Iterative Registration of Multiple 3D Data Sets using Covariance Matrix

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Abstract

In 3D data processing registration is the process of aligning multiple 3D data sets in a common coordinate system. Previous registration methods rely on accurate mechanical positioning devices, or on manual processing to estimate the viewpoints. In addition, most algorithms require many processes: feature extraction, matching, and surface segmentation. This paper presents an iterative method for automatically registering multiple 3D data sets using covariance matrix without a-prior knowledge about 3D transformation between views. For an accurate registration, our method uses both the 3D transformations giving a relative pose between the 3D data sets, and the projective matrix representing projection of 3D space to 2D image. By minimizing the difference of two covariance matrixes of the overlapping regions in two 3D sets, we can make a precise registration of multiple 3D sets without the above complex procedures that are prone to errors. In experimental results, we demonstrate the capabilities of the registration method on various complex 3D data sets.

1. Introduction

Range imagery is increasingly being used to model real objects and environments, and the laser sensors have simplified and automated the process of accurately measuring the 3D structure of a static environment[1]. Since it is not possible to scan the complete object at once due to topological and geometrical limitations, several range images showing only partial views of the object must be registered. Therefore, registration, the process of aligning multiple 3D data sets in a common coordinate system, is one of the most important problems in 3D data processing[2]. More specifically the process provides a pose estimate of the input views that is a rigid body transformation including 3 rotations and 3 translations.

The obtained poses can be specified for a single view in world coordinates or with respect to a pair of views. Figure 1 shows that there is the relationship of the 3D data sets. Each input range data, $\boldsymbol{R_1}$, $\boldsymbol{R_2}$, …., and $\boldsymbol{R_n}$, consists of 3D points in camera's local coordinate system. Generally the first local coordinate system is fixed to the common coordinate system. In order to register all range data sets, a local coordinate system of each 3D set is transformed to the common coordinate system. As shown in Fig. 1, transformation between two data is represented by homography matrix, $\boldsymbol{H}$. This paper mainly considers the first step in the registration that is to estimate the relative pose between 3D data sets.

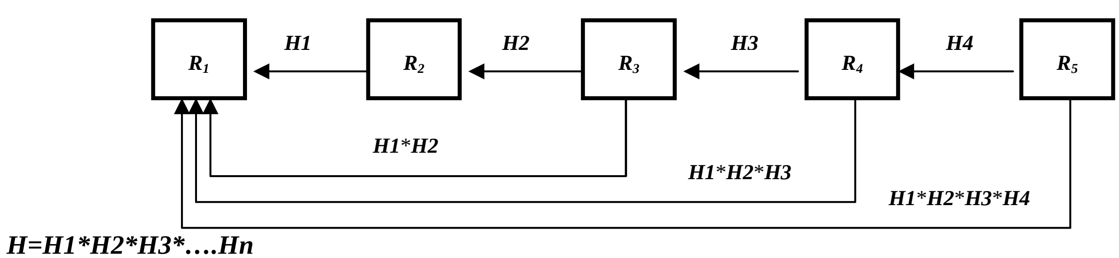


Fig.1. the relationship of the 3D data sets.

Previous approaches required manual assistance including specification of initial pose estimates or relied on external pose measurement systems, so many limitations and the set-up equipments are required. On the contrary automatic registration is to automatically recover the viewpoints from which the views were originally obtained without a-prior knowledge about 3D transformation between views. In order to calculate the pose for arbitrary rotation and translation parameters, we need to know at least 3 corresponding feature points between the 3D data sets. Once correspondences have been established, numerical minimization is used to determine object rotation and translation. However, automatically detecting suitable features in general scenes and matching them is extremely difficult and currently no reliable methods exist. In addition, another possibility is to ask the user to supply the features, but this is very labor intensive and often not very accurate. A popular method for registering a model to a 3D data set is the iterative closest point algorithm (ICP)[3]. The two main difficulties in ICP, determining the extent of overlap in two scans and extending the method for multiple scans, have been a focus of much further research{4]. Furthermore, ICP requires a-priori knowledge about an approximate estimate of the transformations.

Horn has presented the method for registering multiple 3D data sets using covariance matrix that represents major and minor axis of 3D points cloud set. When the 3D data sets are rotated and translated, we compute the translation parameters between the 3D data sets by using the centroid of each 3D point set, and the rotations through eigen-value decomposition that gives a pose estimate between the 3D data sets[5]. Because this method has two shortcomings: correspondence problem and occlusions. however, it is difficult to make a precise registration. For more accurate registration, we propose an automatic registration method using both the projective matrix and the 3D transformations. In our method, the analysis of covariance provide rough 3D transformations, and we calculate the projective matrix representing projection of 3D space to 2D image by using the range images and the intensity[6]. Then, the proposed method transforms the current 3D data set and the camera position into the next view, vice versa, and extracts the overlapping regions between two views. By minimizing the difference of two covariance matrixes of the overlapping regions in two 3D sets, we can more refine the 3D parameters than previous methods using the only covariance matrix. Because our algorithm can register multiple 3D data sets without feature extraction, matching, and surface segmentation, we obtain more accurate registration results in reasonable time. The experimental results show the capabilities of the registration method on various complex 3D data sets.

2. Algorithm Description

This paper presents an automatic registration method to calculate 3D rigid transformations that align range views using no prior knowledge about the 3D transformation between views. Our method has as its input two overlapping range images along with their associated intensity images. The output is the relative 3D transformation between these two images. Figure 2 shows the overview of the proposed method.

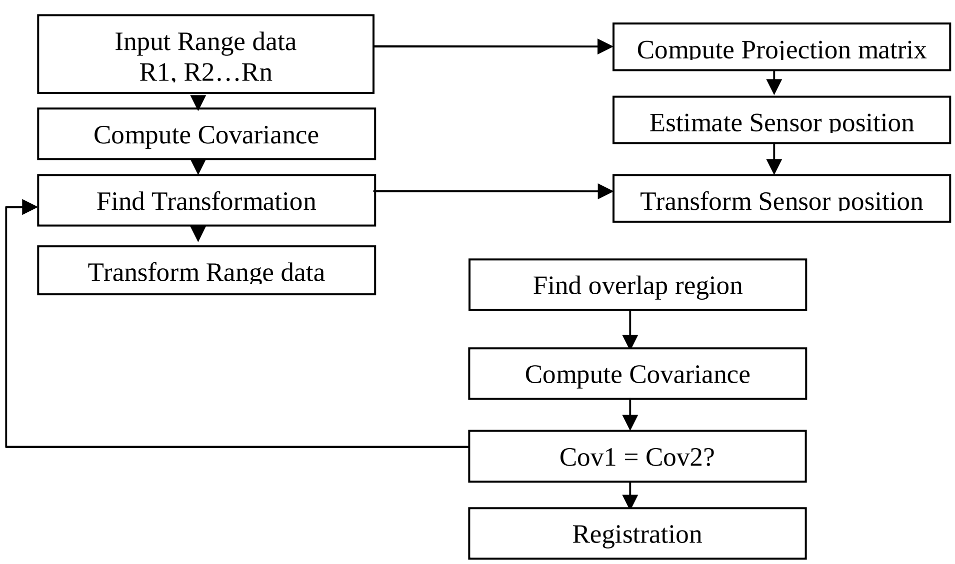


Fig. 2. Diagram for our algorithm.

2.1 Coarse registration using variance matrix

Horn has presented the registration method based on covariance matrix[5]. The matrix provides major and minor axis of 3D points cloud, so defines a new object coordinate. The optimal bounding box of 3D data used for collision detection or ray-tracing, is constructed by using the axes. When the 3D data set is rotated and translated, we can compute the rotation matrix through eigen-value decomposition that gives a pose estimate between the 3D data sets. The mean vector consists of the means of each variable and the variance-covariance matrix consists of the variances of the variables along the main diagonal and the covariances between each pair of variables in the other matrix positions. The mean vector is often referred to as the centroid and the variance-covariance matrix as the dispersion or dispersion matrix.

$$\mathbf{C} = \frac{1}{N}\sum_{j=0}^{n}\vec{\mathbf{V}}_{\mathbf{j}} \tag{1}$$

$$\mathbf{Cov} = \frac{1}{N}\sum_{i=0}^{N-1} (V_i - V_C)(V_i - V_C)^T \tag{2}$$

At the first, we calculate the centroid of 3D points cloud by summing the x and y coordinates of each point then dividing the number of the points. When the 3D data set is rotated and translated, we can compute the rotation matrix through eigen-value decomposition that gives a pose estimate between the 3D data sets. As mentioned in the introduction, because it is very difficult to establish correspondences on 3D data sets, however, the method based on covariance matrix can not make a precise registration. In addition, the method takes no consideration of the case that some parts of the 3D-object may be occluded or lie in shadow. Therefore, the method based on covariance provide just a rough 3D transformations to a certain extent, and Figure 3 shows the registration results have much errors.

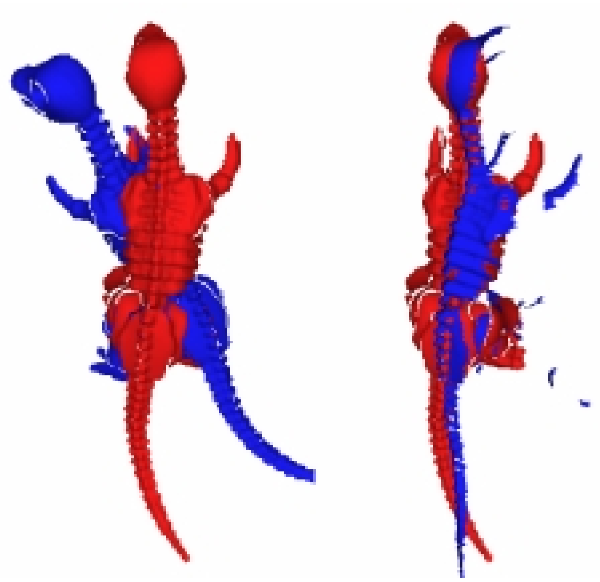


Fig. 3. Registration results based on covariance matrix.

2.2 Iterative registration by inverse projective transform

Since range data acquired in different position may have similar shape, the method based on covariance matrix cannot find the correct 3D transformations. In above section, the method based on covariance provides rough 3D transform parameters. For integration of all range images in a complete geometrical model, a finer registration results are needed. If the initial pose differs too much from the pose of the object, it is difficult to construct a precise model due to occlusions and so on. The more overlapping regions in 3D data sets, the more precise registration is performed. Therefore, we assume that individual range images will have a significant overlap for an automatic registration[7].

At the first, we compute the projective matrix that represent projection of the 3D data into its associated intensity image, and determine the camera position of each 3D set. Since our algorithm uses as its input two overlapping range images along with intensity images, a precise projective matrix can be obtained. Second, we obtain the covariance matrix, then 3D transformations through eigen-value decomposition. In the next step, we transform the current 3D data set and the sensor position into the next view, and vice versa, then extract the overlapping regions between two views. Figure 4 shows backward projection by the 3D transformations and the visibility criteria.

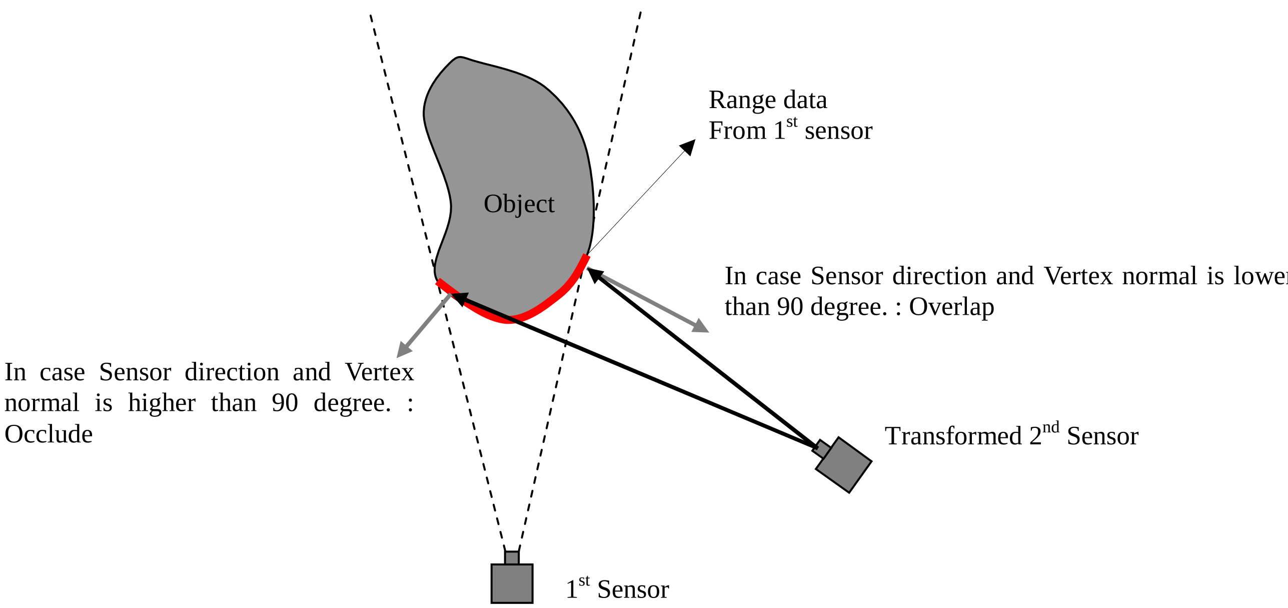


Fig. 4. Backward projection by the 3D transformations and visibility criteria.

After the first 3D data set is inverse transformed into the second by using the 3D transform parameters, we determine whether views contain overlapping scene regions. Here, we check the visibility criterion which is the basis for detecting self-occlusions and scan errors. In case that dot-product between vertex normal and sensor direction is lower than threshold, we define an occluded surface. When the registration between two images is correct these overlapping portions of both images should blend together with little error, since they represent the same surface regions. However, since 3D data sets are acquired from different view points or at different times, the registered surface may be different each other due to occlusions and so no. By minimizing the difference of two covariance matrixes of the overlapping regions in two 3D sets, we can more refine the 3D parameters than previous methods using the only covariance matrix.

2.3. The proposed algorithm

The algorithm can be summarized as follows:

1. Compute the projections **P1**, **P2** by relation of 3D space to 2D image, and determine the camera positions by $\mathbf{C = -P^{-1}*p}$
2. Compute the covariance matrix **(Cov1**, **Cov2)** and the centroid of each 3D point sets by average point, and find local coordinates by eigen-value decomposition of both covariance matrix.

$$\mathbf{Cov1} = \mathbf{U_1 D_1 U_1^T}, \quad \mathbf{Cov2} = \mathbf{U_2 D_2 U_2^T}$$

3. Find transformation **H.**

$$\mathbf{H} = \begin{bmatrix} U_1 U_2^{-1} & O_2 - O_1 \\ 0_3^T & 1 \end{bmatrix}$$ where, O is the centroid of 3D data set.

4. Transform the second 3D data set **(V_2)** and the camera position **(C_2)** into the next view, and vice versa, then extract the overlap regions between two views.

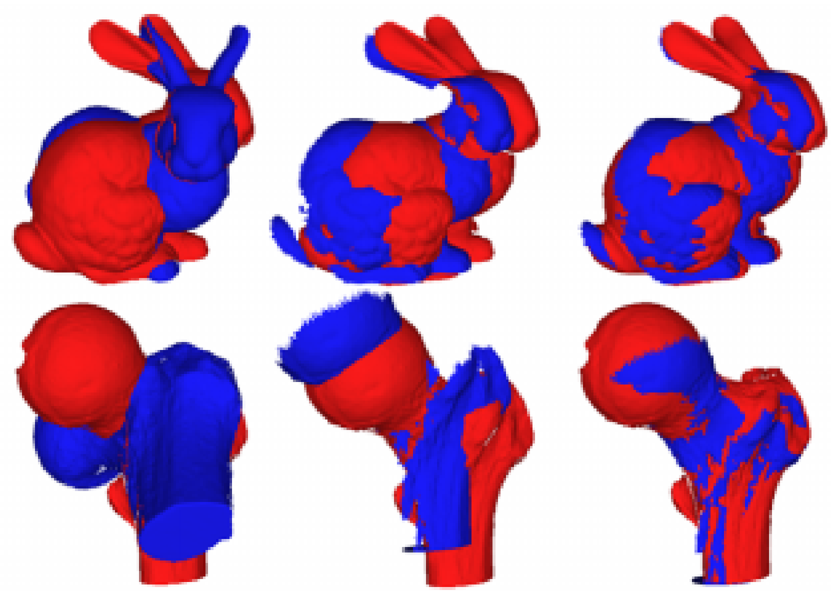
$$\mathbf{C_2' = H * C_2}, \quad \mathbf{V_2' = H * V_2}$$

($C_2' - V_1$) • V_1n > 0 : Overlap region
($C_1 - V_2'$) • V_2n > 0 : Overlap region , where Vn is vertex normal vector.

5. Iterate 3, 4, and 5, up to the difference of two covariance matrixes of the overlapping regions in two sets is minimized, and obtain the final transformation parameters.

3. Experimental Results

We have demonstrated the capabilities of the proposed registration method on various complex 3D data sets. Our method has been tested on full sized 3D range images, which contain from 60K to 100K data points. Triangulation of the 3D data may provide an extremely large and unnecessarily complex description of an object. To reduce this complexity, points having a differential coefficient are selected in our experiments at the first. In consequence, this selection of 3D points can decrease the data size as much as that of 40~80 percentages approximately. Then the sampled points are triangulated by Delaunay triangulation. The input data is obtained on University of stuttgart[8].

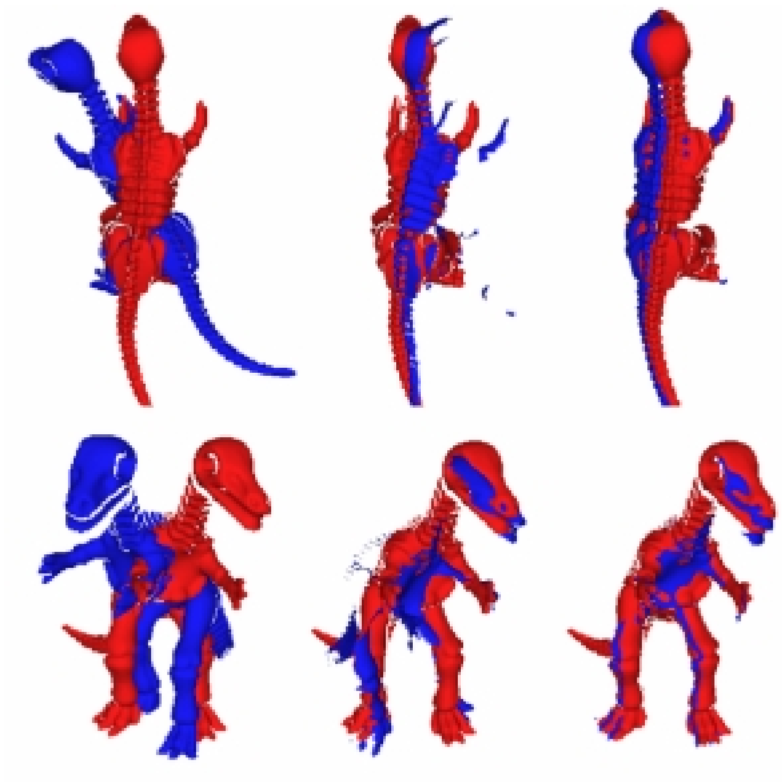


$$\mathbf{R} = \begin{bmatrix} 0.658 & -0.243 & 0.713 \\ 0.160 & 0.970 & 0.184 \\ -0.736 & -0.007 & 0.677 \end{bmatrix}$$

T = (-39.152, -5.481, 8.998)

$$\mathbf{R} = \begin{bmatrix} 0.642 & 0.672 & 0.369 \\ -0.116 & 0.561 & -0.82 \\ -0.758 & 0.484 & 0.483 \end{bmatrix}$$

T = (-40.48, 51.68, -9.36)



$$\mathbf{R} = \begin{bmatrix} 0.932 & -0.116 & 0.343 \\ 0.257 & 0.880 & -0.40 \\ -0.255 & 0.461 & 0.850 \end{bmatrix}$$

T = (-13.598, 19.24, 23.02)

$$\mathbf{R} = \begin{bmatrix} 0.617 & -0.448 & 0.647 \\ 0.350 & 0.893 & 0.283 \\ -0.704 & -0.052 & 0.708 \end{bmatrix}$$

T = (-66.524, -25.85, 21.08)

Fig. 5. Left: Initial pose of range data, Center: Transformation by covariance, Right: Iterative method.

Figure 5 shows our method can register 3D data sets more accurately than previous method does. When the relation of range data is translation and rotation around one axis, we find very accurate transformation. In addition, as the overlapping regions between 3D data sets increase more and more, the proposed method shows more performances. The experimental results show that our automatic method can make a precise registration of the 3D data sets without a-prior knowledge about 3D transformation between views. It is expected that additional consideration of the occluding surfaces can provide more accurate registration results.

4 Conclusion

This paper presents a new iterative method for automatically registering multiple 3D data sets using covariance matrix. Previous registration methods relies on accurate mechanical positioning devices, or on manual processing. For accurate registration, our method uses both the obtained 3D transformations giving a relative pose between the 3D data sets, and the projective matrix representing projection of 3D space to 2D image. By minimizing the difference of two covariance matrixes of the overlapping regions in two 3D sets, we can make more accurate registration results in reasonable time without the previous processes that are prone to errors including feature extraction and matching, etc. The experimental results have demonstrated the capabilities of the registration method on various complex 3D data sets. Further study will include additional consideration of the occluding surfaces for more precise registration and integration of all range images in one complete geometrical model.

Acknowledgements

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