

Institut für Computergraphik und
Algorithmen

Technische Universität Wien

Karlsplatz 13/186/2

A-1040 Wien

AUSTRIA

Tel: +43 (1) 58801-18601

Fax: +43 (1) 58801-18698

Institute of Computer Graphics and
Algorithms

Vienna University of Technology

email:

technical-report@cg.tuwien.ac.at

other services:

<http://www.cg.tuwien.ac.at/>

<ftp://ftp.cg.tuwien.ac.at/>

TECHNICAL REPORT

Variance Comparison for Volumetric Industrial CT Data

Muhammad Muddassir Malik, Christoph Heinzl and M. Eduard Gröller

Institute of Computer Graphics and Algorithms,
Vienna University of Technology

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Abstract

This paper proposes a novel technique for the direct comparison of a surface model with the corresponding industrial CT volume. We do not require the generation of a mesh from the CT scan and instead perform comparison directly with the raw volume dataset. Our technique uses the information from the surface model to locate corresponding points in the CT dataset. We then compute various comparison metrics to perform distance analysis and normal analysis. The metrics are presented to the user both visually as well as quantitatively. The comparison techniques are divided into two groups namely global comparison techniques and local comparison techniques. The global techniques color code the datasets to provide an overview, while the local techniques can be used for a localized examination and for determining precise information about the deviation between datasets.

1 Introduction

Comparison of two almost identical datasets is very important for the continuously rising demands of quality control in industrial engineering. Recently there has been a whole body of work in the area of variance comparison between two surface models. Originally the basic intent for the comparison of two surface models was to measure the differences introduced during the simplification of the mesh datasets. The high number of vertices and edges were hard to process in real time due to limited processing power available in earlier hardware. Therefore it was necessary to simplify the datasets by reducing the number of triangles in planar areas and keeping the resolution of the mesh in curved regions. This initiated research to simplify mesh datasets in such a way that the rendering speed is maximized while the mesh distortion is limited. Distortions

introduced through mesh simplification led to research on the variance comparison between mesh datasets.

In the manufacturing industry it is necessary to produce mechanical parts as close to the computer aided design model (CAD) of the part as possible. Engineers use CAD tools like AutoCAD, Catia, ProEngineering etc. for designing, which are purpose built tools for engineering drawings. In triangulations of datasets designed through such tools, the number of triangles in planar regions is small whereas curved regions are defined with comparatively higher number of vertices and edges. The CAD model is considered to be the ground truth during the manufacturing process. To verify the accuracy of the production process, manufactured parts are scanned with an industrial computed tomography (CT) machine. The volumetric dataset from the CT scan is compared to the CAD model of the part (called surface model henceforth). The variance comparison between the two datasets is supposed to clearly identify erroneous regions in order to improve the production process.

The most common method for variance comparison is to generate an iso-surface mesh from the CT scan and to compare the two surface models. This may not be the ideal case. First, the generation of a mesh from the CT dataset requires a surface extraction algorithm, typically involving reconstruction artifacts. Therefore we observe loss of important high frequency information. Additionally, if we also try to simplify the mesh dataset, then there is a further deviation from the ground truth. Second, mesh generation for a given iso-value may not be interactively possible during the comparison process. Therefore, the need to do a comparison with a higher or lower resolution mesh may lead to a delay in the examination process. Third, a CT dataset goes beyond a surface model and has information about the interior of the mechanical part as well. Losing this information limits the examination possibilities of the CT dataset.

Figure 1 shows a designed CAD model in (a), direct volume rendering (DVR) of the industrial CT scan in (b)

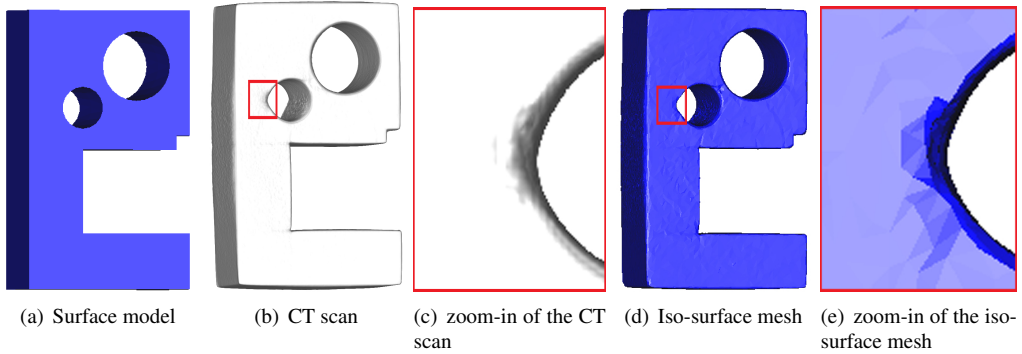


Figure 1: (a) CAD model. (b) Direct volume rendering of the test part 1, manufactured according to (a) and scanned with an industrial CT machine. (d) Iso-surface mesh extracted from the CT dataset. (c) and (e) show zoom-ins of the red rectangles on the CT dataset and the iso-surface mesh respectively. Reconstruction artifacts are visible in (e).

and an iso-surface mesh extracted from the CT scan in (d). In figure 1(d), all the internal information of the volumetric dataset is lost. Zoom-ins of the areas marked with red rectangles in figure 1(b) and (d) are shown in (c) and (e) respectively. We observe reconstruction artifacts in figure 1(e). We used flat shading to increase the visibility of the artifacts.

In this paper we present a novel system to perform variance comparison directly between the surface model (which is the ground truth) and the raw dataset obtained from the industrial CT scan. As we compare the surface model directly with the volumetric dataset, we successfully avoid any reconstruction artifacts. The proposed method provides an interactive variance comparison system. We avoid delays in the examination process and embed the complete comparison pipeline in a single system (section 5).

Our system uses DVR for visualizing the raw datasets. Techniques for the exploration of volumetric datasets can be easily integrated into the proposed system. We thus combine volume visualization and variance comparison in our system, which are both working interactively but independently. The visualization techniques help the user both in searching for the deviations and to accurately and precisely view the deviations present in the datasets. We do not assume any prior information about the shape or topology of the datasets being compared.

Comparing a surface and a volumetric model requires a prior registration. We provide a point-set to point-set registration in our system (section 3.1). The global and local variance comparison techniques are detailed in sections 3.2 and 3.3 respectively. We have a GPU implementation for the rendering of the surface model and

the CT dataset. The system is interactive and performs all operations in real time (section 4).

2 Previous Work

Large number of triangles are inefficient to render and also hard to stream over a network. Subsequently, algorithms are proposed to simplify meshes [CMS98], [Tur92]. Mesh simplification distorts the original shape to some extent and therefore techniques are proposed to measure the differences between two meshes.

Metro [CRS98] is a general tool designed to compare two surfaces. One of the surfaces is scan converted to points and then the distance between each point and the other surface is measured. Aspert et. al [ASCE02] propose to use the Hausdorff distance for measuring differences which is computationally and memory wise efficient.

A variety of metrics and visualization techniques are proposed by Zhou and Pang [ZP01] to measure mesh differences and present the information visually. The combination of metrics and visualization methods intend to help users test and calibrate various mesh simplification algorithms and find what suits their specific requirements.

Turk presents an algorithm [Tur92] to create multiple levels of detail from a surface model. Samples are randomly distributed over the surface and subsequently the relaxation process spreads them uniformly. In the final step the user can choose a surface from a discrete set of surfaces to perform comparison.

The above mesh comparison techniques do not need registration. As the simplified mesh is extracted from the original mesh, both meshes are perfectly aligned. In the case of a surface to a CT dataset comparison, both of which originate from a separate process, there is a need to perform registration. We have included a modified version of the iterative closest point algorithm [BM92], [NP00] for dataset registration. A survey of registration algorithms, specific to medical datasets is provided by Wang et. al [MV98].

There has been some recent work on the variance comparison for industrial CT data. These methods however introduce a preliminary step to the variance comparison process, where an iso-surface mesh is generated from the CT dataset. Heinzl et. al. propose a technique for generating a feature preserving mesh from a CT dataset [HKKG06]. They use filtering to suppress noise and a watershed filter to create a binary dataset. In the final step a surface model is created using elastic surface nets, which is then used for variance comparison. There is a whole body of work in the area of surface extraction, which is considered to be out of scope for this work.

3 Variance Comparison

Our variance comparison system is divided into global and local comparison techniques. Global techniques provide a visualization of the variance between the surface model and the volumetric dataset. This can be combined with any of the volume visualization algorithms that are already available. Local techniques are used on top of the global comparison techniques for user guided analysis. The use of graphics hardware makes all this possible in real time.

An overview of our system is shown in figure 2. The output of the registration step is applied to the surface model which is transformed to closely match the orientation and scaling of the volumetric dataset. Both forms of the comparison, i.e. global and local comparison techniques, query the surface model for the necessary information but work completely independent from each other. The results of the query, meta data from the CT dataset and the chosen visualization technique are used to compute quantitative data and to produce images. Images generated through global and local analysis techniques are displayed in separate windows. Thus the user can use the global and local analysis techniques simultaneously.

Global comparison techniques consist of distance analysis and normal analysis. Distance analysis shows the

deviation in the length, width and depth of the dataset features. Normal analysis precisely locates differences in curvature and compares the surface smoothness of the two datasets.

An overview of both distance analysis and normal analysis is illustrated in 2D in figure 3. The surface model is depicted by a dashed oval whereas the CT dataset is shown by a blue object. Two regions of deviation are marked with red circles. Zoom-ins into the regions highlighted by red circles show normal analysis on the left and distance analysis on the right. The variance in the direction of the normal vector of the surface model (red arrow) and the gradient of the CT dataset (blue arrow) is called normal analysis. The distance analysis is performed by calculating the Euclidean distance between the surface model and the corresponding interface in the CT dataset. Figure 3 indicates the importance of finding corresponding points on the two datasets.

Local comparison techniques consists of various methods that provide precise quantitative metrics and visualization. We provide ray profile analysis, meta data and a magic lens as building blocks of the local comparison techniques in our system. Ray profile analysis visually presents the data and deviations along a ray, cast from a user specified location. Meta data displays quantitative information about the deviations along a ray. A magic lens is used for dual purposes. First, it is used to zoom-in/out of the volumetric dataset. Second, it extracts the variance between datasets and presents it to the user in a more expressive manner than the distance analysis (section 3.3).

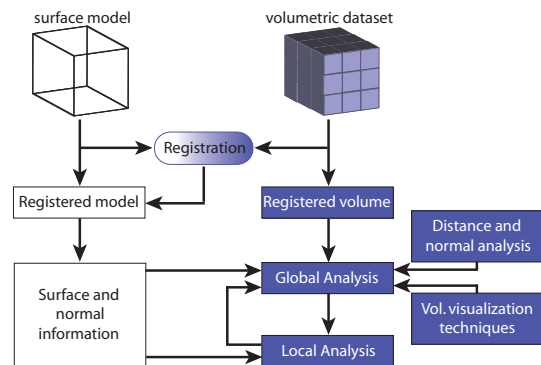


Figure 2: Variance comparison system overview. Global and local comparison techniques are independent of each other and can be used simultaneously.

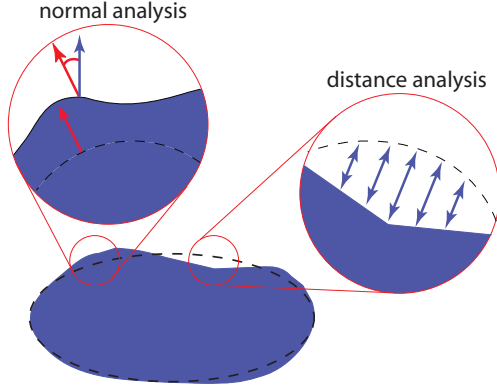


Figure 3: Dashed oval depicts the surface model and the blue object indicates the CT dataset. Normal vector of the surface model and the gradient of the CT dataset are drawn as red and blue arrows respectively. Distance analysis and normal analysis are shown in the left and right zoom-ins respectively.

3.1 Surface Model to CT Dataset Registration

The iterative closest point algorithm (ICP) performs rigid registration and produces a transformation matrix as output. The output matrix transforms (translation, scaling and rotation) the surface model (moving dataset) to closely orient it to the CT dataset (fixed dataset).

The algorithm iteratively produces a matrix to transform the moving dataset. After each iteration, the mean square error (equation 1) between the datasets is calculated. The iteration continues until the mean square error becomes stable, i.e., there is no change in error from one iteration to the next. At this point, the composited matrix of all the transformations and the final error of the registration process are returned. In equation 1, n is the number of reference points, s_i and m_i depict points over the fixed and moving datasets respectively, q_R and q_T represent quaternions for rotation and translation respectively and $R(q_R)$ is the rotation matrix formed from q_R .

$$f(e) = \frac{1.0}{n} \sum_{i=1}^n \|s_i - R(q_R)m_i - q_T\|^2 \quad (1)$$

We analysed the errors introduced by ICP into the measurement process. Repetitive measurements showed that the average error introduced is less than the minimum error we intend to measure.

3.2 Global Variance Comparison Techniques

Global variance comparison is based on distance analysis and normal analysis. Both of these analysis methods require the specification of a corresponding point on the CT dataset for each point on the surface model. We extract spatial locations and normals for a set of uniformly distributed points on the surface model. For each surface point we want to identify the corresponding interface location in the volumetric dataset. Starting from the surface point we traverse the volume data along the surface normal (both in positive and negative orientation). The resulting density profile is used to identify the interface point as the position with highest density gradient (first order derivative is maximum and the second order derivative is zero).

In figure 4(a), we illustrate the concept of locating an interface point in the volumetric dataset. The CT dataset (blue object) is traversed along the two rays (red). One ray traverses in the direction of the surface normal (black arrow) and the other in the direction opposite to the normal. We perform edge detection along both the rays, looking for the interface of the CT dataset. The green strip joining the two red arrows is the area where the two rays shot in the volumetric dataset overlap. We have to initiate the rays from one step behind the spatial position obtained from the surface normal (black dot) to cater for an interface, which may be present right at the spatial location.

We use the first order derivatives and thresholding to look for an interface location in the CT dataset. Figure 4(b) and (c) show graphs, that plot the scalar values encountered by the ray traveling along the surface normal in the positive and the negative orientation respectively. The plots of the first order derivatives for both the rays are shown in figure 4(d) and (e) respectively. The two horizontal yellow lines depict the threshold for the first order derivatives. The first peak, with derivative above the threshold is considered as the corresponding point in the CT dataset. This point is shown as a cross, both in figure 4(a) and (d).

As we find a corresponding point in the volumetric dataset, we store its spatial location, direction (normal or opposite to the normal) along which it was found and the gradient. The information extracted from the surface model and the CT dataset, provide all the required parameters to evaluate the metrics for distance analysis and normal analysis.

The distance analysis shows the deviation between the datasets as Euclidean distance. For each spatial location on the surface model, we have already computed

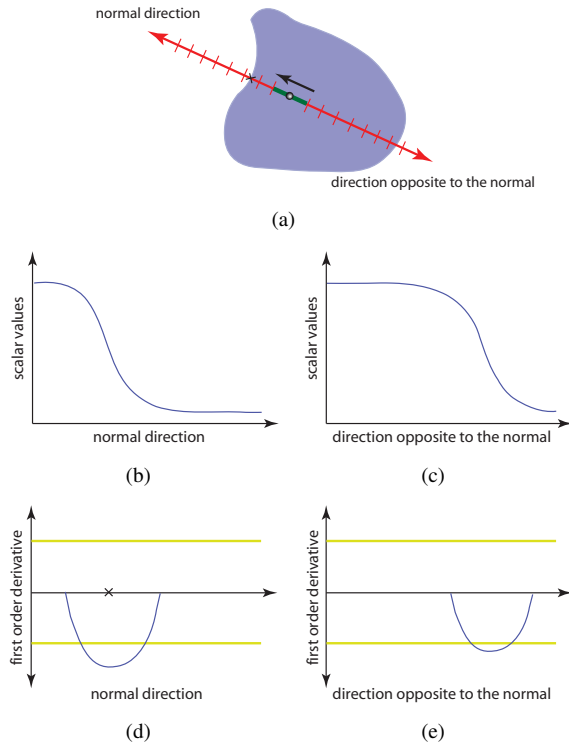


Figure 4: Rays (red) are shot in the CT dataset along the surface normal (black arrow), both in the positive and the negative orientation. Density profiles of the two rays are shown in (b) and (c). We perform edge detection using first order derivatives (d) and (e) to look for a corresponding point (black cross) in the CT dataset.

a corresponding location in the CT dataset. For two datasets without any deviations, the two spatial locations obtained from the datasets should be exactly the same. We compute the difference between the spatial locations on the surface model and their corresponding locations in the CT dataset. We also have information about the direction (normal or opposite to the normal) in which the corresponding point in the CT dataset was located. Using this information we color code the dataset for distance analysis.

Figure 5 shows test part 1 (top) and test part 2 (bottom) scanned in an industrial CT and rendered using the distance analysis algorithm. Areas color coded as green show the deviation in the normal direction whereas the red regions show variance in the direction opposite to the normal. The bright red strip on the top left image is a major variance as is visible from the brightness of the color compared to the greenish skin over the rest of

the test part 1. The zoom-in of the major variance is displayed in the top right image.

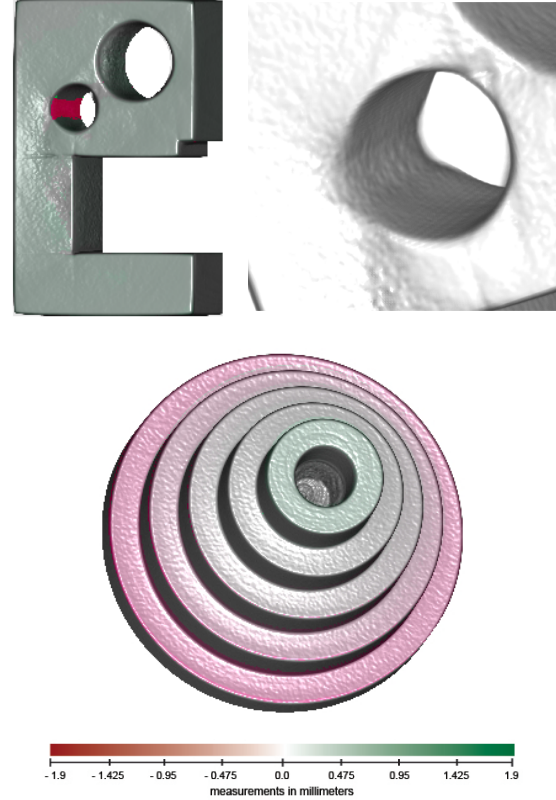


Figure 5: Test part 1 (top left) and test part 2 (bottom) rendered using distance analysis. The top right image shows a zoom-in of the deviation shown by the red color coding in the top left image.

We propose normal analysis as an efficient method for the comparison of surface smoothness. Normal analysis compares the orientation of the normal vectors extracted from the surface model and the gradients obtained from the CT dataset. The angle between the normal vector and the gradient indicates the variance in the curvature of the surface model and the interface of the CT dataset. Surface model is designed using a vector graphics software and thus has sharp edges. Volumetric dataset on the other hand is generated from an industrial process and thus, does not match the smoothness and exactness of the surface model. Roughness and variation in curvature over the CT dataset may be hard to visualize using the distance analysis due to extremely small deviations. These deviations however, will be easily emphasized by the normal analysis.

Figure 6 illustrates the utility of the normal analysis. Distance analysis will either show little variance or no



Figure 6: Black dashed line and the blue line depict a surface of the surface model and an interface of the CT dataset respectively. Surface model and the interface overlap in the region marked with a red oval, however normal analysis will correctly report a deviation in slope.

deviation at all in the region marked with an oval. On the other hand, the normal analysis will correctly show a constant deviation all along the interface shown in figure 6.

Figure 7(a) and (b) show our test parts rendered using normal analysis. In (a) all the corners and the major variance already shown in figure 5 (top right) is colored. The red base of test part 2 (b) shows the rough surface of the CT dataset. This roughness is not present in the surface model. The color scale can be changed dynamically by the user. We emphasized the response of the normal variance by appropriately setting the color scale, as shown at the bottom of the figure 7. Normal analysis is very fast to compute and provides detailed comparison of the smoothness of the surface model and the CT dataset.

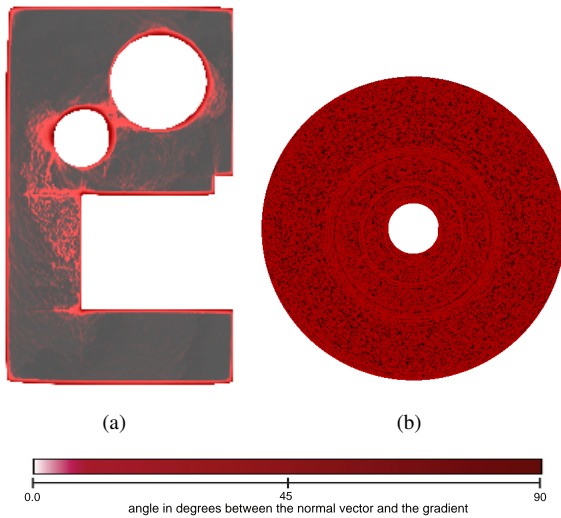


Figure 7: Test part 1 (a) and test part 2 (b) rendered using normal analysis.

3.3 Local Variance Comparison Techniques

Local variance comparison techniques are grouped into ray profile analysis and magic lens. Ray profile analysis displays the accurate deviation between the datasets both as a plot and quantitative numbers. Magic lenses are used to zoom-in/out of the dataset and to view variance graphically.

Ray profile is generated by recording the data as encountered by a ray, shot into the surface model and the CT dataset at a user specified location. The ray records the density values encountered in the CT dataset and the intersection points in the surface model. The results are presented with intersection points from the surface model overlaid onto the ray profile from the CT dataset. The edges along the ray profile can be generated by performing first or second derivative edge detection. The user can see the deviation between the intersection points extracted from the surface model and the interface locations evaluated from the ray profile. Meta Data displays the difference between the edge detected in a ray profile and the intersection point found in the surface model quantitatively. This provides precise information about the deviation in the datasets.

Figures 8(a) and (b) show two ray profiles taken from the test part 1. The ray profile in figures 8(a) is extracted from a location with deviation to the surface model, whereas the ray profile in (b) has no deviation. Vertical red lines show the intersection points detected in the surface model. First derivative of the ray profile is plotted in blue. The vertical axis of the plot extend from -1 to 1 and the axis are drawn in blue. The plot in figures 8(c) shows a complete ray profile, from start to end of the CT dataset registered with the intersections points from the surface model.

We have included a dual purpose magic lens in our system. The user can specify an arbitrary size rectangle over the volumetric dataset to zoom-in. The rest of the variance comparison techniques are unaffected of the zoom-in/out. Both the datasets are kept registered and global and local comparison operations are executed normally on the datasets. The zoom-in shown in the top right image in figure 5 was generated using magic lens.

The magic lens can also provide a precise graphical view of the variance in the neighborhood of a user specified location. Figure 9 depicts a surface of the surface model (gray) and the interface of the CT dataset (blue). The surface and the interface intersect each other and we initialize the magic lens over the datasets at the location shown by a red rectangle. The large red rectangle on the left depicts the response of the distance analysis

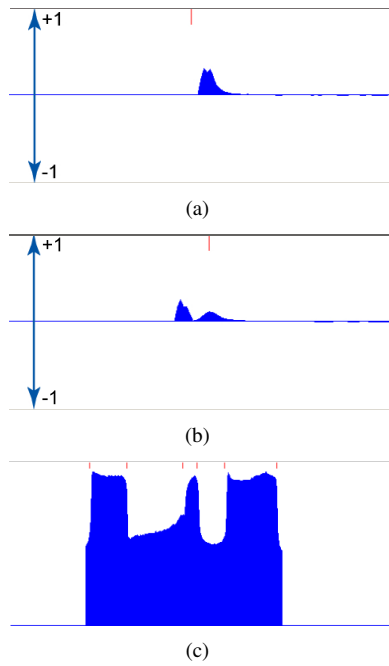


Figure 8: In (a), the intersection point of the surface model (red vertical lines) deviate from the interface location (blue peak) in the CT dataset. In (b) the intersection point and the interface location show no deviation. Complete ray profile of the CT dataset (blue), registered with the intersection points of the surface model (red) is shown in (c).

in the area where the magic lens has been placed. The color coding shows a transition from the deviation in the direction of the normal (green) to the deviations in the direction opposite to the normal (red). However, the exact variance is hard to visualize by color coding alone. Magic lens plots the variance as shown in the zoom-in of the magic lens in figure 9. The black lines depict the surface of the surface model. The deviation of the CT dataset is shown by curves drawn along the black lines. The deviation in the normal direction is shown by a green curve, drawn below the black line, whereas the deviation in the direction opposite to the normal is drawn by a red curve above the black line. The distance between the green or red curve and the black line represents the amount of deviation present between the surface of the surface model and the interface of the CT dataset.

Figure 10 is a snapshot of the magic lens as obtained from the test part 1. The magic lens is depicted on the test part 1 as a blue rectangle. The resulting display of the magic lens is shown on the right. We observe

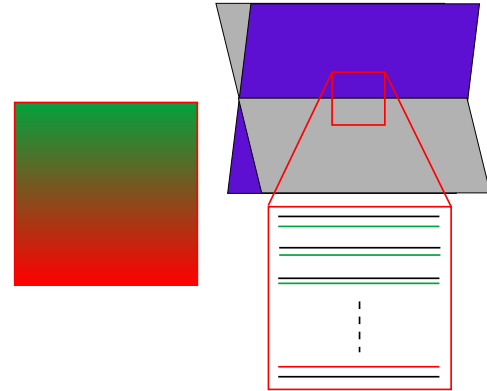


Figure 9: Magic lens (red rectangle) is initiated on the surface of the surface model (gray) and the interface of the CT dataset (blue). The response of the distance analysis in the area where the magic lens is placed is shown by the large red rectangle on the left. The zoom-in of the magic lens shows the deviations as plotted by the magic lens.

variance in the direction opposite to the normal as the test part is color coded red but the exact variance can not be perceived only through distance analysis. The magic lens, however, shows the variance of the interface of the CT dataset with respect to the surface model in a much expressive manner. We can see higher variance in the top left of the magic lens, compared to the bottom right.

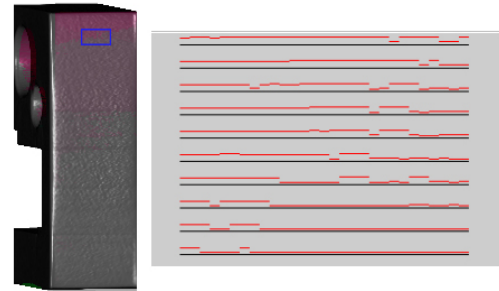


Figure 10: Magic lens is initiated on test part 1 (blue rectangle on the left image). Variance between the surface model and the CT dataset is shown in the magic lens display on the right. Black lines depict the surface of the surface model. Distance between the black lines and the respective red curves show the amount of deviation present. The red color of the curves shows that the variance is in the direction opposite to the normal.

4 Implementation

We implemented variance comparison on an AMD Athlon, 2.1 GHz CPU and an NVidia GeForce 6600 graphics board. The system renders the volumetric data and the surface model side by side. Both the datasets are synchronized and any operation (rotation, scaling, ray profile analysis etc.) on one dataset modifies the other dataset accordingly.

We maintain a central queue for the events performed in the synchronized mode. An operation initiated on one of the datasets, also pushes an event into the central event queue and releases a signal. The other dataset pops the event from the queue and executes it. Separate windows are provided to render ray profile analysis and magic lens. As we perform all the rendering (surface model and the CT dataset) and computing intensive operations on the GPU, the complete system operates in real time (table 1).

Table 1: Performance of variance comparison tools for the two test parts. Surface models of the test part 1 and the test part 2 consist of 310 and 200000 triangles respectively. Resolution of the CT datasets for the test part 1 and the test part 2 are 164x263x90 and 280x279x218 respectively. The view port is set to 512x512.

Analysis	test part 1 (fps)	test part 2 (fps)
DVR	13 - 14	10 - 11
Distance analysis	8 - 9	7 - 8
Normal analysis	8 - 9	7 - 8
Local analysis	interactive	interactive

We have included feature peeling [MMG07] as one of the volume visualization techniques in our system. Using this technique the user can explore the hidden parts of the volumetric datasets. In figure 11 we apply feature peeling on the test part 2 to view occluded regions of the dataset. Volume visualization techniques can be easily embedded into the present system and this greatly enhances the usability of our system, compared to the earlier solutions.

5 Discussion

We have proposed a novel variance comparison system that performs comparison directly between the surface model and the raw dataset. Our technique avoids any preprocessing of the raw dataset and therefore the whole process works interactively in a single system.

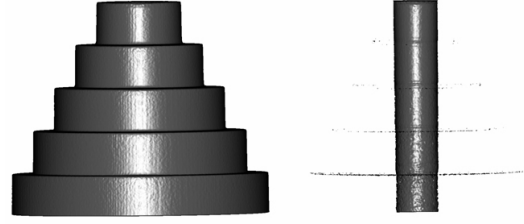


Figure 11: Feature peeling applied to the test part 2. (a) Test part 2. (b) Occluded region of the test part 2 revealed by removing the occluding layer.

We compared our results with a recent method proposed for robust surface detection pipeline for effective variance comparison [HKKG06]. They extract a feature preserving mesh from the raw dataset and then perform comparison between the surface model and the extracted mesh. The preliminary step of mesh extraction has a four step pipeline. In the first three steps, an anisotropic diffusion filter, a gradient filter and a watershed filter are in turn applied to the raw dataset. In the final step before generating the mesh, constrained elastic nets are applied. Thus the solution is divided into two major systems.

Generation of surface model using their technique requires 4:58 minutes for their workpiece 1 (339x525x16) and 10:23 minutes for their workpiece 2 (561x559x436). Our method has no preprocessing delays (see section 4 for details) as the inputs to our technique are the surface model, which is the ground truth for the comparison process and the raw dataset, which is produced from an industrial CT scan. We tested our system using their workpiece 2 and all operations (DVR, global analysis, local analysis, feature peeling) performed interactively.

The accuracy of the proposed technique was analyzed using three synthetic datasets. We created three cube datasets (64x64x64) with a known registration and variation from the surface model. One dataset had no deviation compared to the surface model, whereas each of the other two datasets had variations in the direction of the normal and opposite to the normal. Our system was able to accurately measure the deviations in both of the datasets. The results were verified using global comparison techniques as well as local comparison techniques. We are currently in the process of analyzing the accuracy of our technique using our test parts. This requires more time as we need physical measurements for comparing our results.

We used two datasets (test part 1 and a piston dataset) with known registration for computing the error introduced by the registration process in our technique. The

test part 1 has a resolution of 164x263x90 and the absolute size of the part is 60x100x30 mm whereas the piston dataset has a resolution of 408x351x355 and has an absolute size of 114x98x99 mm. Registration was performed five times on each of the datasets and the difference between the resultant registration and the known registration was recorded. Our measurements show that the average error introduced is 0.028mm.

6 Conclusion and Future Work

We have presented a variance comparison system that compares a surface model to the industrial CT scan of specimens, especially in the preproduction phase and for first part inspection of new industrial products. We avoid any intermediate steps for data enhancement and surface extraction. Two set of tools, namely global comparison techniques and local comparison techniques provide comprehensive comparison opportunities. The system is implemented on graphics hardware and all proposed methods work in real time.

In the future we intend to expand the tool set by plugging in more volume visualization algorithms. It may also be interesting to quantitatively measure the difference between the two datasets. The deviations throughout the datasets can be accumulated and provided to the user as a single number. This will help the user to perform fast and accurate quantitative comparisons.

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