Clinical Case Study: Spine Modeling for Minimum Invasive Spine Surgeries (MISS) using Rapid Prototyping

V. N. Chougule[1]*, A. V. Mulay[2], B. B. Ahuja[3]

[1]Department of Mechanical Engineering, MES College of Engineering, Pune-411001, MH, INDIA

[2]Department of Production Engineering & Industrial Management, College of Engineering, Pune-411005, MH, INDIA

[3]Director, College of Engineering, Pune-411005, MH, INDIA

Abstract

Bio-modeling are generally referred as models of human body parts for clinical diagnostic, surgical planning as well as development of surgical guides or implants during surgeries. For critical surgeries in spine for spinal corrections in scoliosis surgeries, etc., these bio-models plays vital role in the Minimum Invasive Spine Surgery (MISS). The MISS is typically keyhole surgeries carried with the help of advanced endoscopic techniques. Typically, MISS suffers with time required to establish pedicle screw axes, X-ray exposure to patient as well as surgical team. These problems can be reduced using bio-models which are retrieved from non-invasive modalities viz. Computer Tomography (CT), Magnetic Resonance Imaging (MRI), etc. used to capture internal details of human organs in DICOM 3.0 format. The internal organs can be distinguished based on density difference between soft and hard tissues and details are recorded as Hounsfield Unit (HU). A novel Graphical User Interface (GUI) has been developed to convert CT data into 3D bio-medical models using Computer Aided Reverse Engineering (CARE) approach. The CT data is transformed to Point Cloud Data (PCD) using image processing techniques. By using a novel algorithm developed, this point cloud data is translated into CAD data i.e. STL format, which can be directly transferred to Rapid Prototyping machines to retrieve 3D bio-models. In current work, the bio-models are validated using Euler's formula for water tight surface and accuracy checked using Surface-Point Difference function of Imageware. The bio-models developed were clinically tried for surgical planning as well as patient training.

Keywords: Bio-models, Minimum Invasive Spine Surgery, Rapid Prototyping, CARE, Point Cloud Data, CT scan, DICOM

1. INTRODUCTION

Recent progresses in information technology and bio-medicine have prompted Computer Aided Design (CAD) to find many novel applications in bio-medical engineering. An integration of CAD and medical technology is referred as bio-CAD. Three-dimensional (3D) bio-CAD model reconstruction from CT medical image has recently become the issue of much attention. It is particularly important in bio-medical engineering since CAD with the help of medical imaging and free-form-fabrication technologies like Reverse Engineering (RE) and Rapid Prototyping (RP) has the capacity to create anatomic models which have diagnostic, therapeutic and rehabilitatory medical applications. Bio-CAD is widely used in many applications such as Computer-Aided Surgery, structural modeling of tissue, design of orthopedic device, implants, tissue scaffolds and freeform fabrication or bio-manufacturing [1-10]. These models also have non-medical applications in the field of passenger safety design and crash analysis [3,4,11]. These can also be used to fabricate prostheses, to perform various simulation and analytical tasks. Number of open source and commercial products for 3D bio-mechanical construction are available, but still, these tools does not appear to be a simple, accurate and reliable for bio-image acquisition and analysis [12]. P. D'Urso [1] refers bio-modeling as the ability to replicate the morphology of the biological structure in a solid substance. D'Urso defines bio-modeling as 'the process of using radiant energy to capture morphological data on a biological structure and processing such data by computer to generate the code required to manufacture the structure using rapid prototyping apparatus'. D'Urso identified five general applications of bio-models viz. (i) for surgical team communication, to educate patients and improve informed consent; (ii) to assist surgeons with diagnosis and surgical planning; (iii) for rehearsal and simulation of surgery; (iv) for creation of customized prosthetics; and (v) for accurate placement of implants.

The 3D reconstruction of biomedical models means rebuilding models from medical image data, which is in discrete form. In medical imaging context, it is often necessary to acquire data one piece at a time in order to view inside details. The CT scanner acquires number of projections from different positions. These different views from human object needs to be combined together to reconstruction of 3D models. Reverse Engineering (RE) is absolutely necessary due to the absence of digital models and complexity of shape [1]. The major steps involved in RE techniques are the data capture, pre-processing data (multiple measurements at different viewpoints). For construction of models, it is usually required to process and extract bone geometries, etc. and convert them into the form required for the specific applications [13]. For using extracted bone geometries, etc. into biomechanical modeling and reconstruction must satisfy topological consistencies (water tight surface/manifold surface or bounds a closed volume) and topological correctness (i.e. accurate definition of bone geometries, etc.) [14], which are absolutely necessary conditions for successful construction of 3D printed models otherwise rapid prototyping process becomes error prone.

2. METHODOLGY

In the present work, an approach of Computer Aided Reverse Engineering (CARE) adopted for data capture based on RE techniques. The current work encompasses major steps using CARE approach viz. Estimation of Point Cloud Data from non-invasive medical images, Preprocessing for noise reduction,

* V. N. Chougule, Email: vnchougule@mescoepune.org, vnchougule@gmail.com

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data segmentation and establish relation between points, etc., Construction of water-tight surface model, export data in CAD compatible format, and develop conceptual models for surgical preplanning, etc.

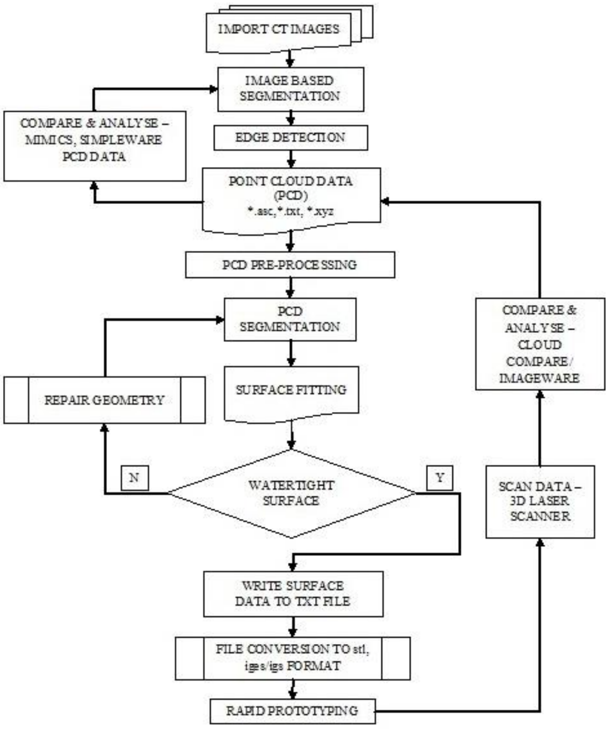


Fig. 1. Methodology

Fig. 1 shows the methodology adopted for conversion of non-invasive CT scan data into 3D bio-models using CARE and RP approach.

2.1 Evaluation of Point Cloud Data

Most of the contemporary researchers highlights the collection the feature points from images using spatial domain methods. Such information includes edges, intersection or corner points, ridges etc. To isolate region or object of interest from background, image segmentation techniques are used. In current work, image segmentation is used to separate the bone from surrounding soft muscles in set of CT images. For image based segmentation, threshold based techniques are widely accepted by researchers [4-10, 15,16]. These techniques can be broadly classified as global and local thresholding. In global thresholding, threshold values can be manually or automatically determined and classified based on its intensity values. Thresholding based techniques can be used to separate out bones from its soft tissues due to high intensity levels or HU values of bones in CT images. However, global thresholding suffers from partial volume effects, high gray level intensity of surrounding pixels due to implants, beam hardening, etc. [17] Digital Imaging and Communications in Medicine (DICOM) is a worldwide information technology standard established in 1993. The standard covers file format and transfer protocol, permitting exchange of data regardless of hardware origin. The X-ray tube emits a conic beam of electromagnetic radiation that selectively penetrates the part of the body being examined; the attenuated radiation [μ] is then encoded by a 2D detector and sent to the processing equipment as a digital radiograph image. The CT image does not show these μ values directly, but the CT numbers according to Hounsfield [18-21] as given equation 1:

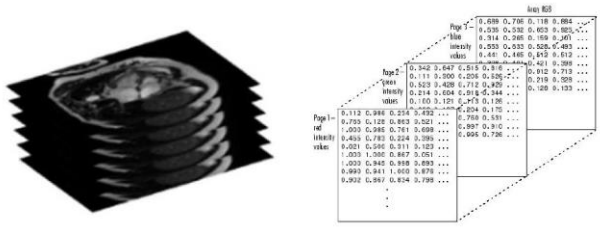
$$CT_{Number} = 1000 * (\mu - \mu_{Water}) / \mu_{Water} \tag{1}$$

where, CT numbers are measured in Hounsfield Unit (HU).

Table 1 Hounsfield unit (HU) for various organs of human body

Predefined threshold value	Minimum	Maximum
Bone (CT)	226	3071
Soft Tissue (CT)	-700	225
Enamel (CT, Adult)	1553	2850
Enamel (CT, Child)	2042	3071
Compact Bone (CT, Adult)	662	1988
Compact Bone (CT, Child)	586	2198
Spongial Bone (CT, Adult)	148	661
Spongial Bone (CT, Child)	156	585
Muscle Tissue (CT, Adult)	-5	135
Muscle Tissue (CT, Child)	-25	139
Fat Tissue (CT, Adult)	-205	-51
Fat Tissue (CT, Child)	-212	-72
Skin Tissue (CT, Adult)	-718	-177
Skin Tissue (CT, Child)	-766	-202

The pixel value of CT images are scaled such that the linear X-ray by attenuation coefficient (h) of air equals to -1,024 and that of water is 0 (zero). The CT number of air and distilled water is defined as -1,024 HU and 0 HU respectively; this scale has no limit in the positive range of values. Medical scanners typically work in a range of -1,024 HU to +3,071 HU. Table 1 illustrates typical range of HU values for different human tissues/organs based on priori studies.



a) Raw CT scan data b) 4-D data representation
Fig. 2. CT scan data representation

In current work, it is proposed to use raw CT scan data for the experimental purpose. The Graphical User Interface (GUI) is developed by using MATLAB software and its embedded functions. The raw CT scan data is read by using *'dicomread'* function and vital information like patient's name, age, image size and resolution; slice thickness, etc. retrieved by using *'dicominfo'* function. Fig. 2(a) shows CT scan data as a stack of images, each image consists of 512 × 512 pixels, with each pixel storing HU value as density at particular location. These data is stored as 4-dimensional array as 4-D variable, of which, first three variables are stored as X, Y, Z co-ordinates respectively and 4th variable is a HU value of corresponding element indicating density value for the same as shown in Fig. 2(b). This 4D data is visualized developed interface *'displayCT'* in MATLAB. Fig. 3 shows segmented data of 65 year male patient for 0 HU and 226 HU values resp.

2.2 Preprocessing Point Cloud Data

Preprocessing is vital for the data measured by using algorithms developed for better good quality and closed surface fitting. The input data contains huge number of points with outliers or noise. Due to the partial volume effects, presence of implants, screws, dental caps, etc. in CT scan images, improper selection of threshold value during image segmentation results into the generation of noise. This noise may introduce duplicates and overlapping surfaces, intersecting or twisted surfaces, dangling edges, etc. So, it's absolutely necessary to remove noise (or de-noising), data reduction (or down sampling), filtering and feature extraction (i.e. segmentation). The unorganized point cloud data is retrieved from non-invasive imaging techniques. For successful reconstruction of surface, these points need to be organized in proper manner or sequence, de-noised and down sampled to avoid errors and reduce computational efforts.

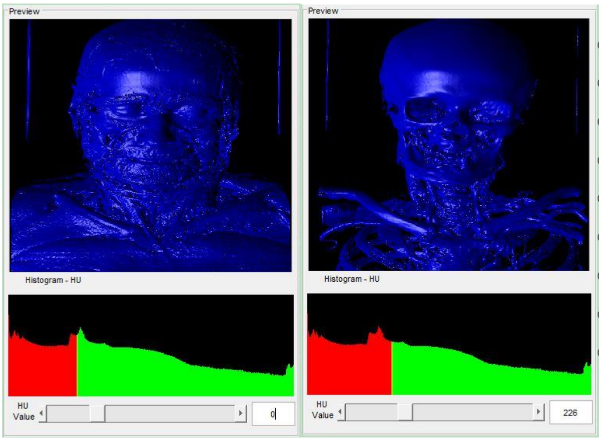


Fig. 3. Dynamic data visualization using displayCT function

2.2.1 De-noising

The point cloud data evaluated from raw CT scan data contains huge number of points along with few invalid points, outliers or noise introduced due various sources viz. CT machine error, data compression, presence of metal implants in human body, different material densities, partial volume effect, etc. The presence of noise makes it impossible to apply classical key point detection and feature extraction techniques. This noise removal is essential step for 3D data processing for reducing errors in construction of surfaces as well as for reducing computational efforts during conversion process. The point cloud data is imported as ASCII file in ASC format as X, Y, Z coordinates and stored in *'pointCloud'* class in Computer Vision System Toolbox of MATLAB. It provides facility for removal of invalid points by using '*removeInvalidPoints'* in point cloud which removes points with *'Inf'* or *'NaN'* i.e. invalid coordinates from point cloud.

2.2.2 Down-sampling

The down sampling of point cloud data can be achieved by using *'pcdownsample'* function. This down sampling can be achieved by three methods viz. *'random', 'gridAverage'* and *'nonuniformGridSample'*. The random method returns down sampled point cloud data with random sampling, without replacement and specified percentage number of points as specified by the users. The *'gridAverage'* method returned point cloud data using a box grid filter of user defined size. The third method returns down sampled data using non-uniform box grid filter with user defined number of points.

2.2.3 Segmentation

Yu Liu and Youlun Xiong [22] classified segmentation processes three major categories, viz. edge-based, region-based and hybrid segmentation processes. Edge-based methods detect edge points based on parameters like normal or curvatures, in a cross-section perpendicular to the edge dividing different surfaces [23,24]. Region or surface based segmentation uses global information such as the homogeneity or similarity of surface properties. These region-based methods are more robust to noise than edge-based ones. However, the region growing methods [25,26] are time consuming as they are iterative and needs to fit surface continually. Hybrid segmentation has been developed by combining the edge and region based information. An algorithm based on clustering is proposed, in which a similarity measure for region merging is obtained from a statistical test [22].

2.2.4 Limitations of Point Cloud Data Segmentation

i. A major problem with surface based segmentation is the presence of noise in point clouds. In a scan surfaces are supposed to be infinitely thin, but noise has the effect of making surfaces thick. This affects the accurate estimation of surface properties in region growing tests often resulting in over segmentation.
ii. Edge based segmentation edges become more difficult to detect and this leads to under segmentation. To resolve the noise problem, hybrid methods which combine edge detection and surface based segmentation algorithms have been proposed.
iii. Surface based segmentation algorithms described surfaces using explicit surface functions (cylinders, planes, surface patches). This complicates the segmentation of implicit surfaces, since these algorithms are developed for some specific applications like industrial installations, etc. As a result, there are very few generic segmentation algorithms.
iv. Many segmentation algorithms perform neighborhood searches. In the absence of a space partitioning scheme this can lead to unacceptable computational overheads, particularly for very large point clouds.

2.3 Surface fitting

Various surface reconstruction algorithms like quadratic surface fitting, B-spline surface fitting, lofted surface fitting and sweep surface fitting methods have been proposed in the literature to fit 3D measured point cloud data into various surfaces [2, 7, 10, 16, 27,28]. To achieve Curvature Continuity (C^2), minimum three degree curve must be fitted through point cloud. Generally, for having three degree curve, Cubic splines, B-spline and NURBS can be used. Among them, B-spline surfaces, especially Non-Uniform Rational B-Spline (NURBS) Surface, are popular due to their ability to accurately approximate most types of surface entities encountered in design and manufacturing application. Based on literature review, a smooth surface is fitted using two approaches viz. (i) Construct layer wise closed curves and generate swept or lofted surface, (ii) Fit surface patches through segmented points.

2.3.1 Swept/loft based surface fitting

Closed B-spine or NURBS curves can be used to represent the contours of the layers to maintain the surface accuracy of the

CAD model [17]. Olya Grove et al. [27] proposed use of medical image data is to reconstruct a surface from serial parallel contours extracted from images. Data points representing the contours of the region interest are extracted and fitted with B-Spline curves, and the sequence of curves is lofted to generate the 3D surface model. These control point based of methods viz. B-splines and NURBS provides excellent coverage but high degree of freedom due to large number of control points. The major challenge in this work is huge number of points, to distinguish between inner and outer bone boundary profile points, detection of nearest points on one surface. These point cloud data after preprocessing for noise reduction, smoothening and sorting can be further utilized for curve network generation through the construction of B-Spline curves which will enable us to achieve Tangential (C^1) and Curvature (C^2) continuity. Further, it is proposed to fit B-spline or NURBS surface through the network of curves. For rapid prototyping, this point cloud data can be transferred to STL file with only Positional Continuity (C^0).

Merits

1. Curve based methods provides additional facilities like lesser file size, less memory requirements, editing, etc., while STL based methods suffers from huge file size, memory requirements and slow processing.

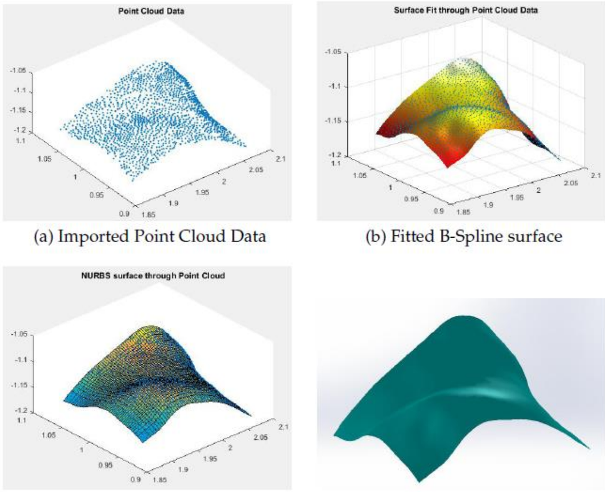
2. Surface generation by sweeping B-Spline curves provides higher degree continuity (C^0, C^1 and C^2) over STL can achieve only positional continuity (C^0).

Demerits

1. This method results into open surface. For water tight surface model, these surfaces require generation of end caps by using commercial software maintaining higher degree of continuity.
2. Curve based methods proves effective for single closed curve in a layer. Modeling becomes complicated with number of closed curves, internal pockets, etc. in a layer.
3. Preprocessing of generated curves is necessary for start of curve as well as direction of closed curve otherwise result into twisted surfaces.
4. Suffers from intersecting curves, branching effect and control on model processing.

2.3.2 Fitting B-Spline NURBS surface patch through segmented points

As per discussions in the previous section, while fitting surface with lofted surfaces through network of curves, major problem of branching and twisting is observed. These due to non-uniform distribution of starting points on closed curves as well as direction of the curves. As application requires smooth surface having higher order continuity to be fitted through point cloud data, it is proposed to fit B-Spline or NURBS surface patches through selected point cloud data. Fig. 4(a) and (b) shows 1,589 points (46 KB) selected from point cloud data estimated from algorithm and a smooth surface is fitted through all these points. Fig. 4 (c) shows fitted NURBS surface (130 KB) with 50 × 50 control points and 10 × 10 degree in X and Y-direction respectively. The higher degree of NURBS surface is selected since its closeness with the point cloud data. This developed NURBS surface is exported as CAD compatible IGES file as shown in Fig. 4(d). This method provides output as an editable IGES files, less memory requirement and better control over surface fit. But, suffers from as developed patch may not be covering complete set of points at lower degree and order. It de-features set of points e.g. loss of minute or small details like small holes, etc. This can be achieved by further subdividing set of points in finer groups and fitting surface patch and then assembling all patches maintaining at least tangential continuity. It requires high level CAD proficiency, which generally hospitals lack.



(a) Imported Point Cloud Data (b) Fitted B-Spline surface

(c) NURBS Surface (d) IGES File in CAD Environment

Fig. 4. Fitting surface patch through segmented set of points

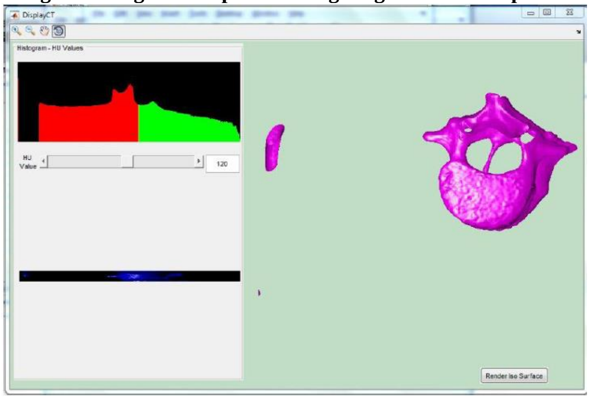


Fig. 5. Dynamic rendering of the results

For developing 3D models automatically, it's absolutely vital to establish relations between surface points using other region based techniques. The relations between neighboring points are established using iso-surfacing approach. It suffers from selection of inner voids with same radiometric data. So, it becomes essential to remove this manually or automatically. These segmented data after pre-processing and surface fitting is exported using developed algorithm as point cloud file in ASCII format or mesh file in STL format for RP or CAD editing purpose.

3. MEDICAL CASE STUDY

Table 2 Specifications of sample CT data

Format	DICOM 3.0
Width	512
Height	512
Machine Model	PNMS-MX 16
Slice thickness	1 mm
Image Resolution	0.2715 mm
No. of slices	20

For the verification of the algorithms developed, Lumbar vertebra (L3) of 5 years old female scoliosis patient suffering from diastigmatolia is discussed (Refer table 2 for specifications). All the development and performance of the algorithms are checked by using Intel(R) Core(TM) i5-4440 CPU @3.10 GHz, 8 GB RAM with 64 bit Windows machine. Input data for the both cases are in DICOM 3.0 format with DCM extension. The input data for the process is from CT scan machines, which scans patient body in slices of user defined slice thickness values ranging from 0.25 mm to 5 mm. Low slice thickness results in more number of slices increasing memory handling issues. The appropriate HU value is selected using algorithm developed in MATLAB as shown in fig. 5. CT scan data is stored as a ‘4D’ array of voxels of *0.2715mm X 0.2715mm X 1mm*. For the development of BioCAD models, these resolution and slice thickness plays very vital role. Generally, for diagnosis of smaller cracks or defects, implant or tool design, etc., lower resolution and slice thickness are advised. Typically, for BioCAD models of skull, spine, etc. slice thickness is recommended less than 0.5 mm. Resampling algorithm has been developed to address the issue of resolution. The results of resampling are tabulated in table 3.

Table 3 Resampling results

Sample	Array Size	Voxel size (mm)	Memory (MB)	Time (sec)
100%	512 × 512 × 20	0.2715 × 0.2715 ×1.0	12.4	39.59
50%	1023 × 1023 × 39	0.1357 × 0.1357 × 0.5	64.0	233.57
25%	2045 × 2045 × 77	0.0678 × 0.0678 × 0.25	554.5	1637.5

By using Chan Vese active edge based segmentation algorithm [29] for 10 iterations, the medical data is segmented for edge detection. In turn these edges are transferred to corner points.

Table 4 Validity of closed surfaces

Parameter	Original	50% sampling	25% sampling
Size X (mm)	46.7	47.6	48.4
Size Y (mm)	44.3	44.8	45.2
Size Z (mm)	19	19	19
Points	43,356	1,84,881	7,70,144
Triangles	86,672	3,69,722	15,40,248
File size (kb)	490	2,036	16,546
Time (sec)	2.277	9.618	40.057

4. RESULTS AND DISCUSSIONS

For manufacturing this developed model of vertebra, the surfaces developed must be water-tight / manifold surface i.e. without any defects viz. holes, intersecting edges, flipped triangles, etc. The water-tight/manifold surface can be verified by Euler’s formula given in equation 1 [30].

$$F - E + V - L = 2*(B - G) \tag{1}$$

where, F - Number of faces,
E - Number of edges,
V - Number of vertices,
L - Number of faces inner loops,
B - Number of bodies and
G - Number of genus or holes.

The developed CAD model of vertebra has 43,356 points, 130,008 edges and 86,672 triangles with surface area of 56.0076 mm^2. The effect of resampling is illustrated in fig. 6. Due to the complexity of structure, internal voids, multiple hole or genus, the estimation of validity of surface developed is performed by using Autodesk NetFabb Standard 2017.1 software. The results are tabulated in table 4, output surfaces are closed and with orientable surface. The surface areas increased with sampling. In no case, surfaces developed with holes, bad edges or flipped triangle. The results show that the developed surfaces are orientable as well as closed or water tight.

The accuracy or closeness of fitted surfaces from the measured point cloud data is verified using surface-point difference function of Imageware software. The normal distance of actual surface from point cloud data found to be in ±0.2 mm for 98.56% points. Fig. 7(a) represents algorithm result for complete spine with 330 CT scan slices. 7(b) represents part of spine model with scoliosis printed using FDM facility for presurgical planning.

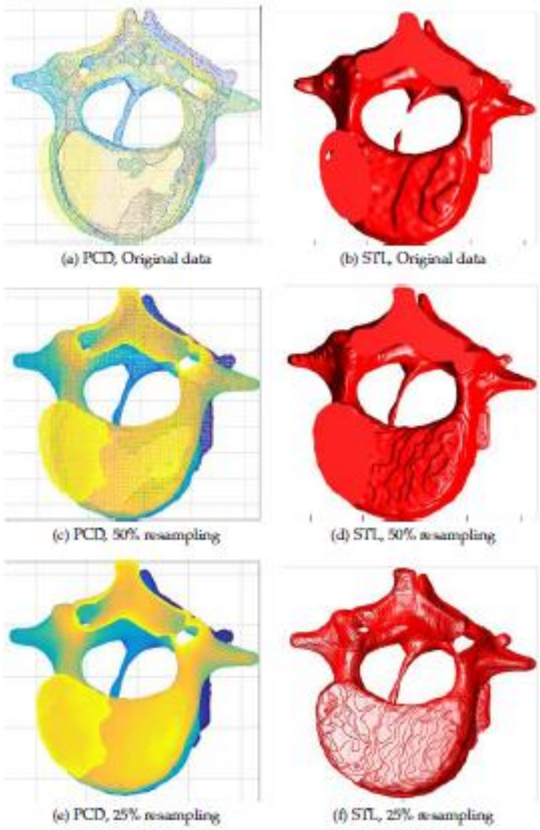
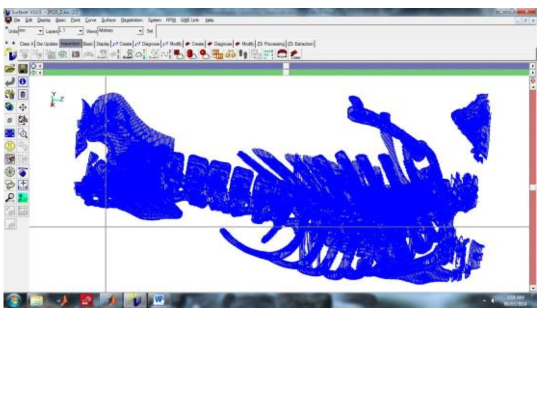


Fig. 6. Resampling results



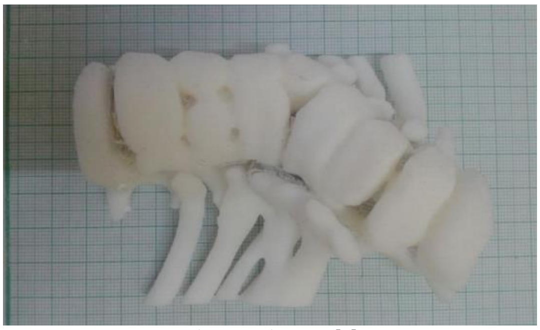


Fig. 7. Spine model

5. CONCLUSION

The major application of current work is to provide accurate and reliable data for the medical practitioners with certain level of confidence. Therefore, the models developed needs to be verified and checked for its quality. Based on more than 20 clinical trials and biomedical modeling of patients of different age groups, the parameters like dimensional accuracy, water-tight surface or valid surface needs to be verified and bio-models manufactured using Fused Deposition Modeling (FDM) RP technique. The models developed for patient specific as well as generalized Minimum Invasive Spine Surgeries (MISS). Also, these applications are further extended to design and development of patient specific surgical guides for maxillofacial as well as critical spine surgeries. Further this application is extended towards auricular prosthesis of female patient, who accidently lost her left ear. The dimensional accuracy plays vital role in the design and development of surgical guides or drilling templates, which needs to be fitted in the body during surgery. The accuracy of models found well within acceptable limits and used during surgeries after suitable sterilization techniques.

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