Object Labeling for 3-D Cross-Sectional Data using Trajectory Tracking

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ABSTRACT

Volume visualization from object cross sections has created the need for object labeling in volume data sets. Labeling techniques for 3D objects vary from the memory-intensive connected-component labeling to the less intense overlap technique. In this paper, a novel labeling technique is presented that represents the objects with curves in 3D and then performs labeling by applying 3D curve tracing techniques and mapping the labels back to the 3D objects. The technique thus attempts to replicate aspects of the human visual approach to the task.

Index Terms- Image processing, tomography, visualization

INTRODUCTION

The increasing usage of volumetric imaging modalities, such as magnetic resonance imaging (MRI) and computed tomography (CT) in areas such as medicine and nondestructive evaluation (NDE) has placed a greater importance on 3D visualization techniques. These 3D visualization techniques have evolved to utilize computer vision systems that mimic human visual systems [1][2]. Techniques in image segmentation, volume rendering, and labeling all make up technologies used in computer vision for object visualization. The issue of development of a rapid, computationally efficient object labeling algorithm that is applied before 3D visualization is addressed in this paper. In particular, the situation of matching 3-D objects in cross-sectional slices such as those obtained in CT is the focus.

One approach, connected-component labeling requires loading the whole 3D volume data set and using thresholding with erosion and dilation to extract and label objects [3][4]. Being based on 3-D morphological operations, this approach is both computationally intensive and memory intensive. One method to overcome the memory and computational constraints of the connected-component technique is using information between two consecutive slices for labeling. The objects are segmented and the labeling is performed using the logical AND operator on the binary segmentation masks. If an object in the first slice overlaps an object in the second slice, then the objects in the two separate slices are considered to be cross sections of the same object. If two objects in slice 1 overlap the same object in slice 2 then the number of overlapped pixels is used as the tie breaker [5][6]. This can result in errors if two objects are close to or cross each other and the data are captured on sparse cross sections.

This technique of using overlap is based on the assumption that there is only a small change in the object cross-sections from one slice to the next. The use of overlap is limited by the distance between cross-sections; if they are relatively far apart then the cross sectional data become sparse and the likelihood of error in the overlap technique increases. Figure 1a shows a data set formed with sparse cross-sections of a volume containing two objects. Figure 1b shows the estimated trajectories of the objects after labeling using the overlap technique.

From the estimated trajectories of each object labeled by the overlap technique (figure 1b) it is seen, in this instance, that the overlap technique incorrectly labels the two objects as three. As the applications for 3D visualizations become more complex and serve as a surrogate to invasive direct human observation [7] [8], it is necessary to develop more accurate approaches. A new 3D object labeling technique is proposed, that is efficient in terms of computation and memory.

One component of the human approach to identifying a whole object in a 3-D scene is begin at some portion of the object and "track" it in 3-D space [9]. This is the dominant component if the different objects are identical (for example steel pipes of the same size). The proposed technique is based on this approach.

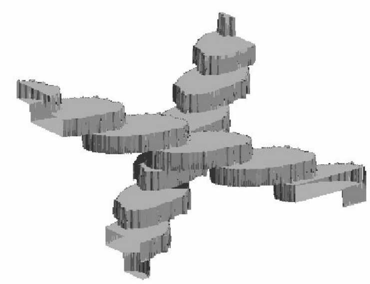


Figure 1a Data Set

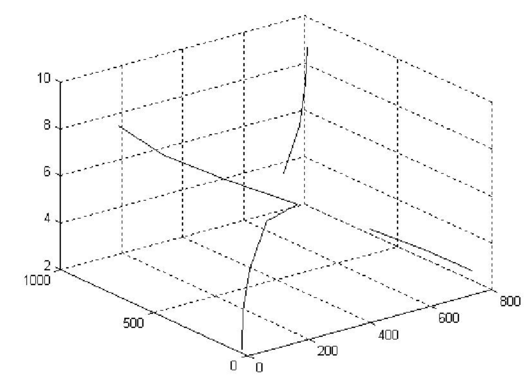
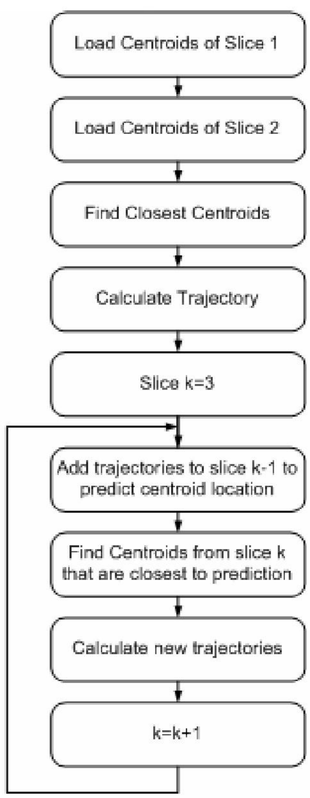


Figure 1b Trajectories of the Objects After Labeling using the Overlap Technique.

Reducing each of the 3D objects in each cross section to a single point for each object would result in a simple sequence from which a human could identify the object trajectories as shown in Figure 2. In this labeling technique the centroids of the objects are used to reduce the binarized cross-sectional objects to a single point. Then 3D curve tracing is applied to these points to determine the trajectories which are then mapped back to the 3D objects. Using the centroids as single point representations of the objects provides an additional benefit by reducing the computational and memory requirements

These inferences regarding the visual system have been applied to curve tracing in 2D images. Raghupathy and Parks address the problem of extracting and linking curve points in an image. In this algorithm curve points are classified by using the property that a curve point has a vanishing first derivative and the amplitude of the second derivative is highest in the direction perpendicular to the curve [10]. Curve points are linked by calculating their orientation from the second derivative and then comparing neighboring curve points with similar orientations. Incorrect linking at junctions is corrected by using the curve orientation to determine the trajectory and look for a suitable match after the junction. This 2D curve tracing is expanded to 3D curve tracing in this paper in application to the proposed labeling algorithm.

ALGORITHM



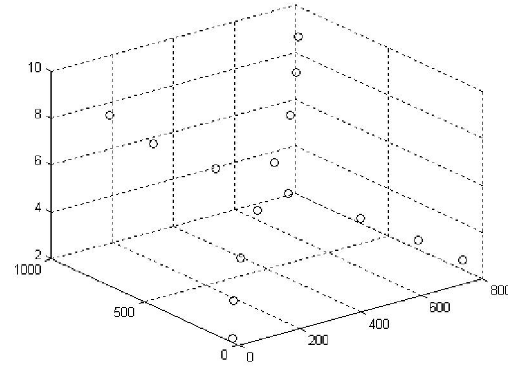


Figure 2 Center of Masses for the Two Objects

Trajectory points are labeled from slice to slice based on the object's estimated trajectory. The trajectory is estimated as a first order bivariate polynomial, then the trajectory estimate is projected onto the plane of the next slice k to be labeled. Centroids in slice k are labeled by minimizing the mean square error between the projected trajectory estimates and the centroids. A threshold is set limiting MSE between a trajectory point and the estimate projection to determine termination of current trajectories. The centroid that minimizes the MSE for each trajectory projection is considered the continuation of the centroid trajectory, with the following rules:

1. Origination:
   If a centroid c is not the centroid that minimizes error for any of the trajectory projections p then c belongs to a new object starting in the current slice k.
2. Termination:
   If a trajectory projection p does not have a centroid that minimizes the error, then the corresponding trajectory is terminated in the previous slice $k-1$.
3. Tie Breaking:
   If centroid c of an object in slice k produces the minimum MSE for two or more trajectory projections, it is associated with that projection that produces the lowest MSE. The MSE for the centroids are re-calculated for the other trajectory projections while omitting the common centroid c, that has already been assigned to a trajectory.
4. Simultaneous Termination and Origination:
   If MSE between a trajectory projection, p and the minimizing centroid c is greater than some threshold t, then centroid c is not an element of the trajectory that projected p. Thus the trajectory is terminated in slice $k-1$, while a new trajectory to which c belongs, originates in slice k.

The polynomial estimate of the trajectory is reduced to a vector in 2D space using the knowledge that the distance between slices is constant. Once a centroid is assigned to a trajectory, the trajectory estimate is updated using the two most recent points added to the trajectory (slice k and $k-1$). This means the trajectory estimate is updated at every cross section to accommodate changes in the object's trajectory without using complex predictors.

All object centroids in a given slice are either assigned to a current trajectory or are used as the start of a new object. Current trajectories that don't continue are considered terminated before moving onto the next slice. Initialization of objects is handled in the first two slices of a new object. Suppose a new object is created in slice k. In slice $k+1$, since there is only one prior point in the object centroid trajectory a location cannot be predicted for the object centroid in slice $k+1$, so the object centroid in slice $k+1$ closest to the object centroid in slice k is assigned to the objects trajectory provided it does not violate any of the before mentioned trajectory rules..

After the curve tracing is complete, curve linkage is performed. Since the labeling is performed from one cross section to the next, the labeling progress is in one direction and can miss object interactions in other orientations. Figure 3a shows the centroids from an object that without curve linkage, could not be correctly labeled no matter which plane was used to capture the cross sections. Two of the orientation planes have rapid trajectory changes, while in the third orientation plane, the object has multiple occurrences in a single cross section because of the object doubling back on itself. As seen in Figure 3b a final step in trajectory tracking is needed to link trajectory curves that are broken up by orientational limitations.

Curve linkage is the final step of the trajectory tracking. This will link separate curves of a single trajectory. Each trajectory curve is extended one slice in each direction, based on the estimated trajectory at the endpoints. If this extension point is in the same slice as the end point for another trajectory curve, then the Euclidian distance between extension point from the first curve and the endpoint from the second curve is calculated. If this Euclidian distance is less then the termination threshold t used in the simultaneous termination and origination criterion discussed earlier, then the trajectory points are continuations of the same trajectory and the two labeled objects are the same object and are thus relabeled as one object.

Once the trajectories are traced, they are mapped back to the 3D objects. This is achieved for each object in each slice by assigning the trajectory label associated with that object's centroid to the object, thus labeling the objects globally.

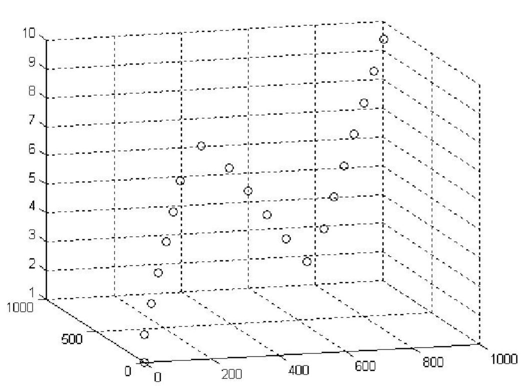


Figure 3a Object Centers of Mass

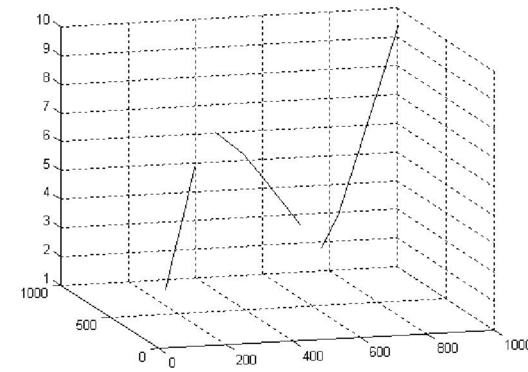


Figure 3b Three Separate Labeled Objects

RESULTS

Both the older overlap technique and the new trajectory tracking for labeling were implemented in MATLAB (Mathworks, Natick MA). Cross sectional slices were synthetically created for two objects that would pass close to each other producing crossing trajectories. Once the objects in each slice were segmented and binarized, they were labeled using both the old overlap technique and the new trajectory tracking technique. Trajectories were calculated using the tracking technique in 10ms while the overlap technique took 110ms. The results of labeling using the overlap technique were shown earlier in Figure 1b. Figure 4 shows the estimated trajectories determined by the trajectory tracking technique. These results demonstrate that the overlap technique incorrectly identified and labeled three distinct objects, while the trajectory tracking technique correctly identified and labeled the two objects and performed the calculations faster. The trajectory tracking technique was also applied to data simulating an object that doubles back on itself as in Figure 3a. Addition of endpoint extension to the trajectory tracking technique resulted in correct labeling as shown in Figure 5.

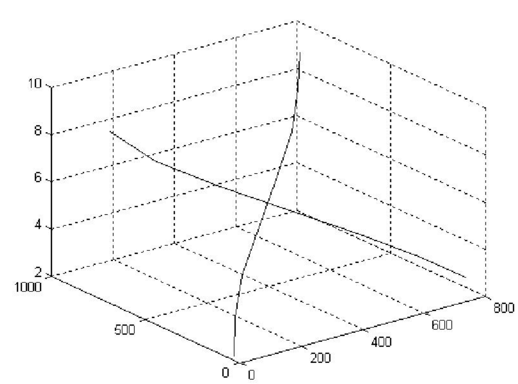


Figure 4 Trajectories of the Objects after Labeling Using Trajectory Tracking.

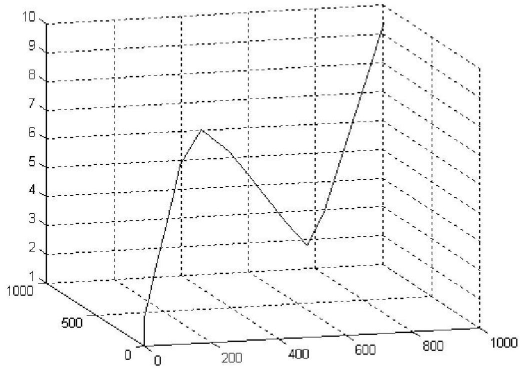
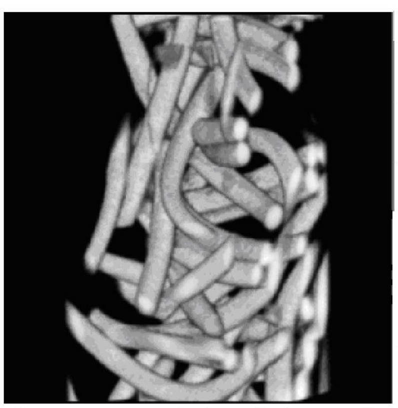


Figure 5 Correctly Labeled Object using Trajectory Tracking with Object Extension

A final experiment was performed by testing the algorithm on a real data set. Cooked pasta was scanned using a MicroCT scanner (GE Healthcare eXplore Locus), cooked spaghetti was selected because of the interweaving and overlapping presented in the data set. Each slice of the microCT data set was segmented and labeled using threshold and connected component labeling in 2D. The slices were then labeled in 3D using the proposed algorithm. Figure 6a is a 3D rendering of the micro CT data before processing and Figure 6b is a 3D rendering of the labeled data.

The algorithm generally works well but fails with slow curving objects at the apex of the curve, if the tangent of the apex lies in the plane of the cross sections. The trajectory of the centroids in these objects has a discontinuity where the two sides of the curve meet resulting in the labeling of separate objects instead of one continuous object. This discrepancy cannot be corrected by increasing the threshold in the endpoint extension since different objects that end near each other would then end up being mislabeled with the same label applied to them.



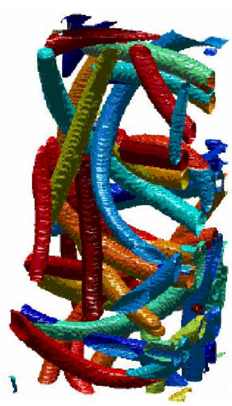


Figure 6a 3D Rendering of microCT data
Figure 6b Labeled microCT data.

CONCLUSIONS

A new 3D object labeling algorithm based on trajectory tracking was developed and compared to the common overlap method. Use of trajectory tracking is a computationally efficient algorithm that uses a minimal amount of memory for calculations and performs calculations faster then the overlap method while producing labeling results in a manner that emulates human perception. Further research is underway to test performance and improve the approach.

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