125 кВ (integrally required 420 kV), and, the scattered radiation was avoided by remoteness from detectors and collimation. Due to loosened radiation power the projections in elongated directions are saturated, fuzzy and noisy. In the fig. 4 the cross section of a blade reconstructed from projections in the fig.2 with FBP algorithm is shown, which illustrates its incapability to overcome the data deficit originated from low source power.

The technique proposed here includes the correction of experimental data considering beam hardening effect. For this the experimental calibration (special x-ray test) was done using the 125 kV polychromatic synogram (fig.2) and the CAD of representation of the known true shape of the regular blade shown in the fig.3 (kind of a quantitative a priory knowledge). The resultant

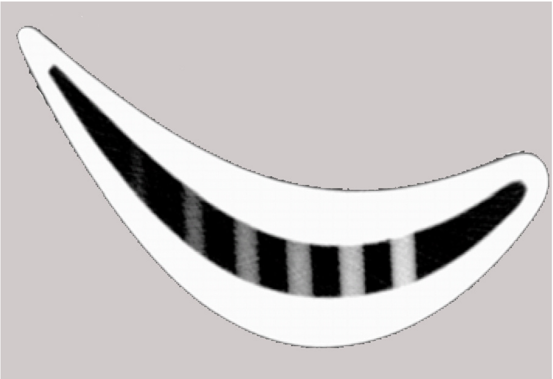

Fig.3 Blade image reconstructed from 480 projections made with 420 kV x-ray source using FBP algorithm

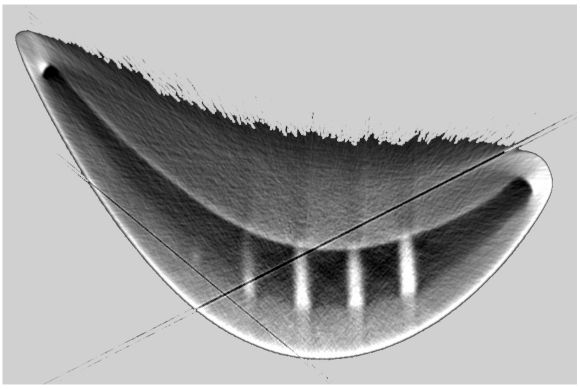

Fig. 4. Blade image reconstructed from 480 projections made with 125 kV x-ray source using FBP algorithm

diagram and its polynomial approximation considering beam hardening effect are shown in the fig.5. It aims to provide correction of all experimental data during the further reconstruction process.

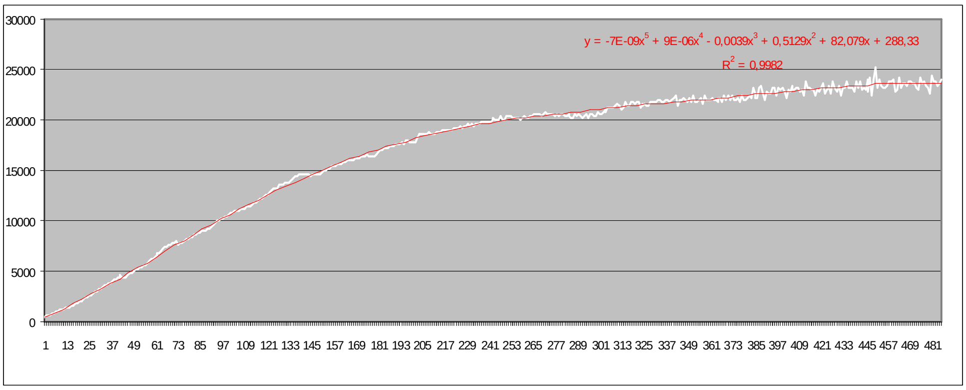

Fig.5. Thickness dependence of the x-ray intensity for turbine blade steel

Finally the Bayesian reconstruction [12] of the blade's image was made basing on only 240 circular projections. In a fig. 6 and 7 the outcomes of iterative reconstruction after 16 and 20 iterations respectively are pictured. The obtained spatial resolution already is close enough to that shown in the fig. 3 and much better than that acquired with regular FBP algorithm in the fig. 4.

Thus the way for compensation of input data incompleteness on the basis of implementation of beam hardening correction in the proposed manner seems to be efficient tool for data correction before starting with Bayesian algorithms basing on available number of projections and a priory known CAD of representation of an object under testing. The further development and elaboration of this approach should allow ton essentially improve the efficiency of the tomographic visualization of complex articles generally and turbine blades in particular using minifocal x-ray sources with low-level voltage.

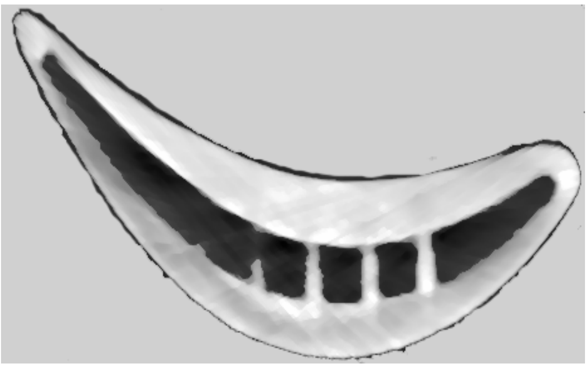

Fig.6. Blade image reconstructed from 240 projections made with 125 kV x-ray source

3. Surface reconstruction of 3D binary industrial object given its CAD representation: the solution of a straight forward problem

The surface S is represented by a set of surface elements $S_u : u = 1,\ldots,U$, $S = \bigcup S_u, S_{u_1} \cap S_{u_2} = 0, u_1 \neq u_2$ specified by triangles with vertexes defining the nodes of a discrete grid. Let assign the projection of the surface element S_u in the n-th detector plane as σ_u^n . The partition of the surface is implemented in such a way that the osculating sides of adjacent triangles and their common vertexes belong only to one of the vertexes.

The direct operator sequentially searches through all inner hull elements for:

(a) the determination of the projection of triangle S_u on the current detector plane
(b) the definition of triangle boundaries
(c) the selection of all pixels $p_j^n : j = 1,\ldots,J_n$ with the center located inside the triangle σ_u^n or on its boundaries
(d) the cross points of the rays, passing through the inner and boundary pixels of the triangle σ_u^n, with the inner and outer object surface.

The ray sums $f_n^c(p)$ for pixel $p_j^n : j = 1,\ldots,J_n$, defining the corresponding ray, are calculated as the distances between corresponding pairs of points. Hence the ray sums can be determined after calculating the forward operator $A(\boldsymbol{R}(M))_n = f_n^c(p), n = 1,\ldots,N$. The functional

$$\delta_n(\sum_k \vec{R}_k(M)) = \sum_{p_1^n}^{p_{J_n}^n} \left| f_n^c(p) - f_n^m(p) \right| / \sum_{p_1^n}^{p_{J_n}^n} f_n^m(p) \tag{1}$$

represents the difference between the current surface S, which is given by a set of discrete grid knots $M_i, i = 1,\ldots,I$, and the surface, being the best fit to the measured data.

Average value of standard deviation is

$$\delta_{mid}(\sum_k \vec{R}(M)) = \sum_n \delta_n(\sum_k \vec{R}(M)) / N . \tag{2}$$

4. Surface reconstruction of 3D binary industrial objects, given its CAD representation: the solution of an inverse problem

The iteration procedure for reconstructing the surface is implemented as follows from[13]. All N rays are passing through every knot M_i , which has an intersection with the corresponding detector planes in the pixels $p_{j*}^n, n = 1,\ldots,N$. For those pixels the differences between the measured and the calculated values of the ray sums $\Delta f_n(p) = f_n^c(p) - f_n^m(p)$ are evaluated in avaerage form. From this result the weighed mean deviation $\Sigma(M_i)$ is determined

$$\Sigma(M_i) = \sum_n \Delta f_n(p) / N \qquad (3)$$

Finally the corresponding displacement of the node M_i is given by

$$h(M_i) = \lambda^{(0)} \times \Sigma(M_i), \quad 0 < \lambda^{(0)} < 1, \qquad (4)$$

where $\lambda^{(0)}$ is the parameter of relaxation for the first iteration.

The displacements are implemented for all nodes $M_i, i = \overline{1, I}$ simultaneously. The iterative process stops, if after three series iterations it fails to receive the better approximation.

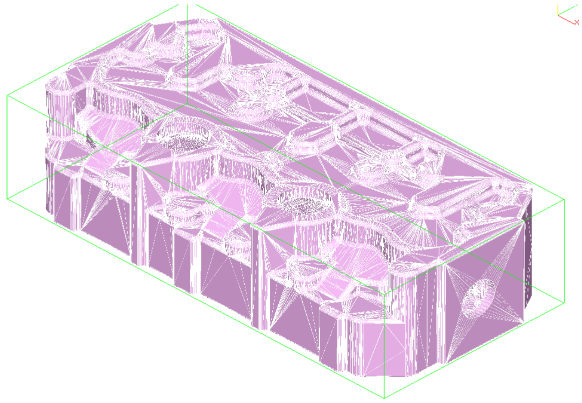

Fig. 7. 3D view of the head (STL format)

The reconstruction of the head of a cylinder block was executed for so-called "circumferential" geometry for projections data collecting. The head was virtually rotated around its longitudinal axes and parallel and cone beam geometry were applied respectively. Three-dimensional object was projected on a flat matrix of detectors, which plane is perpendicular to a central ray of conical source. The distance from the source to the plane detector and rotation axes was 1000 mm and 700 mm respectively. 60 projections were done, that is much less, than is used for the regular computed tomography (several hundred projections). Voxel representation of this object was created. To check the reconstruction accuracy seven holes were simulated in head's internal walls. The diameters of the holes varied from 2 mm to 8 mm with a step of 1 mm. The model 60 projections of the head of a cylinder block, both for parallel and for conical beams of rays were obtained. In the fig. 7 the head of a cylinder block in the STL format is shown. To illustrate them the corresponding simulated central cylinder head projection is shown in the fig. 8: left – supposing a source with sufficient voltage, named original; right – truncated supposing the source voltage is sufficient to penetrate through the 80 mm thickness steel wall, named truncated. Truncation was used to simulate the insufficiency of the source voltage to irradiate too large thickness material. The right picture visually demonstrates a loss of information with low energy source radiation.

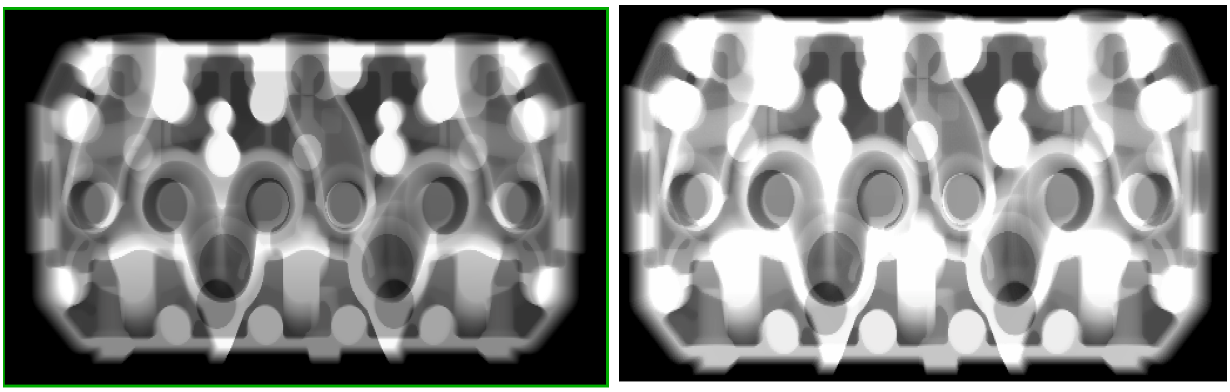

Fig. 8. Central cylinder head projection: left – original; right – truncated for 80 mm thickness

For the image reconstruction both the Bayesian and newly developed hull voxel algorithm were used. The demonstration of their capability is shown in the fig. 9 and fig. 10.

Fig.9 shows the central cylinder head projection after reconstruction by the Bayesian algorithm: left – using simulated complete data set (sufficient power source); right – using truncated data. It is clear that complete raw data set even from 60 x-ray projections is sufficient to be proceeded within Bayesian algorithm to acquire perfect reconstruction with available resolution of the simulated holes. Meanwhile the application of truncated data (fig. 9 right) yields blurred reconstructed image with strong resolution lost.

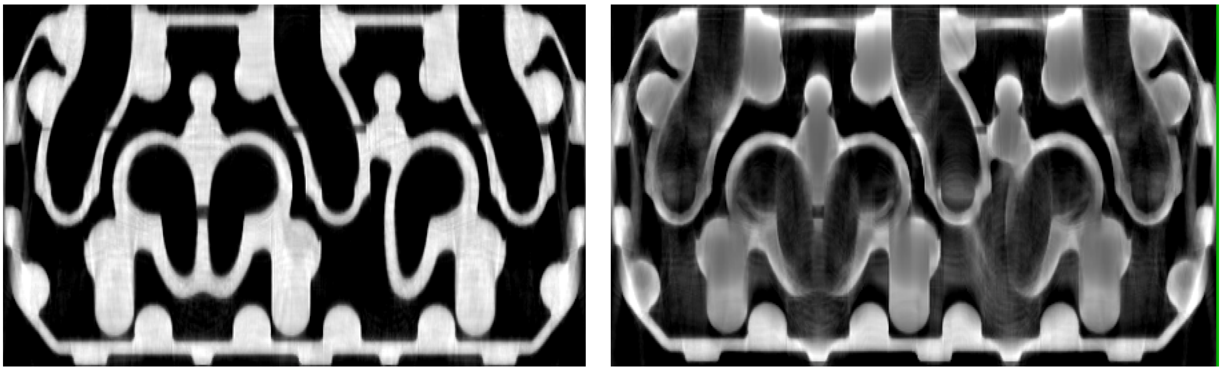

Fig.9. Central cylinder head projection after reconstruction by the Bayesian algorithm: left – using simulated complete data set (sufficient power source); right – using truncated data.

In the fig. 10 the central cylinder head projection after reconstruction by hull-voxel algorithm from truncated data with binary a priori supposal is presented. Note that truncated data means that the depth with linear absorption law is limited to 80 mm while the data from all excessive thickness are lost on the projections. Meanwhile, the minimum direct thickness of the steel in the cylinder head is 200 mm. Thus the algorithm shows a strong capability comparing the images in the fig.9 and the fig. 8, right, respectively. For both images reconstruction the same truncated data were used.

Fig.10. Central cylinder head projection after reconstruction by hull-voxel algorithm from truncated data and binary a priori supposal

Conclusion

The newly developed hull-voxel method of reconstruction of 3D images of industrial objects given restricted number of projections and extremely low voltage x-ray source has ensured high quality of reconstruction.

References

[1] Vengrinovich V.L., Denkevich Y.B. ,Tillack G.-R., Heine S. X -ray 3D reconstruction using minimal projections and maximum a priori knowledge. Proc. International Conference “Computer methods and Inverse Problems in nondestructive Testing and Diagnostics”, 21-24 Nov., Minsk, 1995, pp. 77-82.
[2] Vengrinovich V.L., Zolotarev S.A., Tillack G.-R., C.Nockemann. X-ray 3D reconstruction of objects with unhomogeneous internal structure using. Proc. International Conference

“Computer methods and Inverse Problems in nondestructive Testing and Diagnostics”, 21-24 Nov., Minsk, 1995, pp. 124-128.
[3] Венгринович В.Л., Денкевич Ю.Б., Тиллак Г.-Р. и К. Ноккеман. Многоступенчатая 3-х мерная рентгеновская томография для ограниченного числа проекций и обзоров. Журнал США «Прогресс в количественном неразрушающем контроле», том 16, Нью - Йорк, 1997, с. 317-323.
[4] Золотарев С.А., Венгринович В.Л. и Тиллак Г.-Р. Трехмерная реконструкция по минимальному числу проекций с внутриитерационным подавлением теневых артефактов. Техн. диагн. и неразр. контроль, Киев, 1998 г., №2, с. 32.
[5] V. Vengrinovich., Yu. Denkevich, G.-R. Tillack. Reconstruction of Three-Dimensional Binary Structures from an Extremely Limited Number of Cone-Beam x-ray Projections. Choise of Prior. Journal of Phys., D:Applied Physics. – 1999. - V.32 - pp. 2505-2514.

[6] V. Vengrinovich, Yu. Denkevich, G.-R. Tillack. Bayesian 3D x-ray reconstruction from incomplete noisy data. In book: Maximum Entropy and Bayesian Methods, ed. by W. von der Linden et. al.. Kluwer Academic Publishers,.1999. - pp. 73-83.7. V. 7. 7.

[7] V.Vengrinovich, Yu. Denkevich, G.-R. Tillack. Limitied projection 3D X-ray tomography using the maximum entropy method. Review of Progress in QNDE, ed. by D. O. Tompson and D.E.Chimenti, Plenum Press, N.Y., 1998. - v. 17. - pp. 403-410.

[8] V. Vengrinovich, Yu. Denkevich, G.-R. Tillack, U.Ewert. Bayesian Restoration of Crack Images in Welds from Incomplete Noisy Data. Review of Progress in QNDE, ed. by D.O.Tompson and D.E.Chimenti, American Institute of Physics, Melville-N.Y., 2000. - v. 19A. - pp. 635-642.

[9] V.Vengrinovich, S.Zolotarev, G.-R. Tillack. Inner pipe’s surface 3D reconstruction for double-connected object from limited projections. Journal of technical diagnostics and NDE. – 2001. - No. 2. - pp.8-11.

[10] Венгринович В.Л Трехмерная томографическая визуализация труб в процессе эксплуатации. / // 4 – ая национальная научно-техническая конференгция «Неразр. Контроль и Техн. Диагн.», - Киев, - 2003 . - С. 46-50.
[11] V. Vengrinovich, Yu. Denkevich, G.-R. Tillack. Reconstruction of Three-Dimensional Binary Structures from an Extremely Limited Number of Cone-Beam x-ray Projections. Choise of Prior. Journal of Phys., D: Applied Physics. 1999. - V.32. - pp. 2505-2514.
[12] V. Vengrinovich, Yu. Denkevich, G.-R. Tillack. Bayesian 3D x-ray reconstruction from incomplete noisy data. In book: Maximum Entropy and Bayesian Methods, ed. by W.von der Linden et. al.. Kluwer Academic Publishers, 1999. - pp. 73-83.
[13] V.Vengrinovich, S.Zolotarev, A.Kuntsevich, G.-R. Tillack. New technique for 2d an 3d x-ray image restoration of pipes in service given a limited access for observation**.** Review of progress in qnde, ed. by D. O. Tompson and D. E. Chimenti, American institute of physics, melville-n.y, 2001. - v. 20a. - pp.756-763.
[14] Zolotarev S.A., Vengrinovich V.L. and Tillack G.-R. 3D Reconstruction of Flaw Images with Inter -Iterational Suppression of Shadow Artefacts. Rev. Prog. in QNDE, Vol 16, ed. by D.O. Thompson and D.E. Chimenti, Plenum Press New-York, 1997.