Inter-slice contour interpolation from 2D cross-sectional medical images via piecewise trend curve analysis

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Abstract--*The 3D surface reconstruction from 2D cross-sections is a significant task, especially in the medical diagnosis. Therefore interpolation methods are necessary but difficult due to the 3D anisotropy between an intra-slice and inter-slice resolution. However, most of the existing literatures are inefficient to ensure the accuracy and robustness of results because of the noises or segmentation errors on the contour of slices. Moreover, the varying trend of the contour curves along the interpolation direction (z-axis), which is a very important factor in object surface description, is not well referred due to the difficulty on its representation in existing methods. In this work, we study an inter-slice interpolation method with a piecewise trend curve analysis to achieve the missing slices employing the underlying piecewise trend curve estimation of slices. The efficiency of our framework is demonstrated by experimental results on the simulated objects and real tumors. According the experimental validation, the method can get better reconstruction performance, especially in the case of objects with complex surface.*

Keywords— Interpolatory contour, adaptive multi-curves approximation, underlying piecewise trend, medical image.

I. INTRODUCTION

With the development of medical imaging technologies, the Magnetic Resonance (MR), Computed Tomography (CT) and 3D Ultrasound (3DUS) technologies are widely used in clinic. Though a series of 2D parallel image slices are generated for the radiologists, doctors or surgeons during the diagnosis process, interactive 3D techniques emerged are expected to improve the accuracy of image-based diagnosis and therapy planning.

The research on inter-slice contour interpolation technique is vital on estimating missing slices for 3D reconstruction from 2D slices. Most of the previous interpolation methods are studied in a simple form, which multi-layer problem is treated as a combination problem of multiple adjacent layers. And these techniques proposed in the literatures can be classified in four categories: *Classics*. Intermediate missing slices are created by interpolating positions of the sequences of corresponding points on the boundaries of the adjacent two slices, including nearest neighbor, linear, a high-order polynomial, and cubic spline interpolation [1–3]. *Morphology*. Such methods attempt to use the dilation and erosion operator to achieve the outline of the intermediate images [4,5]. *Implicit function*. Slices are expressed by the implicit function, and then the intermediate images are interpolated between the implicit functions [6–8]. *Set*. In such methods, the cross sections are represented as a set, and the new cross-section is introduced by a new geometric weighted average of two sets [9]. Because the *Classics*-based, *Morphology*-based and *Set*-based methods only involved adjacent slices, the interpolated results may be affected by irregular contour, the noise or error easily. And although the *implicit function*-based methods can employ several slices simultaneously, suitable function is difficult to be constructed with the increase of the number of slices more and more.

Therefore, three key issues that the aforementioned methods cannot be well considered will be well solved in our work: *Piecewise structural integrity on 3D object surface*, which can deals with the 3D reconstruction from a global perspective, and can describe the interrelation among slices as much as possible; *Extrapolation ability*, which can predict the first slice's predecessor and the last slice's successor, is important to deduce the globality from locality; *Insensitivity to noises and errors*, which can guarantee the robustness of the algorithm and the accuracy of the results, and can reduce the disturbance from scanning noises and segmentation errors on medical images.

In this paper, we propose a new inter-slice contour interpolation method based on varying trend among slices' contours, which is considered as an ordered set of points with connecting some piecewise defined curve along the reconstruction direction. Our main contribution lies in providing a new scheme for achieving missing slice on 3D surface reconstruction, while it can ensure the accuracy of results and improve the robustness in the presence of noises and errors. The experiments demonstrate a superiority of the proposed algorithm over the state-of-the-art methods on synthetic object and real breast tumor.

The rest of the paper is organized as follows. In section 2, we will introduce the conception of structural integrity. Following section 3, the proposed method will be explained in more details. Experimental results will be given in section 4 to verify our work, before the conclusions and future work in section 5.

II. STRUCTURAL INTEGRITY ON 3D OBJECT SURFACE TREND

In this section, we present the conception of structural integrity on trend. Supposed 5 slices of a sphere named -2#, -1#, 0#, +1#, and +2# are shown in Fig.1. The slice 0# which has max radius of the sphere is called the key slice. Slice -2# and +2#, slice -1# and +1# are symmetrical with respect to the key slice.

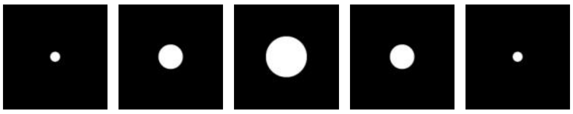


FIGURE 1. FIVE SLICES OF A SPHERE NAMED -2#,-1#,0#,+1#, AND +2# FROM LEFT TO RIGHT

Here the key slice 0# is assumed to be missing, the sphere is obviously impossible to be recovered by those methods which just employ the adjacent slices (e.g. -1# and +1#). But if we refer the structural integrity information, the overall trend of the sphere surface can be estimated, while the key slice is able to be deduced. So it is necessary to take advantages of the structural integrity.

III. THE PROPOSED METHOD

The flowchart of our proposed method is shown in Fig.2. Given two consecutive slices (binary or gray images), their contours of ROI (region of interest) are extracted by segmentation. The objective is that *n* slices will be interpolated between the two contours.

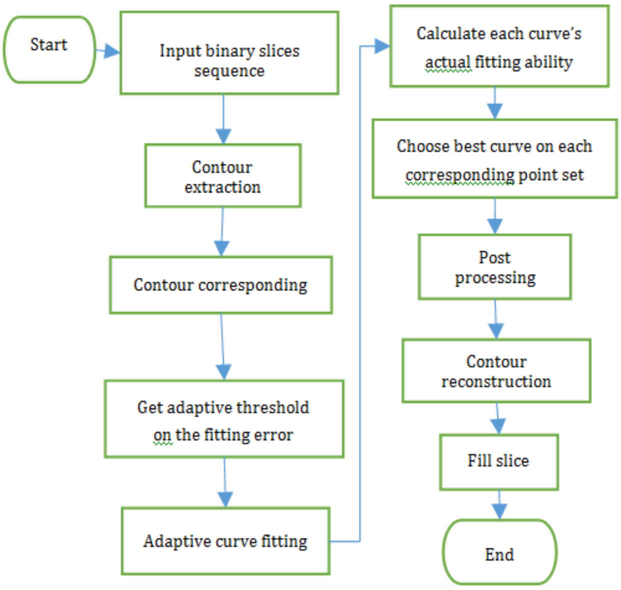


FIGURE 2. FLOWCHART OF THE PROPOSED METHOD

3.1 Z-axis feature points correspondence

Curves lying on surface play a significant role for depicting the object surface. Therefore, we extract corresponding points located on each slice, and then the curves can be fitted from locus of points as the z-axis contours of surface. These points are called trend points. The problem is considered like this: Given a set of corresponding points sequences L is generated as shown in Eq.(1).

$$L = \{L_t\}_{t=0}^{m} \tag{1}$$

In order to improve computational efficiency, the most representative trend curve of surface will be extracted. Moreover, some noise points may be produced during the process of manual or program segmentation, so that they have to be eliminated. In addition, the position of each point is very important in the future reconstruction of z-axis direction, we must guarantee that the feature points are uniformly distributed on the contour of slice. Otherwise, some reconstruction areas will be lost due to the lack of observation points. Therefore, we adopt a robust feature points extraction method based on adjacent curvature similarity and circumference average sampling on the input contours. Specifically, L must satisfy the following constraints:

- The sum of distance between all pair matching points on all slices should be as small as possible;
- The helix handedness of lines between all matching pints on adjacent slices should be as same as possible;
- There are not intersections of lines connected by all pair matching point; the feature points are uniformly distributed on the contour of each slice.

3.2 Trend curve estimation

In this section, a parametric curve $s(t) \subseteq X$ is computed to estimate the trend of ordered point set L. In order to simplify the fitting computation of the L_t obtained by section 3.1, we fit LX_t on X-axis and LY_t on Y-axis, respectively. k_i is the position of the current slice in the original slice sequence. They are defined as follows:

$$LX_t = \{(k_1, x_{k_1}), (k_2, x_{k_2}), \cdots (k_n, x_{k_n})\} \tag{2}$$

$$LY_t = \{(k_1, y_{k_1}), (k_2, y_{k_2}), \cdots (k_n, y_{k_n})\} \tag{3}$$

$$k_i = (i-1) * m + i, i = 1, 2, \cdots n \tag{4}$$

The problem of trend analysis was considered as a deterministic component that needed to be subtracted out in order to obtain a stationary time series. Let us define a time series of length N as $X = (x_0,...,x_{N-1}), x_n \in \mathrm{R}$. There are a variety of definitions of trend but all of them imply the following model:

$$x_n = (t_n + r_n), or \ \ X = T + R, \tag{5}$$

where $T = (t_0,...,t_{N-1})$ denotes a *trend* and $R = (r_0,...,r_{N-1})$ is referred as *residual*. The latter can have both deterministic and stochastic parts. Here, the *trend* can be considered as the varying contour, and the *residual* can be as the noises and segment errors in the contour trend of surface.

3.3 Piecewise trend curving with adaptive threshold sse

A single fitting curve can hardly approximate the contour trend of 3D objects because of the high complexity of surfaces, especially for the medical tissues. We adaptively select the most approximate parametric curve from a curve list which almost covers all the fitting curves in mathematics. Meanwhile, there set an adaptive threshold *sse* (Sum of Squares due to Error) to restrain residual. The curve list is shown in the Table 1.

TABLE 1
THE CURVE LIST

Curve	Expression
Polynomial	$p_5x^4 + p_4x^3 + p_3x^2 + p_2x + p_1$
Fourier	$a_0 + a_1\cos(xw) + b_1\sin(xw) +$ $a_2\cos(2xw) + b_2\sin(2xw)$
Exponential	$ae^{bx} + ce^{dx}$
Gaussian	$a_1 e^{-(\frac{x-b_1}{c_1})^2} + a_2 e^{-(\frac{x-b_2}{c_2})^2}$
Smoothing spline	$\min(p\sum_i w_i(y_i - s(x_i))^2 + (1-p)\int(\frac{d^2s}{dx^2})dx)$

Furthermore, for fitting the contour curve more accurately in the case of objects with complex surface, trend descriptions must be as accurate as possible. So trend estimators adopted must be piece-wisely. That is, it can be well suited to analyze contour curve with an underlying piecewise curve trend. The kinks, knots, or changes in slope of the estimated trend can be interpreted as abrupt changes or events in the underlying dynamics of slices contours. In other words, within each interval defined by the (adaptively chosen) knots, trends are respectively estimated by suitable curves. Here, one threshold *sse* (Sum of Squares due to Error) is set to cut contours of surface into pieces. Then curves are able to be piecewise fitted adaptively. The process of adaptive curve fitting using least square method for LX_t is as following. Refer to Algorithm 1 for the details.

ALGORITHM 1
THE ADAPTIVE MULTI-CURVES SELECTION FOR LXT

```
Set the thresholds maxError of sse for all curve fittings
repeat
  for each curve Q in the Table. 1 do
      set count = Initial fit point number
      repeat
         set FitAbility(Q_i) = count
         if ε ≤ maxError then
            count = count + 1
         end if
      until ε > maxError
  end for
until The rest points of LX_t all are fitted
```

3.4 Post-processing of adaptive fitting

The trend curves, which express overall trend of the 3D object's surface, can be fitted by the aforementioned processes. But the curves should pass through every point of the input slices so that it can be keeping trend and smoothing. Hence we propose a method to solve this problem. Suppose the curve is Q_i, its section interval is $(x_i,y_i),(x_{i+1},y_{i+1}),...,(x_j,y_j)$, we will adjust Q_i for any consecutive points $(x_p,y_p),(x_{p+1},y_{p+1})$, $p = i,i + 1,...,j$.

$$Q_i^{'}(x) = Q_i(x) + g(x), \tag{6}$$

$$g(x) = \frac{(y_{p+1} - Q_i(x_{p+1})) - (y_p - Q_i(x_p))}{x_{p+1} - x_p}(x - x_p) + y_p, \tag{7}$$

where $g(x)$ is the line between $(x_p,y_p - Q_i(x_p))$ and $(x_{p+1},y_{p+1} - Q_i(x_{p+1}))$ as well as $x_{p+1} \neq x_p$ is required. The adjustment of curve is according to Eq.6. In addition, we just adjust the curve's low order term so that the curve can keep its overall trend.

IV. EXPERIMENTAL RESULTS

In order to express the advantage of our proposed method objectively, we evaluate it over the two types of 3D objects, including synthetic and real breast tumor. In this study, four metrics are used for comparison the difference between the interpolated slice and the ground truth slice to evaluate the performance: False Negative Volume Fraction (*FNVF*), False Positive Volume Fraction (*FPVF*), True Positive Volume Fraction (*TPVF*), and Similarity Index (*SI*). They are defined as follows:

$$FNVF = \frac{L_{grd} - L_I}{L_{grd}}, \tag{8}$$

$$FPVF = \frac{L_I - L_{grd}}{L_{grd}}, \quad (9)$$

$$TPVF = \frac{L_{grd} \cap L_I}{L_{grd}}, \quad (10)$$

$$SI = 1 - \frac{(L_{grd} - L_I) \cup (L_I - L_{grd})}{L_{grd} \cup L_I}, \quad (11)$$

where L_{grd} is the ROI of the ground truth slice and L_I is the ROI of the corresponding interpolated slice.

Specially, *FNVF* represents the ratio of non-intersectional region in ground truth to the ground truth. The smaller the value is, the better the effect of interpolation represents. *FPVF* is the ratio of non-intersectional region in interpolated slice to the ground truth. The smaller the value is, the smaller the false cover region occupies, and the better the result of interpolation is. *TPVF* represents the ratio of intersectional region between ground truth and interpolated slice to ground truth. The larger the value is, the better the performance of algorithm is. On behalf of the overall interpolation similarity, *SI* is a comprehensive evaluation. The higher the value is, the more similar the interpolation ground truth and the interpolated slice are.

4.1 Bi-directional cone

A bi-directional cone was designed from a circle whose center is moving along a line and radius is constantly changing, as shown in Fig. 3. Every slice of it is a circle. And the trend curve is straight lines actually. We got 20 slices of the object as input slices and interpolate 9 slices between each two of the slices. Then evaluate the slices obtained by interpolation, and the result is shown in Table 2.

We can conclude that the proposed method performed better than other interpolations from Table 2 and Fig. 4. The actual surface of the bi-directional cone is two intersected lines. The propose method fits the surface easily based on the input slices because line is one of the curves exploited by the proposed method. Other interpolations are not suitable for this occasion that the centers of the slice have large offsets because of their interpolation mechanism.

TABLE 2
THE RESULT OF FOUR INTERPOLATIONS ON BI-DIRECTIONAL CONE

Method	*SI*	*FNV*	*FPV*	*TPV*
Linear Interpolation	74.24%	18.23%	12.87%	81.77%
Literature[3]	87.00%	12.68%	0.41%	87.31%
Literature[4]	77.75%	20.26%	3.06%	79.74%
Our method	97.61%	1.07%	1.36%	98.92%

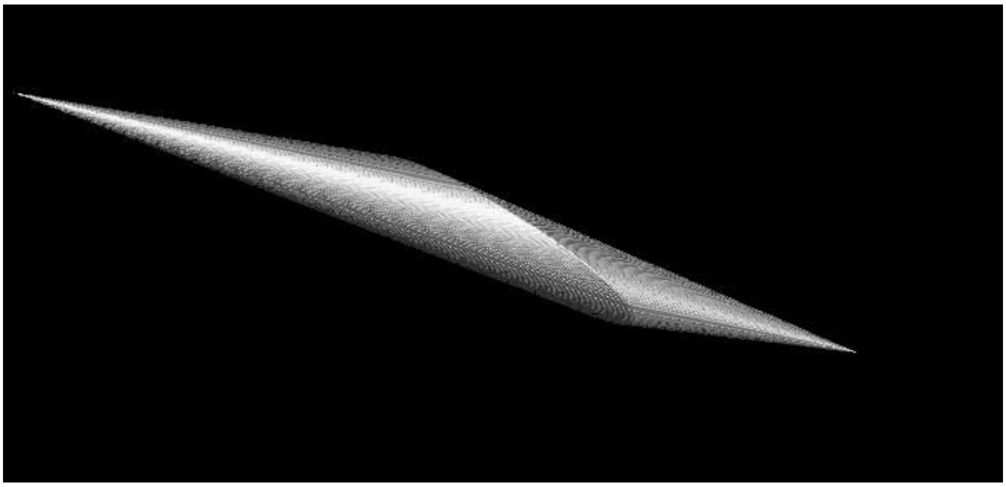
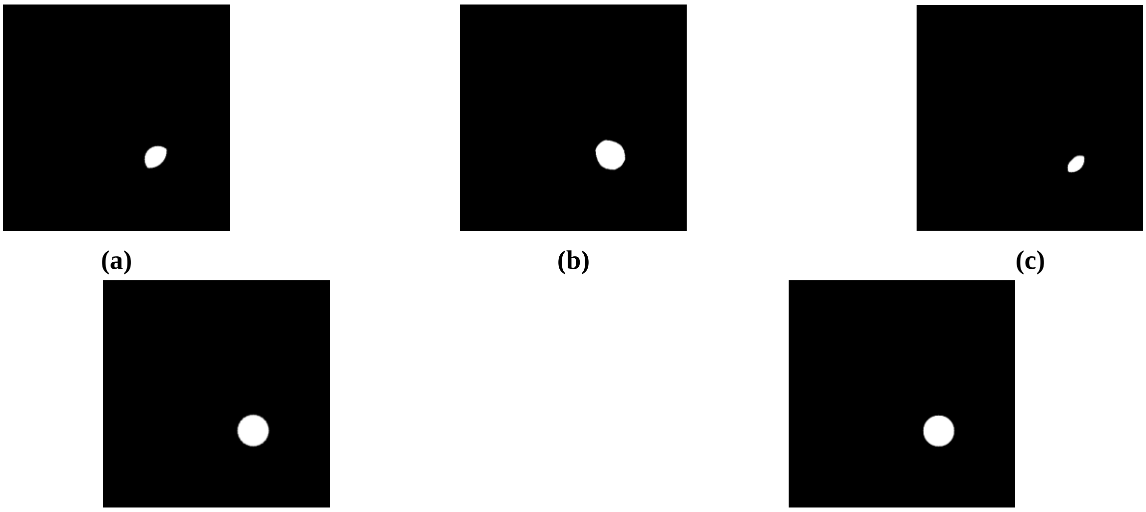


FIGURE 3. BI-DIRECTIONAL CONE



(a) (b) (c)

(d) (e)

FIGURE 4. (a) – (e) ARE INTERPOLATED BY LINEAR INTERPOLATION, LITERATURE[3], LITERATURE[4], OUR METHOD AND GROUND TRUTH, RESPECTIVELY

4.2 Real breast tumor

Ultrasound breast tumor contours are applied to evaluate our method. These images are provided by Second Affiliated Hospital of Harbin Medical University. The ground-truth of tumor contours are segmented by an auto-segmentation program, and then the doctors corrected them which are wrongly segmented, as shown in Fig. 5. And the result, which 9 slices are interpolated between adjacent input slices, is shown in Table 3 and the interpolated slices are shown in Fig. 6.

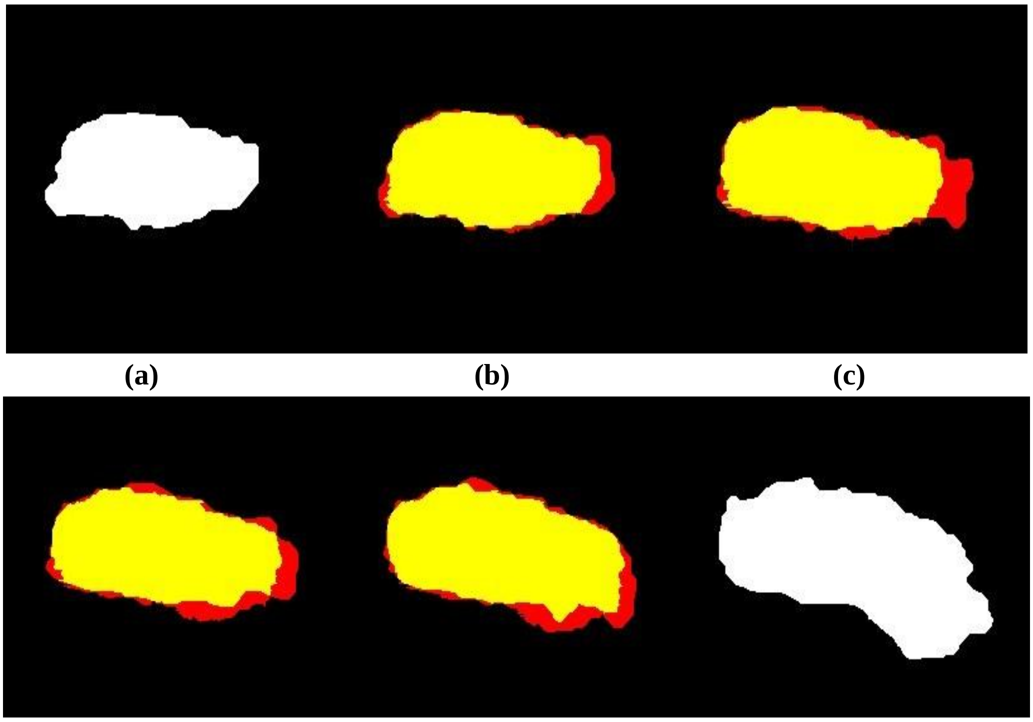
(a) (b)

FIGURE 5. (a) IS AN ORIGINAL TUMOR SLICE; (b) IS THE SEGMENTED CONTOUR OF (a)

TABLE 3
THE RESULT OF FOUR INTERPOLATIONS ON BREAST TUMOR

Method	*SI*	*FNV*	*FPV*	*TPV*
Linear Interpolation	91.09%	6.06%	3.12%	93.94%
Literature[3]	94.82%	2.78%	2.54%	97.22%
Literature[4]	88.03%	1.11%	0.93%	88.87%
Our method	97.03%	1.08%	1.94%	98.92%

The experiment shows that the proposed method has the excellent performance on the real tumor. Compared to other methods, our method indeed benefits from the insensitivity to noises and errors.



(a) (b) (c)

(d) (e) (f)

FIGURE 6. (a) and (f) ARE THE START AND END CONTOUR SLICE, RESPECTIVELY; (b) - (e) ARE THE SUCCESSIVE CONTOURS (RED COLOR) INTERPOLATED BY OUR METHOD BETWEEN THE START AND END SLICES AND GROUND-TRUTH (YELLOW COLOR), RESPECTIVELY.

V. CONCLUSION AND FUTURE WORK

In this paper, the inter-slice contour interpolation problem is considered as an estimation problem of surface trend along z-axis, which consists of some connecting piecewise defined curve according to an ordered set of points. Therefore we have proposed an adaptive piecewise multi-curves approximation for achieving the curves. By taking the consideration from perspective of integrity strategy and trend analysis, robustness and accuracy can be efficiently improved to the 3D interpolation with respect to the objects with complex surface and in the presence of noises and errors. Our experiments demonstrated the performance, not only for synthetic objects, but also for real medical tumors. In future work, we will furthermore study the possible combination of the multi-curves in order to reduce the high computational complexity, and consider the possibility of its application in 3D volume reconstruction and the 3D segmentation problems.

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