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Generation of Missing Medical Slices Using Morphing Technology

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Abstract

To estimate the locations and intensities of pixels that would appear in the nonexistent intermediate slices. This paper presents a new method for generation of the missing medical slices from give two slices. It uses the contours of organs as the control parameters to the intensity information in the physical gaps of serial medical slices. The snake model are used for generating the control points required for the elastic body spline morphing algorithm, which were previously manually specified. Contour information derived from this segmentation pre-process is then further processed and used as control parameters to warp the corresponding regions in both input data slices into compatible shapes. In this way, the intensity information for the interpolated intermediate slices can be derived more faithfully. In comparison with the existing intensity interpolation methods, like linear interpolation, which only consider corresponding points in a small physical neighborhood, this method warps the data images into similar shapes according to contour information to provide more meaningful correspondence relationship.

1 Introduction

Interpolation in general is desirable whenever the original data that are collected lacks the resolution or detail that is desired. One might then ask why one doesn't simply acquire the data at the desired resolution initially. This is not possible for a number of reasons. First, one may not know at collection time what the desired final resolution. Another limiting factor may be that the desired resolution may not be within the capabilities of the device used to collect the data. A third reason is the time that is required to collect the data. The device may require an inordinate amount of time to capture the data at the desired resolution. Another problem may be the vast amount of storage that may be required to store the data at full resolution.

Medical imaging systems are not exceptions to the above problems[17]. These devices typically collect the data in a slice by slice fashion. These slices are then stacked to produce a 3D representation of the data. And these 3D volumes can be even further stacked to form a four dimensional representation of the data. Typically the distance between adjacent data elements within a single slice is different from the spacing between adjacent data elements in two neighboring slices. If the sampling is the same at all dimensions, then the data are isotropically sampled. Interpolation is used to convert non-isotropic data into isotropic data. Interpolation in general and shape-based interpolation[9,13] specifically can be used to help solve these problems. Image morphing may be used to overcome these problems or can be used to generate the missing slices.

Image morphing is the technology used to generate a result image by cross dissolve two different images. It is a powerful tool to generate intermediate frames for animation to convert from one frame to another frame smoothly[1]. In this work, we adopt morphing techniques to generates the inter slices medical images based on elastic body spline transformation with semiautomated feature extraction by using snake model [10] to define the feature correspondence. The main purpose of this work is to estimate the locations and intensities of pixels that would appear in the nonexistent intermediate slices using morphing technology.

The algorithm consists of the following three steps:

[1] **Pre-Segmented Hierarchical Step**
We use an active contour model initialized with a pre-segmented process to extract the contours of the features of interest,

[2] **Matched Contour Step**
Matched contour are converted into directed pair of points to be used for the elastic body spline warping algorithm, and

[3] **Cross-dissolve Step**
Cross dissolve two deformed slices to generate the intermediate slices.

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The reminder of this paper is organized as follows. In section 2, we describe the relationship between our work and previous published work. This is followed by the description of the interpolation methods: contour-based interpolation,intensity-based interpolation and shape-based interpolation. Pre-segmented process based on snake model are given in section 3. Section 4, explain the warping and cross dissolve transformation to generate the intermediate slices. Mutual information description is given in section 5. Finally, conclusions with some experimental results are discussed in sections 6 and 7.

2 Previous Work and Interpolation Methods

The resolution of data obtained from medical imaging modalities has the characteristic that the slice thickness is usually much larger than the pixel size within a single slice, and the gap between slices is usually much larger than the in-plane resolution. The non-isotropic resolution in these images will adversely affect subsequent visualization and analysis processes. The quantitative and qualitative accuracy of visualization and analysis can be enhanced by a suitable interpolation process, in which the original data are interpolated to meet the isotropic requirement.

Broadly, image interpolation techniques can be divided into three categories. One is contour-based interpolation[5,7,10,15] that takes a set of binary images representing cross-sectional boundaries of objects segmented from the intensity value data and generates a new set of interpolated binary sequence representing the surface of the object. Second is intensity-based interpolation[8,11] that takes the original voxel intensities representing whatever physical quantities and generates a new set of interpolated voxel intensities. Last category is shaped-based interpolation[3,7] that takes a set of binary images representing cross-sections of object segmented from the intensity-value data and performs morphological interpolation between the shapes of the contours.

Contour-based interpolation algorithms, usually represent the cross-sections as a set of oriented contours derived from a segmentation pre-process[9], and the goal of these algorithms is to determine the intermediate contours by reconstructing smooth surfaces covering the exteriors of the set of original binary data contours given. For these algorithms to obtain a unique solution, assumptions have to be made at three different levels corresponding to the following three major task of a surface reconstruction[14]. (1) contour association must be explicitly available to specify which contours on one slice are to be connected to which contours on the adjacent slice. (2) contour matching that relates the points on one contour to the points on the other associated contour must be established using some syntactic rules, e.g., minimal scan length[17]. (3) given the correspondence between vertices, an interpolation surface has to be constructed. Besides the feature selection problem, association problem, correspondence problem, branching problem, merging problem, and surface fitting problem to be addressed in this approach, one major drawback for applying this approach to medical image processing is the loss of detailed anatomical information. Since only the information from contours of selected feature is used in the interpolation process, a lot of critical information in the form of image intensity variation would be lost.

In comparison with the contour-based approach, relatively fewer researches were conducted to improve the intensity-based interpolation techniques. The goal of intensity-based process is to reconstruct a 3D continuous signal from the original samples of the data slices. One of the most widely used intensity interpolation technique is linear interpolation. Other intensity interpolation methods use higher order interpolation kernels such as bi-cubic, tri-linear, tri-cubic, and polynomial spline interpolation[18]. In general higher order interpolation can produce smoother images because more sample values are used in the estimation. However, there are several drawbacks to these methods. For example, they can assume only a single type of variability in intensity, such as linearity. Data variation assumptions can lead to inaccurate estimation if the actual variation is not the same as the assumed variation.

Instead of using the binary slices information to reconstruct a smooth interpolation surface, the shape-based interpolation scheme uses the geometric properties of the cross-sections and generates a set of interpolating cross-sections directly. Raya et. al.,[16] calculate the interpolating cross-sections by interpolating the distance to the cross-sectional boundary. This method assumes that the corresponding regions do overlap, and the result is a distance to the cross-sectional boundary and then intensity filling operation has been used to calculate the content of the interpolate region. Shape-based algorithms are deterministic and produce satisfactory results when their assumptions are fulfilled, which may not be always true in medical images.

3 Hierarchical decomposition

To improve the performance of the morphing results, a hierarchical decomposition process is proposed to simplify the work of the user interface. A segmented image can be considered as a set of regions $\{R_i | i = 1, 2, .., n\}$, where R_i is the $i-th$ region in the segmented image and its surrounded and defined by the contour C_i. Due to the segmentation process, we have to satisfy the following condition that for any two different regions, they do not intersect with each other. That means, when calculating the warp, each region need only reference the contour that encloses this region and the contours that are directly contained in this region. For example, in Figure 1, the pixels that are in region R_2 but not in R_3 or R_4, only need to reference contours C_2, C_3, and C_6.

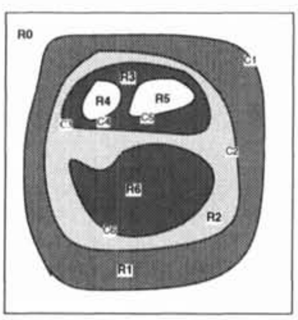


Figure 1. Hierarchical segmented image

4 Morphing Algorithm

Image morphing is a combination of warping images and cross dissolve algorithm. In this section, we will going to explain the warps the data images into similar shapes according to contour information based on elastic body spline to provide more meaningful correspondence relationship. Then the in-between slices can easily generated by cross dissolving the positions of correspondence features and their shapes and colors.

4.1 Warping Analysis

The elastic body spline is based on Partial Differential Equation of Navier[1,2] that describes the equilibrium displacement of the elastic body subjected to forces. Once image features are paired with a correspondence points p_i and q_i, we can construct the EBS transformation and use it as interpolation map from R^2 to R^2 relating these set of corresponding feature points.

In point based warping a set of n point pairs $(\vec{p_i}, \vec{q_i})$ are selected in the source and destination images. For instance, $\vec{p_1}$ is the coordinate of a feature point in the source image that corresponds to a feature located at coordinates $\vec{q_1}$ in the warped image. The displacement between the point sets are:

$$\vec{r_i} = \vec{q_i} - \vec{p_i}. \tag{1}$$

The coordinate transformation must be determined such that it matches the displacements at the points $\vec{r_i}$ and interpolates them elsewhere. The coordinate transformation $C_{trans}(\vec{x})$ is defined by

$$C_{trans}(\vec{x}) = (\vec{f_x}(\vec{x}) \ , \vec{f_y}(\vec{x})) \tag{2}$$

$\vec{f_x}(\vec{x})$ and $\vec{f_y}(\vec{x})$ are both Elastic Body Spline that represent displacements and take the form:

$$\left.\begin{aligned} \vec{f_x}(\vec{x}) &= \sum_{i=1}^{N} K(\vec{x} - \vec{p_i})\vec{w_{i1}} + A_1 \cdot \vec{x} + \vec{b_1} \\ \vec{f_y}(\vec{x}) &= \sum_{i=1}^{N} K(\vec{x} - \vec{p_i})\vec{w_{i2}} + A_2 \cdot \vec{x} + \vec{b_2} \end{aligned}\right\} \tag{3}$$

$A_i \cdot \vec{x} + \vec{b_i}$ is the affine part of the EBS in which $A_i = [\vec{a_{1i}} \quad \vec{a_{2i}}]_{(2\times2)}$ with $\vec{a_{ij}} = [a_{i1} \quad a_{i2}]$, j=1,2 and i=1,2 and $\vec{x} = [x \ \ y]^T$.
$K(\vec{x})$ is given by the following form:

$$\vec{u}(\vec{x}) = K(\vec{x})\vec{w} \tag{4}$$

where $K(\vec{x}) = [r(\vec{x})^2(M_1)I - (M_2 - 5)\vec{x}\vec{x}^T]r(\vec{x})^2$

$$M_1 = 3\alpha ln[r(\vec{x})] - \beta, \qquad M_2 = 12ln[r(\vec{x})]$$

I is 2x2 identity matrix, $r(\vec{x}) = |\vec{x}|$, and $\alpha = 12(1-k) - 1$,

$k = \frac{\lambda}{2(\lambda+\mu)}$ is Poisson's ratio, $\beta = 18(1-k) - 2$.

Equation(4) is the fundamental solution of the Navier equilibrium partial differential equations for the elastic body subjected by forces that serve as the constraint equations in the elastic body:

$$\mu\nabla^2\vec{u}(\vec{x}) + (\mu + \lambda)\nabla[\nabla.\vec{u}(\vec{x})] + \vec{F}(\vec{x}) = 0 \tag{5}$$

$\vec{u}(\vec{x})$ is the displacement of a point within the body from the original position $\vec{x}$. ∇^2 and ∇ denote the Laplacian and Gradient, respectively. μ and λ are the Lame coefficients which describe the physical properties of the elastic material. $\vec{F}(\vec{x})$ are the external forces distributed everywhere in the body; we should select these forces so that the warping of the elastic body spline is smooth. There are many different ways to derive forces[4], such as using information from the input data, from external knowledge (i.e., interactively or from a knowledge base) or from some other processes. These forces should be selected so as the generate a smooth warp:

$$\vec{F}(\vec{x}) = \vec{w_i} r(\vec{x})^2 ln[r(\vec{x})], \quad (6)$$

$\vec{w_i}$ is the strength of the force field, $\vec{F}(\vec{x})$ and $\vec{x}$ are all 2D vectors.

The elastic body spline coefficients are computed by solving system of linear equations [1,2]. Its can be evaluated by using equation (3) as the interpolation function that interpolates scattered data points that satisfy $f(\vec{p_i}) = \vec{q_i}$ if and only if L is not singular.

Figure (2) illustrates some warping results using Navier splines with different Poisson's rate, 0.2 and 0.4 respectively. The source slice is in the left of the slices sequence.

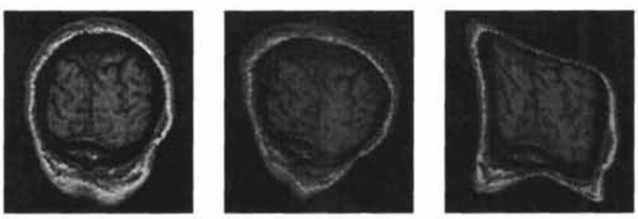


Fig. 2 Example for warping results

4.2 Inter-slices Transformation

With the information gathered in the pre-segmented step using traditional Snake model, we can now perform the elastic body spline morphing algorithm to blend the two source images. Given two images I_s and I_d, with variable $\alpha \in [0,1]$, an in-between image I_α is created such that I_α is similar to I_s at $\alpha \longrightarrow 0$ and similar to I_d as $\alpha \longrightarrow 1$. We assume that the variable α varies from 0 to 1, so that the source image I_s continuously changes to the destination image I_d. The in-between images of I_α are defined by creating a new set of feature points from their positions on I_s to the positions on I_d.

Since we use the same initial contours for segmenting the two source images, the vertex corresponding can be easily maintained, and the interpolated polygonal contours are generated by interpolation the positions of vertices.

Let W_s be the warp function which specifies the corresponding point on I_d to each point on I_s. When it is applied to I_s, W_s has to distort I_s to match I_d in the positions of features and their shapes. Let W_d be the warp function from I_d to I_s. It is required to map the features on I_d to the features on I_s when it distorts I_d. The in-between images could be defined by using the following deformed cross dissolve function:

$$I_\alpha = [1 - K(\alpha)]W_s^\alpha(I_s) + K(\alpha)W_d^{1-\alpha}(I_d) \quad (7)$$

$K(\alpha)$ is the transition control defined on the image. It determines how fast each point on I_s moves to the corresponding point on the destination image I_d. Also, it determines how much the colours of each point on I_s reflected on the correspondence point on $I(\alpha)$. $K(\alpha)$ controls the rate of transition in equation 7. For the colours transformation, linear interpolation cannot defined on the distorted images $I_d(\alpha)$ and $I_d(\alpha)$ but on the given images I_s and I_d, respectively. Hence, we used the transition control $K(\alpha)$ to attenuate the colours intensities of I_s and I_d before applying warp functions. The transformation of positions and colours can be independently handled by specifying different transition function.

5 Mutual Information Analysis of the Morphed Images

The mutual information measure is derived from a statistical analysis of a noisy communication channel, and is a measure of information transmitted across that channel. This measure is alternatively referred to as relative entropy or transformation. The measure makes no assumption about the functional form of the channel. Mutual information has been proposed independently for various medical image registration applications by Collignon et al [8]. The mutual information between an image m and an image n defined from the 2D probability distribution of intensities is:

$$I(M,N) = \sum_{m \in M} \sum_{n \in N} p(m,n) log \frac{p(m,n)}{p(m)p(n)} \quad (8)$$

where M is the set of intensities in image m, and N is the set of intensities in image n present in the region of overlap of the two images. This can be expressed in terms of the information present in image $mH(M)$, the image $nH(N)$, and the combined image $H(M,N)$:

$$I(M,N) = H(M) + H(N) - H(M,N) \quad (9)$$

In other words by maximizing mutual information we minimize the information in the combined image with respect to that present in the two component images.

6 Experimental Results

Figure 3. Animated In-between slices for MRI foot data

Figure 3, shows the animated in-between sequences of MR foot data, the source slice at number i in the leftmost of the first row and the destination slice in the rightmost of the last row at number $i + 8$, and the other are generated in between slices. Figure 4 shows the animated sequences of the MRI brain data, the source image in the leftmost of the first row and the destination one in the rightmost of the second row.

Figure (5) shows the comparison between two different interpolated methods. Figure 5(a,b) represents the two input slices and Figure 5(c) shows the intermediate slice using linear interpolation method, Figure 5(d) shows the intermediate slice using our algorithm. It is clear from the result to see that the difference between linear interpolation and morphing technology to generating the intermediate slice. In case of linear interpolation, the result look like overlaps two slices,because we do not consider the warping process, just we apply the direct interpolation on the two given slices.

In the following we study the measurements of the accuracy of the interpolated slice using two metrics: correlation coefficient (CC) and mutual information (MI). Table(1) shows the visual inspection of the morphed slice using morphing technology shows a good approximation for generating the missing slices, in case the distance between the given two slices is large. We then measured the accuracy of interpolated results using two metrics: correlation; and mutual information. The correlation coefficient and mutual information give higher values for good morphing result as desired.

Table (1) Measurements of morphing accuracy between source, target an d morphed images

image	*CC*	*MI*
source	0.910	0.503
morphed by linear interpolation	0.71	0.294
morphed by elastic body spline	0.978	0.894
target	0.8701	1.058

7 Conclusion

Slices of image data are often too far apart to provide accurate reconstruction in 3D. Sometimes you may need to interpolate the data in between the images. This can be done, but it must be stressed that this generated data is only an educated guess and should not become a substitute for acquiring real data at the level of resolution desired in the final 3D reconstruction. A morphing technique based on spline is a relatively good starting point in this area. In this paper, we have proposed an image morphing algorithm to generate the inter medical slices from give two slices based on elastic body spline[1]. Beside the feature specification and to reduce the difficulties to define these feature, we adopt a semiautomatic method to simplify the work of user interface by using snake model. To deform the slices into similar shapes and generate the intermediate form, in this paper we used elastic body spline morphing algorithm to interpolate whole images, also to interpolate the interested region. In comparison with the existing intensity interpolation algorithms, which only consider corresponding points in a small physical neighborhood, this method warps the data images into similar shapes according to contour information to provide more meaningful correspondence relationship. The results show that this method generate more realistic and less blurred interpolated images easily when the local intensity variation is significant.

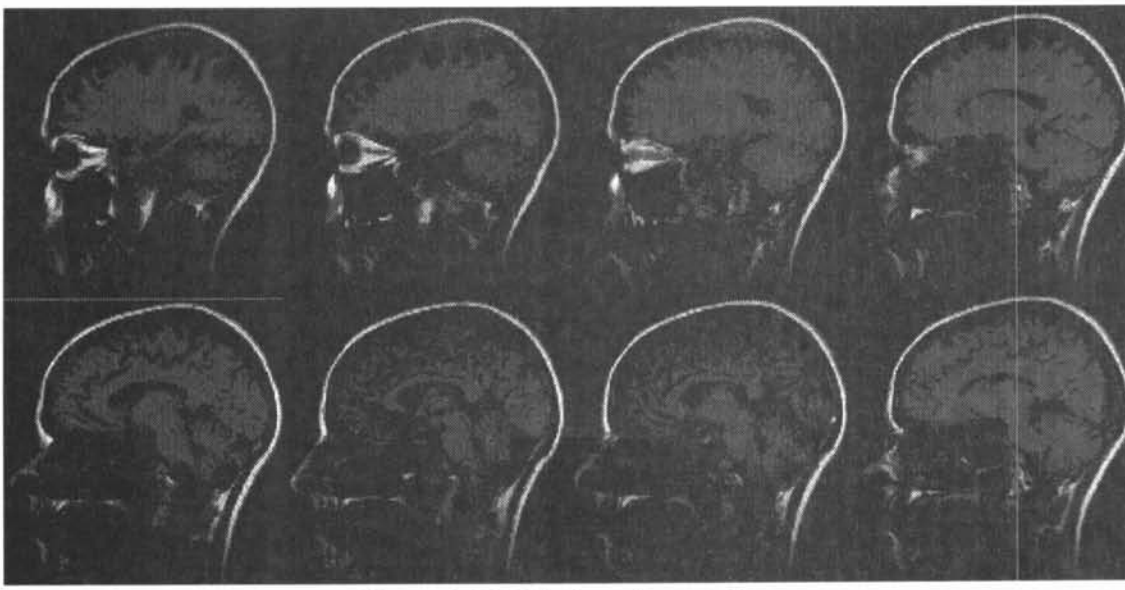
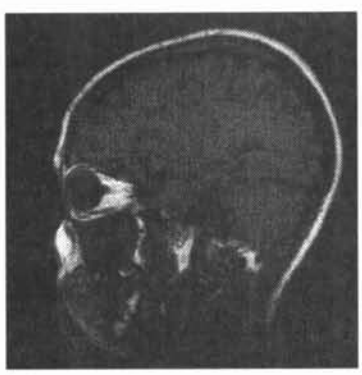
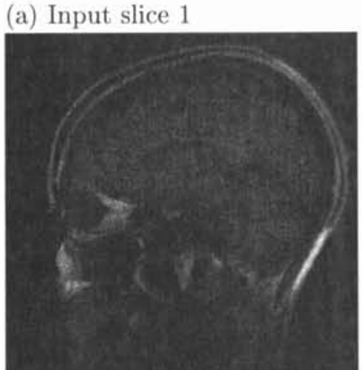
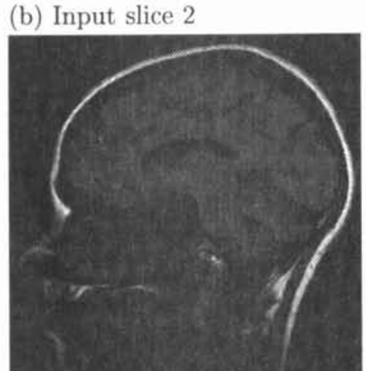


Figure 4. MRI brain animated slices



(a) Input slice 1 (b) Input slice 2





(c) Linear interpolation (d) Elastic spline interpolation

Figure 5. Comparison between different interpolated slices

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