

Novel registration algorithm for 3-D images captured from multiple views of object surface

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Abstract: A novel algorithm of 3-D surface image registration is proposed. It makes use of the array information of 3-D points and takes vector/vertex-like features as the basis of the matching. That array information of 3-D points can be easily obtained when capturing original 3-D images. The iterative least-mean-squared (LMS) algorithm is applied to optimizing adaptively the transformation matrix parameters. These can effectively improve the registration performance and hurry up the matching process. Experimental results show that it can reach a good subjective impression on aligned 3-D images. Although the algorithm focuses primarily on the human head model, it can also be used for other objects with small modifications.

Key words: image alignment; 3-D image; 3-D capture; image registration; iterative least-mean-squared algorithm

Physical 3-D objects occlude themselves. To capture the full geometry of a moderately complicated object may require as many as a dozen of 3-D images from different views. Therefore, registration is the necessary step in creating an integrated 3-D model of an arbitrary 3-D object from multiple 3-D images. This registration step currently relies on accurate mechanical positioning devices, or on manual processing. The idea of using the 3-D image itself to perform the registration automatically is attractive. ICP^[1] is a general-purpose, representation-independent method for an accurate and computationally efficient registration of 3-D images including free-form curves and surfaces. It uses a mean-square distance metric which converges monotonically to the nearest local minimum. But it requires that every point on one surface has a corresponding point on the other surface. 3-D images captured from multiple views cannot satisfy such a constraint. Some methods re-triangulate each range image, and then attempt to match the triangulations. The difficulty is that the resolution of the triangulations is selected heuristically and the matching process is rather complex^[2]. It has been extended to include the nonlinear optimization and robust estimation techniques to minimize the registration error. Rusinkiewicz et al. used a real-time ICP variant by assuming that the relative motion between two consecutive range images in the acquisition is small^[3]. Roy-Chowdhury et al. proposed a technique for the registration of two images of a face obtained from different viewing angles by matching two-dimensional (2-D) shapes of the different features of the face^[4]. Other methods to register 3-D images without any approximately correct initial transformation such as Ref. [5] must be based on enough common corner-like feature points and must be accompanied with 2-D intensity images to compute the fundamental and the essential matrix. The problem is that the above limitations and their complex calculation cannot be satisfied in most 3-D capturing applications.

1 Algorithm Description

In this paper, we propose a simple way to automatically register multiple 3-D images. It is based on only two facts in 3-D capture as follows: First, there is some overlapping area between every two 3-D images captured from adjacent views of the object. Secondly, there is a character of stochastic curvature variance on the overlapping area so that there will be unique optimal position for adjacent 3-D images matching exactly. They are easily satisfied in 3-D observation of a natural object and also the basic requirements of other data-based 3-D image registration schemes. Our algorithm uses vector/vertex-like features as the basis of the matching process because an important indication for the registration is the coincidence of both vectors and vertices of the corresponding surface cells. When being captured, the sample points of the 3-D image can be originally organized in a 2-D array. That means, for any point P on the 3-D image surface, we can determine immediately which point is next to point P and which points are around point P . This will remarkably speed up our matching process.

The registration algorithm has its input of a sequential of overlapping 3-D images captured from different

Received 2005-06-10.

Foundation item: The Technologies Innovation Program of Jiangsu Province (No. 7604005067).

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views of a physical object. The output is a sequential of the relative 3-D transformation that converts each 3-D image to a common coordinate system. The algorithm is as follows:

- ① Let A, B, C, \dots be a 3-D image respectively one by one. Set the common coordinate system to that of one 3-D image, for example: A ;
- ② Locking the position of A , register B to align with A . We can get the transformation $\mathbf{R}_B, \mathbf{T}_B$ as the result (The matching step will be described in more detail next);
- ③ Locking the position of A and B , register C to align with B or A , we get the transformation $\mathbf{R}_C, \mathbf{T}_C$. Do the same operation on D, E, \dots to register them one by one and get the transformation $\mathbf{R}_D, \mathbf{T}_D, \mathbf{R}_E, \mathbf{T}_E, \dots$

2 Matching Process

Let A, B represent two adjacent 3-D images respectively. Locating A , the matching process will find out an optimal transformation \mathbf{R}_B and \mathbf{T}_B for B to align with A . Matching process can be described as follows:

Step 1 Divide A into plane cells in the form of triangles. Define G_A and V_A is the set of plane cells and the set sample points of A , respectively. Define g_a, v_a is an element of G_A and V_A , respectively. We have $g_a \in G_A, v_a \in V_A$. Because the points of A are organized as 2-D array, we can note g_a as $g_a(i, j)$ and v_a as $v_a(p, q)$.

Step 2 Doing the same processing on B , we get $G_B, V_B, g_b(i, j), v_b(p, q)$ and $g_b(i, j) \in G_B, v_b(p, q) \in V_B$.

Step 3 Set the initial transformation matrices to be \mathbf{R} and \mathbf{T} :

$$\mathbf{R} = \begin{bmatrix} \cos\phi\cos\theta & \sin\phi\cos\theta & -\sin\theta \\ -\sin\phi\cos\phi + \cos\phi\sin\theta\cos\phi & \cos\phi\cos\phi + \sin\phi\sin\theta\cos\phi & \cos\theta\sin\phi \\ \sin\phi\sin\phi + \cos\phi\sin\theta\cos\phi & -\cos\phi\sin\phi + \sin\phi\sin\theta\cos\phi & \cos\theta\cos\phi \end{bmatrix}, \quad \mathbf{T} = \{T_x, T_y, T_z\}$$

where ϕ, θ, φ are the angles revolving about axis x, y, z , respectively; T_x, T_y, T_z are the translation along axis x, y and z , respectively. The initial \mathbf{R} and \mathbf{T} can be created crudely and interactively by aligning B with A on computer-screen.

Step 4 Set $\Delta\mathbf{T}_0$ and $\Delta\alpha_0$ to be the initial increment of transformation matrix, D to be the maximum distance between vertex and its corresponding plane cell, $\Delta\mathbf{t}_{\min}$ and $\Delta\alpha_{\min}$ to be the least increment.

Step 5 Transform B : $B = \mathbf{R}B + \mathbf{T}$.

Step 6 For every p, q that the vertices $v_b(4p, 4q) \in V_B$ on surface B , search one plane cell $g_a(i, j) \in G_A$ which is the closest to $v_b(4p, 4q)$ within the distance D . Because only 1/16 of total vertices of V_B involved in matching process, the calculation complexity is reduced to 1/16 of that using all vertices. Let V'_B, G'_A be the subsets of V_B and G_A respectively whose elements have been matched in the above matching process. Assume that M is the number of elements of both above subsets. Because only 1/16 vertices of V_B take part in matching process and only a small part of vertices can be found the closest g_a within the distance D , M is far less than the element number of V_B and G_A .

Step 7 Let v_{b_i} be one element in V'_B , g_{a_i} be its corresponding plane cell of G'_A , d_i be the distance between v_{b_i} and g_{a_i} , \mathbf{v}_{Ai} be the vector of g_{a_i} , \mathbf{v}_{Bi} be the mean vector of 4 triangle plane cells in G_B whose vertex is v_{b_i} , where $i = 1, 2, \dots, M$. Calculate

$$d_p = \frac{1}{M} \sum_{i=1}^M d_i, \quad d_v = \frac{1}{M} \sum_{i=1}^M \|\mathbf{v}_{Ai} - \mathbf{v}_{Bi}\|$$

Step 8 Use the LMS algorithm as the following to calculate each element of \mathbf{R} and \mathbf{T} :

$$\begin{aligned} \theta_{k+1} &= \theta_k - \Delta d_v \frac{\partial d_v}{\partial \theta}, & \phi_{k+1} &= \phi_k - \Delta d_v \frac{\partial d_v}{\partial \phi}, & \varphi_{k+1} &= \varphi_k - \Delta d_v \frac{\partial d_v}{\partial \varphi} \\ T_{x_{k+1}} &= T_{x_k} - \Delta d_p \frac{\partial d_p}{\partial T_x}, & T_{y_{k+1}} &= T_{y_k} - \Delta d_p \frac{\partial d_p}{\partial T_y}, & T_{z_{k+1}} &= T_{z_k} - \Delta d_p \frac{\partial d_p}{\partial T_z} \end{aligned}$$

until d_p and d_v are less than a threshold or k is equal to a given number. Because d_p and d_v represent the average value of difference between two corresponding points and two responding vectors respectively, the threshold of d_p can be set as about 1/100 of the distance between two adjacent points in 3-D data matrix, and the threshold of d_v can be set as about 1/100. Δ is a constant factor.

3 Experiments

Fig. 1 is a 2-D image of a human head model. Fig. 2 shows the 3-D images captured from three views of the real model. Fig. 3 shows the integrated 3-D image after registration. We use the OpenGL tool to display the 3-D data. Fig. 3 is the integrated 3-D image after aligning the three 3-D images which are the 3-D images captured

from three views (Fig. 2(a) is of the left view, Fig. 2(b) is of the right view and Fig. 2(c) is of the top view.) of the human head model shown in Fig. 1. There is no obvious imprint on the connective areas among different views. Compared with the distances measured on the real model by the point-point instrument, the final error of whole registration process is 0.2 percentage compared with the real model. The maximum error is about 0.3 mm.



Fig. 1 2-D image of a human head

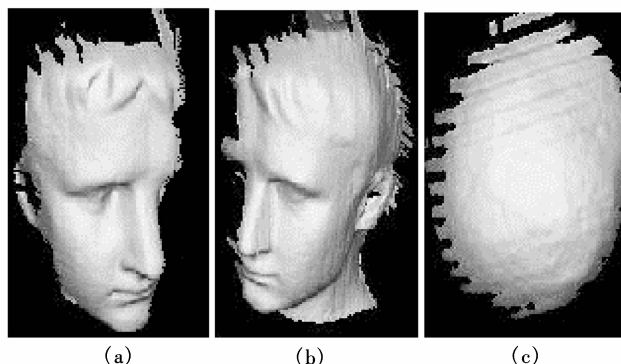


Fig. 2 3-D images captured from three views of human head model



Fig. 3 Integrated 3-D image

4 Conclusion

In this paper, we present a simple way to automatically align multiple 3-D images based on two facts in 3-D capture. The prior information can be easily obtained when capturing original 3-D images. The algorithm uses vector/vertex-like features as the basis of the matching process because an important indication for the registration is the coincidence of both vectors and vertices of the corresponding surface cells. These remarkably improve the registration performance and hurry up the matching process. An application of this method to the 3-D model registration of a human face is demonstrated.

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物体表面不同角度采集的三维图像配准的一种新算法

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摘要:提出了一种能有效实现物体表面三维图像数据配准的算法. 该算法利用了三维数据采集时的三维点的阵列信息, 这些三维点的阵列信息在采集原始三维数据时可以很容易获得, 同时, 还利用了三维数据矢量/顶点相似特征作为数据匹配的基础. 采用迭代最小均方误差算法来自适应优化变换矩阵参数. 这些方法可以有效地提高三维图像配准的性能, 加快匹配过程的运算速度. 实验结果表明该算法可以获得较好的配准后三维图像的主观效果. 尽管该方法主要针对人头模型, 但经过少许修改后即可适用于其他物体.

关键词:图像对齐; 三维图像; 三维采集; 图像配准; 迭代最小均方误差算法

中图分类号:TP391.41