Three Dimensional Reconstruction of Medical Spiral CT-Scanner Images, For Industrial Parts

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***Abstract*- In this paper we study the accuracy of reconstruction of an industrial part from a medical spiral CT[1] scanner. The reconstruction is performed using the periodic Bspline representation algorithms. We study the several acquisition methods and reconstruction parameters and use the methods such as sharp edges detection and reconstruction to exhibit the influence of them on the overall reconstructed model. Finally we use Rapidform software to compare the reconstructed model with original CAD model of part after a registration which minimizes the distance between the two models.**

Keywords: surface reconstruction, Bsplines, curve and surface approximation, Spiral CT-Scan

I. Introduction

"Tomography" literally meaning is "the image of cutting". So, Computed Tomography (CT) systems provide non-destructively the result expected by cutting a part in a particular plane [1]. From the past in medical branches great improvements have been made in computed tomography techniques and in the last decade we can also see the usage of that in reverse engineering and CAD modeling. Computed Tomography (CT) first was an inner-health analysis tool for industrial parts such as composite products. From 2D slices of the examined part, information about porosity and lacks could be extracted easily. Thus, CT became logically a powerful 2D dimensional tool. But nowadays with new methods, CT became a 3D industrial digitalization tool. In this work our aim is to providing 3D reconstruction of an industrial part from medical spiral CT scanner.

There exist several reconstruction methods of tree dimensional models from volumetric images. A first class of methods consists in creating a set of contours on each slice and then applies a meshing algorithm that links contours on neighboring slices. But we have chosen a reconstruction method based on the Bspline approximation theory.

Henceforth, the organization of the paper is as follows. In Section 2 we used an image processing method to extract data points from CT images. Section 3 briefly presents required background for Bspline approximation. The surfa is outlined in Section 4. The section 5 discusses the accuracy of proposed method followed by the last section which presents some experimental points and concludes the paper.

II. Image processing

Nowadays digital images do not need different image filtering techniques due to improved quality. Usually edge detection is first step in image processing to extract features and data points. Several edge detection methods exist that divided into two important categories: Local methods and Global methods. Local methods are simpler and they need short time to process but global methods are more accurate [2]. The obtained edges play an important role in the quality of the final model. Thick and interrupted or undetected edges cause error in next steps. The edge detection algorithms such as Sobel are among primary methods which can not produce thin and continues edges. Thus, we can not use this algorithm for desirable specification of CT images and the Bspline approximation. We need an appropriate algorithm that can produce thin and continues edge in which the continuity of each edge represented by a data structure and being capable of eliminating weak edges and noises. In the current work we used Canny edge detection algorithm [3] which can extract thin and continuous edges. Figure 1 compares the results of above mentioned algorithms.

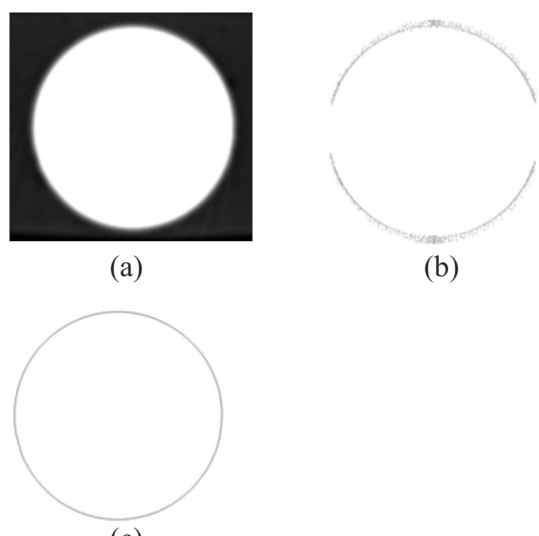

Fig. 1 .comparison of different edge detectors
a- original image b- Sobel edge detection c- Canny edge detection

III. Bspline Curve Theory

After extracting 2D data point, a curve approximation method is required to construct smooth curve. The Bspline theory can define free-form curves in a concise representation. In order to design a Bspline curve, we need a set of control points, a set of knots and a set of coefficients, one for each control points called Bspline basis functions. A parametric p^{th} degree Bspline curve is a piecewise polynomial curve defined by:

$$C(u) = \sum_{i=0}^{n} N_{i,p}(u) P_i$$

Where P_i's are control points and $N_{i,p}(u)$'s are Bspline basis functions of degree p which defined recursively as follows:

$$N_{i,0}(u) = \begin{cases} 1 & \text{if } u_i \le u < u_{i+1} \\ 0 & \text{otherwise} \end{cases}$$

$$N_{i,p}(u) = \frac{u - u_i}{u_{i+p} - u_i} N_{i,p-1}(u) + \frac{u_{i+p+1} - u}{u_{i+p+1} - u_{i+1}} N_{i+1,p-1}(u)$$

The degree of a Bspline curve is independent of the number of control points. More precisely, we can use lower degree curves and still maintain a large number of control points. We can change the position of a control point without globally changing the shape of the whole curve (local modification property). Moreover, there are some other techniques for designing and editing the shape of a curve such as knot modifying algorithms.

Bspline curve approximation
In approximation technique, the strict requirement that the curve must pass all data points is relaxed. In other word, the curve does not have to contain any data point. To measure how well a curve can "approximate" the given data points, the concept of error distance is used. The error distance is the distance between a data point and its "corresponding" point on the curve. Thus, if the sum of these errors is minimized, the curve will follow the shape of the data points closely. A curve obtained this way is referred to as an approximated curve.
In this work we use global Bspline curve approximation method [4] to construct smooth curves over extracted data points. As depicted in Figure 2 the approximated curve follows data points closely.

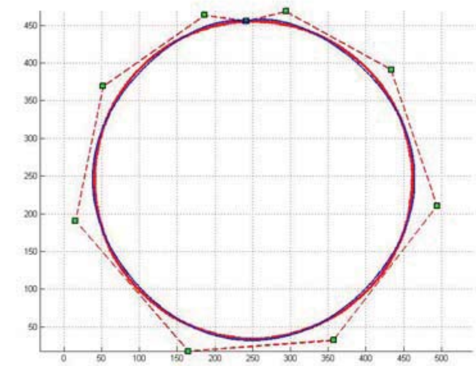

Fig. 2. Control polygon and approximated Bspline curve of degree 3 over 400 data points

Periodic Bspline curve
In above approximation, the first and the last knots have multiplicity of p+l. This will generate the so called clamped Bspline curves. In order to have C^2 continuity at the start-end junction points, we have the converted clamped into a close curve [5].
There are many ways to generate closed curves. The common algorithms are either wrapping control points or wrapping knot vectors. First the knot vector is chosen for open end condition, then by one of the above mentioned methods closed curve can be constructed.

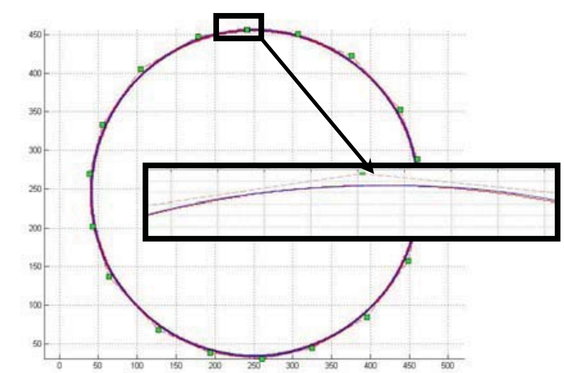

Fig. 3. Closed Bspline curve of degree 3.

The curve has proper continuity at the start-end junction point, i.e. C^{p-1} continuity which forming a closed loop. In zoomed inset continuity at the start and the end point is illustrated.

IV. Surface reconstruction

There are two types of surfaces that are commonly used in modeling systems, parametric and implicit. Parametric surfaces are defined by a set of three functions, one for each coordinate. One of the most powerful and popular parametric surface representation formula is Bspline surfaces which can assumed as isoparametric curves and formulated mathematically by tensor product format.

The tensor product technique constructs surfaces by "multiplying" two curves. Given two Bspline curves, the tensor product method constructs a surface by multiplying the basis functions of the first curve with the basis functions of the second and uses the results as the basis functions for a set of two-dimensional control points. Surfaces generated this way are called tensor product surfaces [5]. The Bspline surface defined by given control points, knot vectors and degrees for each direction can be expressed by:

$$P(u,v)=\sum_{i=0}^{m}\sum_{j=0}^{n}N_{i,p}(u)N_{j,q}(v)P_{i,j}$$

Where $N_{i,p}$ and $N_{j,q}$ are Bspline basis function of degree p and q. Because of tensor product representation, the coefficient of each control point is the product of two one-dimensional Bspline basis function, one for each direction. Figure 4 depicts the basis function variations for Bspline surface.

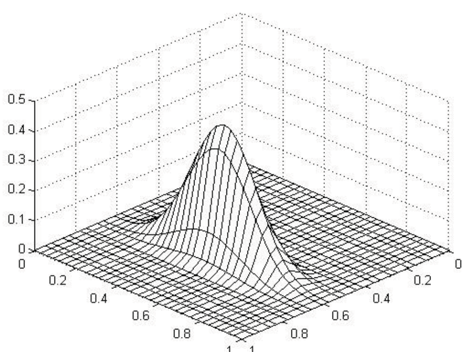

Fig. 4. Basis function for Bspline surface which is product of two one-dimensional Bspline basis function

To achieve final model we should approximate a Bspline surface to data point cloud. Since the initial data are structured as closed contours in one direction and open in the other direction, the isoparametric curves will consequently be closed in one direction and open in the other direction. However, this may be not satisfying for some common shapes which are closed volumes like anatomic shapes.

Bspline surfaces also have different types in each direction. They can be independently clamped, close or open along each direction. If a Bspline surface is closed in a direction, then all isoparametric curves in that direction are periodic curves. Figure 5 illustrate some types of Bspline surfaces.

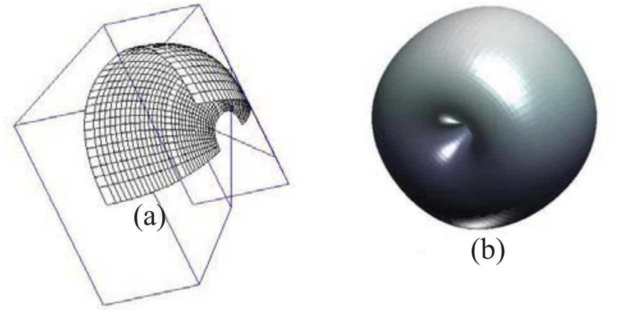

Fig. 5. Different types of Bspline surfaces
a- Open Bspline surface with 11 control points and it's control net
b- Two direction closed Bspline surface (torus)

Bspline surface approximation

Surface skinning is a process of passing a smooth surface through a set of data points [6]. In CT imaging the data points represent cross-sections of an object so they often referred to as cross-sectional curves. Using the Bsplines theory, it is possible to show a surface in concise representation**.** There are several methods to approximate Bspline surface over data point cloud [7]. As it can be seen in surface approximation algorithm, the constructed surface does not require passing the data point cloud. Also, the number of control points and the degree can be chosen independent of the number of data point.

The current work implements the global surface approximation method for surface skinning [8] in which parameters are selected by the Centripetal method [9].

Increasing accuracy by detecting sharp edges and reconstruction

Sharp edges are not approximated accurately by Bspline surface approximation algorithms which is the main source of approximation error. The amount of this error can be reduced by increasing the number of control points as shown in Figure 6.

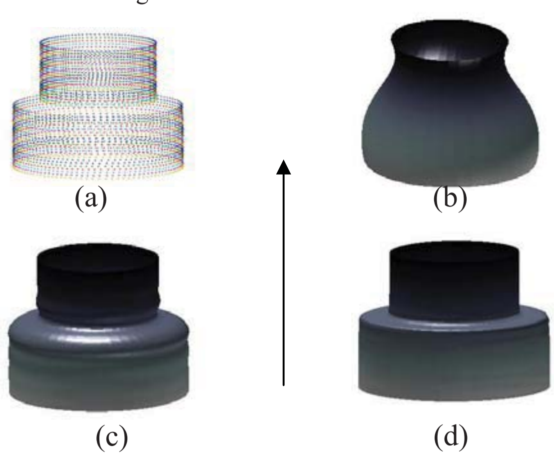

Fig. 6. Influence of increasing the number of control points on sharp edges reconstruction

a- cloud points b- approximated Bspline surface of degree(3,3) with 5 control points in sharp edge direction c- Bspline surface from degree(3,3) with 15 control points in sharp edge direction d- Bspline surface from degree(3,3) with 30 control points in sharp edge direction

As can be seen, by increasing the number of control points sharp edge error decreased but it cannot be eliminated completely.

Based on Bspline curves theory, sharp edges could have been created by increasing multiplicity of a knot or introducing a multiple control point [5]. Figure 7 illustrates the influence of the multiple control point method on creating a sharp edge.

Fig. 7. Exact sharp edges by creating multiple control point.

In summery, the p+1 multiple control points enforced the curve to pass through the multiple control point location. This fact results in creating a sharp edge on approximated surface.

Using corner detection algorithms in image processing sharp edges are firstly detected and then the multiple control point method is implemented. This process will reduce approximation error without increasing control points. In fact corners are local image features characterized by locations where variation of intensity function in volumetric edge direction is high. Several methods exist for detecting corners that each of them has its own advantages. In this work image corners are detected using the KLT[1] method [10] as depicted in Figure 8.

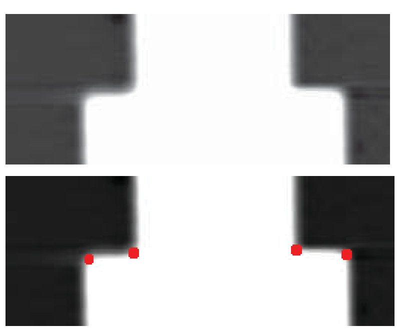

Fig. 8. Corner detection with KLT method

V. Inspection of the reconstructed model

In the present work, the reconstruction accuracy of industrial test part which is digitalized by a medical spiral CT scanner is evaluated. The CT scanner provides a set of slices along z axis that are combined into a single volumetric image. The method described in Section 2 is then applied to the captured images. The total error E_t is actually the result of the cumulative effect of four errors: the error of acquisition E_a, the error of image processing E_i ,the error of reconstruction E_r and the true shape difference between the industrial part and its original CAD model E_s .The sample part is composed of planar, cylindrical surfaces and also sharp edges , see Fig. 9.

The CAD model is the reference for evaluating the accuracy of reconstruction.

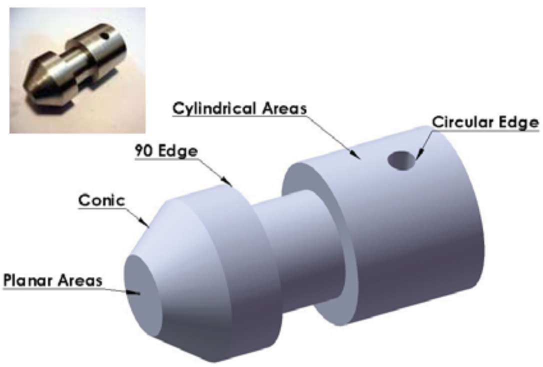

Fig. 9. Aluminum sample part.

At the first step, the data points of each slice are extracted using image processing algorithm. The data point cloud is obtained by assembling the data points of each cross section, as shown in Figure 10.

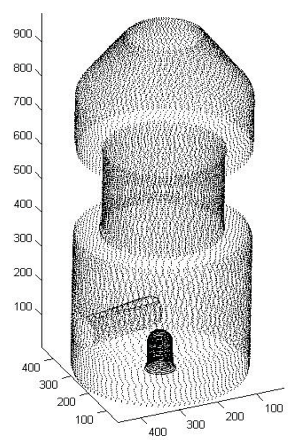

Fig. 10. Extracted cloud point from 2D images

After constructing the approximated Bspline surface, it is compared with the CAD model. Rapidform[2] is chosen to

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[1] Kanade Lucas Tomasi Method

[2] . www.rapidform.com

report the deviations of reconstructed surface with the CAD model. This means that the system calculates the shortest orthogonal distance of each point on the surface with the CAD model. The deviations are visualized by means of colored deviation plots, i.e. each polygon point of the measured data is colored according to its deviation from the CAD data.

The colored deviation map (see Fig. 11) illustrates comparison of the CAD model with scanned cloud point.

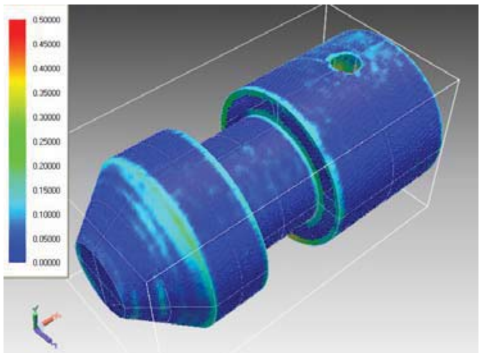


Fig. 11. Deviation of cloud point from original CAD model

The mean distance between the CAD model and cloud points is 0.05mm. The median distance increases on sharp edges to 0.4mm. Reported results show that computed tomography method operates weaker on sharp edges.

The results obtained from comparing the approximated model with original CAD model shows 0.05mm median distance. There is a very small deviations at the smooth areas of the model. However, due to the lacks of approximation method and elimination of wiggling at sharp edges, the deviations on these areas increase to 0.25mm and up to 0.5mm at some points. In order to clearly show the deviations, the error distribution with 0.1mm acceptable tolerance on the sample part is depicted in Figure 12.

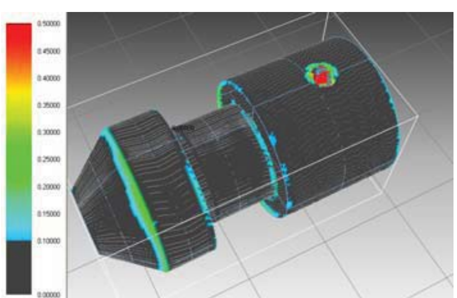
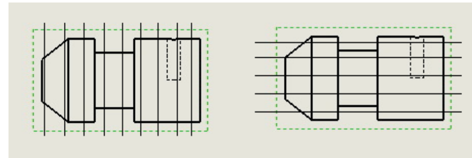


Fig. 12. Deviation of reconstructed model from original CAD model with acceptable tolerance (0. 1mm).

The orientation of the part with respect to the scanning direction is one of the most important parameters. If the part is rotated by 90 degrees from the reference position (see Figure 12) the results of reconstructing the upper whole are slightly better in comparison with the reference case.



(a) (b)

Fig. 13. orientations of sample part
a. reference position
b. secondary position.

After processing of CT images in the new orientation, the deviation of the reconstructed model is decreased. This can be explained by observing that new detected curves are continues on each slice through the whole. Figure 14 illustrates result of reconstruction after imaging from sample part in new orientation.

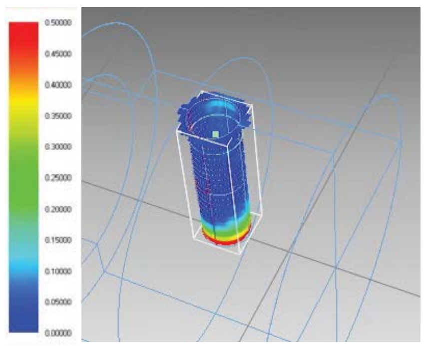


Fig. 14. Deviation of reconstructed model from original CAD model.

VI. Conclusion and perspectives

From our experiments we draw the following conclusions:

1. To reduce image deviations for industrial parts its better to set them in an environment with at least three different densities. For this purpose we float our test part in crystal paraffin.
2. We have observed a good approximation of the geometry in the areas of low curvature. This examination proves CTscan images to be particularly well suited for the inspection of smoothly curved mechanical parts.
3. The orientation of part with respect to the scanning direction has an important influence of the accuracy of reconstruction. The best orientation is obtained when the number of surfaces having their normal vector in the scanning sections is minimized.

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