Biomedical Data Interpolation for 3D Visual Models

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ABSTRACT

Computed Tomography (CT) is an X-ray technique that produces 2D biomedical slice image data. In such images, the slice spacing is much greater than the spacing of individual samples on a slice. Thus, a robust interpolation method to generate quality intermediate images for the reconstruction of 3D biomedical model is necessary. The subject of this paper is to compare three different interpolation techniques: linear, cubic spline, and Fourier interpolation for generating intermediate slices. Linear interpolation is shown to be the best of the three interpolation techniques. This research also shows that without the image segmentation or the matching process poor intermediate images will be generated.

Keywords: Computed Tomography, interpolation, 3D biomedical model

1. INTRODUCTION

2D biomedical image often do not give enough information for the surgeon to make an accurate assessment of the patient's condition. A 3D biomedical model provides views of internal organs, bones, tissues, muscles and other body parts which only seen during therapeutic surgery. Because of the additional insight revealed by 3D display, a surgeon might decide not to perform surgery.

Computed Tomography (CT) is an X-ray technique that overcomes the contrast problems encountered with normal radiography [Rich91]. CT produces images that are essentially pictures of slice of the body. Unfortunately, such images tends to have a slice spacing greater than the spacing of individual on a slice. Insufficient sampling images may not be able to generate realistic 3D model. A proper interpolation method is thus necessary to fill in the missing slices for reconstruction of volume images.

In this paper we apply a CT image matching method to determine the correspondence between points in two slices. Then, three different interpolation methods, linear, cubic spline, and Fourier interpolation was used for generating intermediate slices. Finally, we use a human visual perception model to measure the qualities of interpolation images.

2. INTERPOLATION METHODS

Interpolation is the process by which one approximates a discrete function, given on a finite set of samples. We can extend the finite set to as an infinite set by using the interpolated data and interpolate again. There are several interpolation methods that can fulfill the application [Lin89]. The simplest one is linear interpolation which can be expressed in the form:

$$f(x) = \frac{1}{x_1 - x_0} \begin{vmatrix} f(x_0) & x_0 - x \\ f(x_1) & x_1 - x \end{vmatrix} \qquad (1)$$

where $x \in [x_0, x_1]$

This form is particularly well adapted to machine computation, since its evaluation involves the continuous operation of a cross product followed by a division.

Cubic spline functions are used widely in computer calculations for the interpolation of continuous functions of one variable. The cubic spline interpolation is considered interpolation by cubic splines to data, where the cubic polynomial pieces meet at that data point (knot) [Rich86]. For the ease of computation, we limit the parametric equation to the use of polynomials as

$$Y_i(u) = a_i + b_i u + c_i u^2 + d_i u^3 \qquad (2)$$

Where $i = 0, \ldots m$ -1 (for m-1 control knots)

It is possible to arrange for successive segments to match the second as well as the first derivatives at joints, using only cubic polynomials. Suppose that we want to interpolate (m+1) points $p_0, \ldots, p_m$ by such a curve. Each of the m segments $Y_0(u), \ldots, Y_{m-1}(u)$ is a cubic polynomial determined by four coefficients. Hence we have 4m unknown values to determine. At each of the (m-1) interiors knots we have four conditions:

$$Y_{i-1}(1) = y_i$$
$$Y'_{i-1}(1) = Y'_i(0)$$
$$Y_i(0) = y_i$$
$$Y''_{i-1}(1) = Y''_i(0)$$

In addition, we have two more known conditions

$$Y_0(0) = y_0$$
$$Y_{m-1}(1) = y_m$$

Thus, we have a total 4(m-1)+2 conditions from which to determine 4m unknown parameters in m cubic polynomial segments.

The one-dimensional Fourier interpolation used in this research uses the Fast Fourier Transform (FFT) method [Libb94]. It assumes the input vector is a periodic vector sampled at equal spaced points. The periodic vector is first transformed to Fourier domain using the FFT. The zero padding is added to resample the original vector and then it is transformed back with more points.

3. IMAGE MATCHING

In CT images, pixels belonging to a tissue in one slice do not necessarily connect to pixels beneath them in next slice. This is because a tissue may blend, shrink, expand, or disappear from one slice to the next. Therefore, the selection of the same feature points in two contiguous images is very important for determining a proper interpolation function.

To solve the so called "matching problem", we use a locally sensitive matching process which was developed for matching of tomographic slices [Arde92]. Let $C(x,y,x',y')$ be a cost vector defined for matching a point (x,y) in a target image to a point (x',y') in the reference image as (see Fig. 1)

$$\begin{aligned} C(x,y,x',y') = {} & u_1[I(x,y) - I'(x',y')]i \\ & + u_2[D(x,y) - D'(x',y')]j \\ & + u_3[\theta(x,y) - \theta'(x',y')]s \\ & + u_4[\sqrt{(x-x')^2 + (y-y')^2}]t \end{aligned} \qquad (3)$$

Where $I(x,y)$, $D(x,y)$, $\theta(x,y)$ and $I'(x',y')$, $D'(x',y')$, $\theta'(x',y')$ are the intensity, gradient magnitude and gradient direction of point (x,y) in the target image and point (x',y') in the reference image, respectively.

The magnitude of (3) is used to measure the dissimilarity between (x,y) and (x',y'). This dissimilarity measure depends on the intensities and gradients of points being matched, and on the disparity between them. The fourth term in the cost function is used to favor the correspondences that have smaller disparities over the ones that have larger disparities. It is likely that a point in the reference image connects to a point in its immediate neighborhood in the target image rather than to a point further away.

The parameters u_1, u_2, u_3, u_4 are weights that specify the relative importance of the intensity, gradient magnitude, gradient direction, and disparity in determination of the correspondences. When the difference in the intensities of images to be matched is small, intensities can be used to match the images; therefore u_1 should be given a higher value than when intensities in the images differ considerably. The gradients in an image depend not only on the absolute intensities, but on the spatial arrangement of the intensities as well. If it is known that the images have similar intensity variations, then u_2 and u_3 should be given higher values than when the images have spatial differences. For example, if one image is a smoother version of another image, then u_2 and u_3 should be given smaller values than when both images have the same spatial resolution. For slices that have similar intensities and gradients, preference should be given to the one that has a smaller disparity value. This is because it is more likely that a tissue point in one image connects to the other in its immediate neighborhood in the next image, than for it to bend and connect to a tissue point far away.

To determine the point (x_m, y_m) in the target image that corresponds to point (x', y') in the reference image, a small search window is selected, centered at (x_m, y_m) in the target image. Suppose the window contains n pixels: (x_i, y_i), $i = 1, \cdots, n$. The cost vector is then used to determine the dissimilarity of each of the n pixels in the window with point (x', y') in the reference image. The point in the window that produces the least cost magnitude is selected as the point corresponding to (x', y'). That is, if

$$C(x_m, y_m, x', y') = \min\{C(x_i, y_i, x', y') \mid i = 1, \cdots, n\} \quad (4)$$

then, point (x_m, y_m) in the target image is selected as the point matching (x', y') in the reference image.

4. THE VISUAL PERCEPTION MODEL

When an image is processed, the root-mean-squared error is the typical method used to measure the image quality [Gree90]. Although this measure has a good physical and theoretical basis, it often correlates poorly with the subjectively judged distortion of the image. This is principally due to the fact that human visual system does not process the image in a point-by-point fashion but extracts spatial, temporal, and chromatic features. In this section, we use a human visual perception model to evaluate the quality of interpolated images generated by previous interpolation methods. The perception model is defined as

$$\rho = \sum_i \sum_j C_{i,j} \times \vartheta_{i,j} \quad (5)$$

Where ρ is the visual perception difference, C is the two dimensional contrast sensitivity response weight matrix, and ϑ is the difference between the energy normalized Fourier coefficients of the first 20 frequencies [Sand93,Wils95].

Since the distance between human's eyes and an object will change the spatial frequencies observed by the viewer [Wils95]. This model assumed that the viewer is looking at an image on a computer screen 24 inches away. To compare the image quality of different interpolation methods, we use (5) to calculate the visual perceptual difference between the estimated interpolated images and the known image. The smaller ρ value, the higher quality of interpolated image.

5. EVALUATING THE RESULTS

The experimental data set used in this research is CT head data provided by the North Carolina Memorial Hospital. It consists of 113 slices. Slices are stored consecutively as a 246x256 array with dimensions of z-113, y-256, x-256 in z-y-x order. The format is 16-bit integers, that is, two consecutive bytes make up one binary integer. We also normalized all image intensities to 0-255 [Chen95].

Firstly, we assume the CT slice 51 (see Figure 2) is unknown. Then, the intermediate images generated from slice 50 and 52 using linear interpolation with, and without applying the matching method are given in Figure 3(a) and 3(b) respectively. When the cubic spline interpolation is employed, we use four reference CT slices (no. 50,52,53 and 54) to accomplish the interpolation. Figure 4(a) shows the interpolated intermediate slice 51 carried out without matching method, and Figure 4(b) shows the same image carried out with the matching method. Using Fourier interpolation, the reference images are slice 50, and 52-65. The interpolated intermediate image without applying the matching method is given in Figure 5(a). Figure 5(b) shows the image carried out with the image matching method.

To compare the performance between interpolation methods, we use the human visual perception model to evaluate the quality of interpolated images. Firstly, we calculate the image energy differences between the original slice 51 and interpolated images. Then, the visual perception differences can be carried out as shown in Table 1. From the definition of visual perception model in section 4, it shows that the linear interpolation method with the image matching method generated the best interpolated image.

6. CONCLUSION

CT produces sampling images may not be sufficient for generating realistic 3D model. In this paper, we used three interpolation methods (linear, cubic spline and Fourier) to fill in the missing slices for reconstruction of volume images. Linear interpolation assumes that the relationship between each two known points is a monotonically increasing or decreasing function. Cubic spline interpolation assumes that the relationship between unknown points is a smooth curve function. Using Fourier interpolation, the intensity value is transformed from the spatial domain to the frequency domain. An appropriate lowpass filter gives the interpolated image.

Before the interpolation process is carried out, the searching for the corresponding pixels in two consecutive slices has to be solved. For this, we used a CT slices matching method for matching of tomographic slices. This method works on images that do not have scaling differences, have very small or no translation and rotation differences, but may have significant local geometric differences. It has only a few parameters that need be adjusted. Once these parameters are fixed, the method works without any user interaction.

When an image is processed, a human visual perception model is used to evaluate the quality of interpolated images. From the experimental results, it shown that the linear interpolation method with the image matching method generated the best interpolated image.

Table 1. Visual perception differences ρ between original slice 51 (with image energy $\vartheta = 2.2485e{+}04$) and interpolated images

Interpolation methods	without matching method	with matching method
Linear interpolation	$\vartheta = 2.1293e{+}04$ $\rho = 214.6885$	$\vartheta = 2.2422e{+}04$ $\rho = 196.1584$ (the best)
Cubic Spline interpolation	$\vartheta = 2.4297e{+}04$ $\rho = 247.1396$	$\vartheta = 2.2282e{+}04$ $\rho = 226.8381$
Fourier interpolation	$\vartheta = 2.2033e{+}04$ $\rho = 251.2280$	$\vartheta = 2.2245e{+}04$ $\rho = 236.4418$

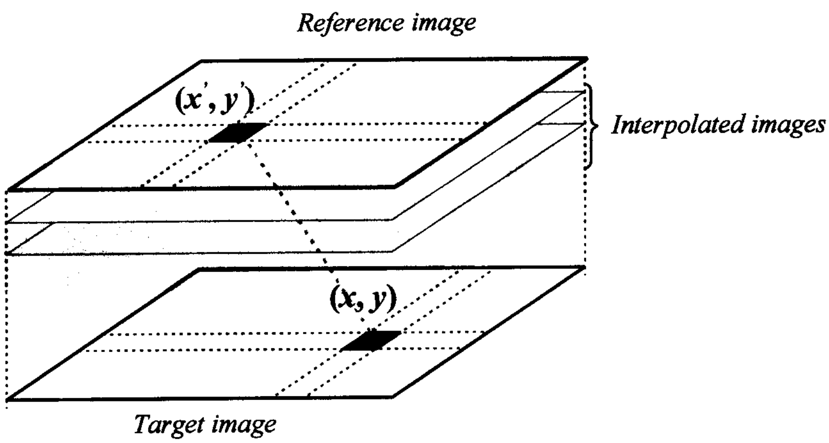


Fig. 1. Two consecutive slices and the matched pixels.

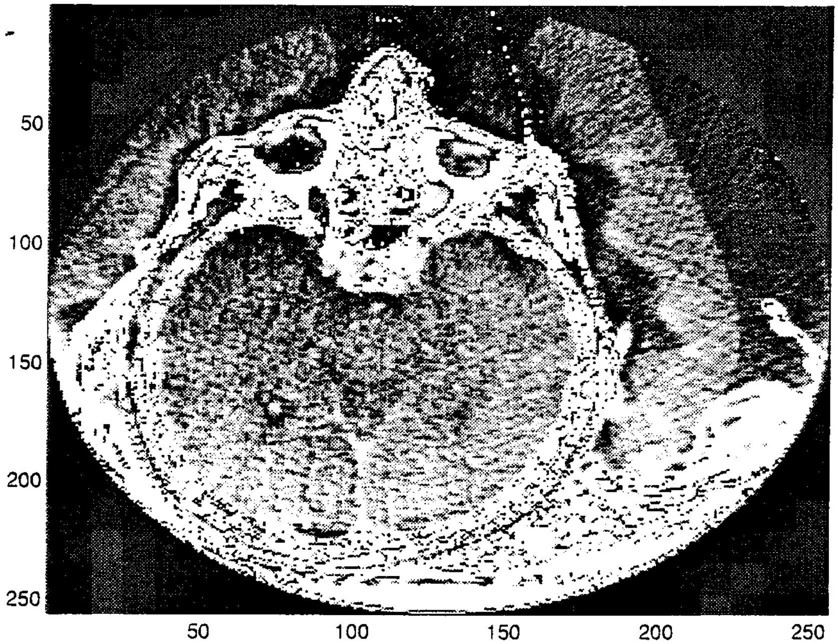
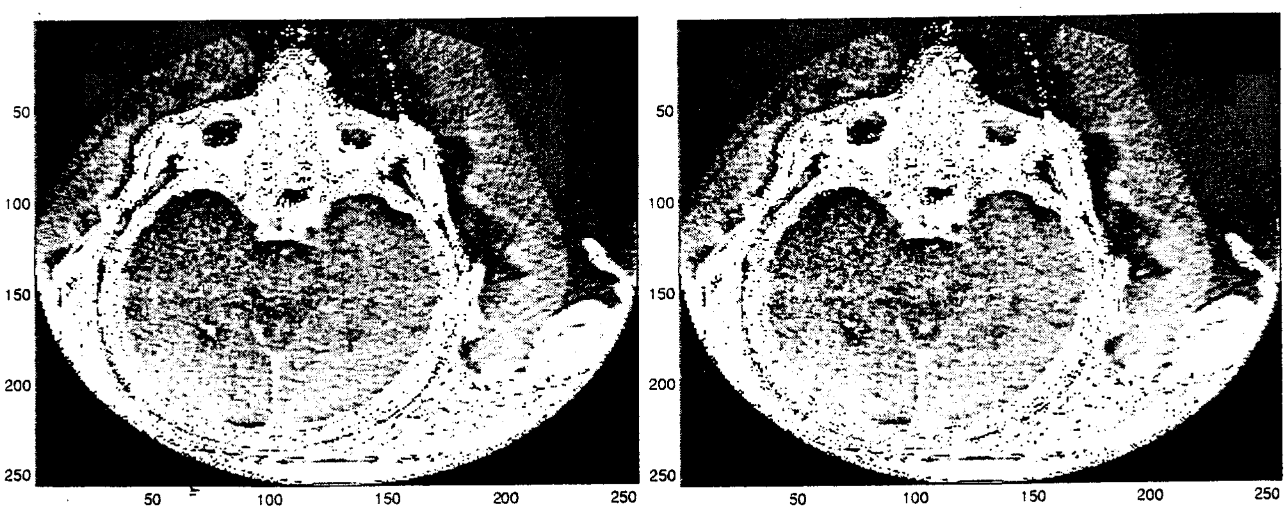


Fig. 2. The original CT slice 51

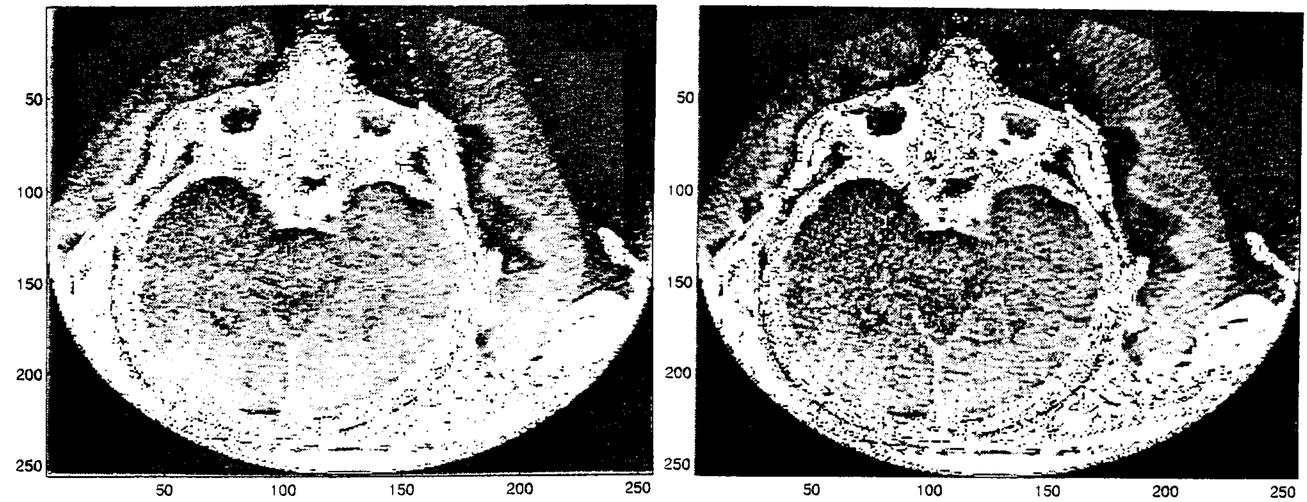


(a)

(b)

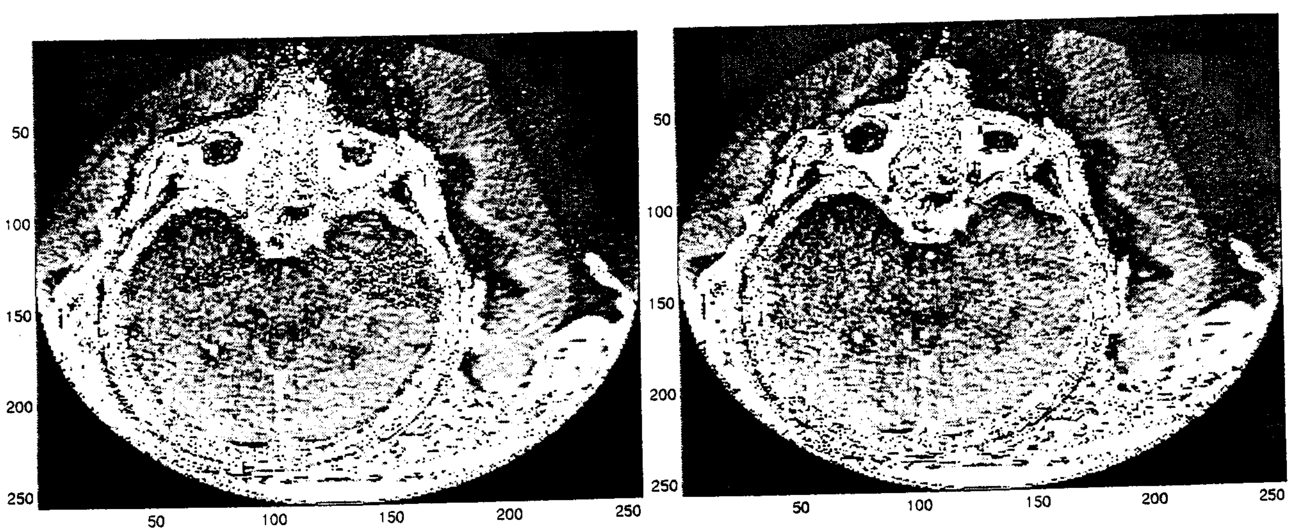
Fig. 3(a). The intermediate image 51 using *linear* interpolation without the matching method.

3(b). The intermediate image 51 with the matching method.



(a) (b)

Fig. 4(a). The intermediate image 51 using *cubic spline* interpolation without the matching method.
4(b). The intermediate image 51 with the matching method.



(a) (b)

Fig. 5(a). The intermediate image 51 using *Fourier* interpolation without the matching method.
5(b). The intermediate image 51 with the matching method.

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