EFFICIENT CORRESPONDENCE CRITERION FOR GRIDDED DEM CO-REGISTRATION

ZHANG Tonggang[*], CEN Minyi, REN Zizhen, YANG Ronghao, FENG YiCong

Department of Surveying Engineering, School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, China - chnztg@gmail.com

Commission IV, WG IV/9

KEY WORDS: Co-Registration, Correspondence Criterion, DEM, Iterative Closest Points

ABSTRACT:

Multi-temporal DEM co-registration provides an efficient technique for automatic analyzing the terrestrial changes caused by the geological hazards. Because this technique does not require any ground control points (GCPs), it can bring us many benefits: 1) avoid the GCP establishment, which is a cost and labor- intensive task; 2) quick response to the natural hazards, especially to the landslides and debris-flows; 3)make full use of remote sensing data obtained before the events. It is very difficult to obtain effective GCP owing to the terrestrial changes, even impossible; 4) analyze the region could not access. Iterative closest points (ICP) is the standard algorithm for surface matching in computer vision and pattern recognition. Its computational efficiency is slower and only suit for relative small data set. It adopts an exhaustive search strategy to find the point-to-point or point-to-normal corresponding pairs. It is very time-consuming, and consumes about 95% time of the whole matching process. Although many modifications have reported to speed up the corresponding pairs searching, it still could not meet the requirement for co-registering the large gridded DEM used in geosciences. This paper proposes an efficiency correspondence criterion for gridded DEM matching, called normal correspondence criterion (NCC), which finds the corresponding points alone the reference DEM normal vector and is optimized with a focus on the gridded date set. The experimental results show that the corresponding points can be determined within no more than 6 iterations in most cases, which yields high efficiency to DEM co-registration. According to the numerous experimental results based on the simulated data sets, DEM co-registration with NCC only use 1/10 time than that used by ICP, and slight larger convergence range.

1. INTRODUCTION

The surface matching is an important task in many applications, such as the scene modeling(Vögtle and Steinle 2000; Rabbani, Dijkman et al. 2007), change detection(Zhang, Cen et al. 2006) and quality inspection(Thoma, Gupta et al. 2005). Among methods have been reported, Iterative Closest Point (ICP) (Besl and Mckay 1992)algorithm has been recognized as the standard method for matching surface in computer vision and pattern recognition(Chetverikov, Stepanov et al. 2005). This algorithm contains three main steps: 1) search the nearest point-to-point or point-to-tangent plane pairs in two surfaces; 2) find the transformation by minimizing the mean squared distance between the paired point-to-point or point-to-surface pairs; 3) apply the derived transformation to second surface and then update the mean squared distance. The above three steps are iterated to give a most optimal transformation, and also the iterations have been proved to be convergence. In this paper, we address the problem of surface matching at the point level. The main contribution of this paper is proposing an efficient correspondence criterion, which reduces the most correspondence search.

This work was motivated by the lower efficiency of ICP and its variant methods, which usually require heavily computation. The point-to-point correspondence criterion proposed by Besl and Paul (Besl and Mckay 1992) uses an exhaustive search strategy. The computational complexity of the original ICP is of order $O(mn)$. m and n are the size of the first and second surface, respectively. 95% run-time is consumed by the searching the correspondence points(Chetverikov 1991). Moreover, this correspondence criterion impliedly requires each point in second surface has one counterpart in first surface. The point-to-tangent plane correspondence criterion proposed by Chen(Chen and Medioni 1999) also requires the searching process, calculating the tangent plane and normal vector for every iteration. This correspondence criterion is much more complex, and also occupies most computational time. Both of them are difficult to work with the larger-size digital surface. In others words, their application is very limited.

2. CORRESPONDENCE CRITERION FOR GRIDDED DEM

2.1 The proposed correspondence criterion

The surface normal vector on P', an arbitrary point on the first surface, will intersect the transformed second surface, the intersection point is assumed to be P. The P' and P are then called corresponding points. This correspondence criterion is called normal direction correspondence criterion (NDCC), and it can be described as

$$\overrightarrow{s \cdot \mathbf{R} \cdot P_i + \mathbf{t}, P_i'} \perp \Omega(P_i') \qquad (1)$$

where $\mathbf{t}$ is the transform, and $\mathbf{R}$ is the 3 by 3 rotation matrix, $\Omega(P_i')$ is the neighboring plane centered on P_i'.

---

[*] Corresponding Author

2.2 Efficient finding the corresponding point

How to find the intersection point P (Fig 1) according to NDCC? It is important issue related to the efficient of the entire matching procedure.
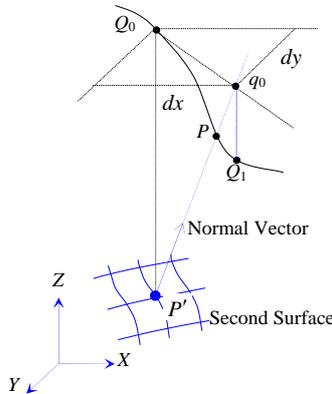
Figure 1 The intersection point

Assume that i is the number of iterations, $P'(X',Y',Z')$ is the point on the transformed second surface, and where the surface normal vector is $\vec{n}(n_x, n_y, n_z)$. $\vec{n}$ can be calculated either by convolution cross for regular gridded date sets only or associated with a local quadratic surface fit.

The intersection point P can be determined by the following steps:
1) $i = 0$, $X = X'$, $Y = Y'$;
2) Project P' to first surface along the Z-axis, an intersection point Q_i can be determined;
3) Find the intersection point q_i between the plane through Q_i and $\vec{n}$, its planar coordinate $(X, Y)_{q_i}$ can be determined by

$$\begin{cases} X_{q_i} = X_{Q_i} + \left(Z_{Q_i} - Z'_P \right) \times \dfrac{n_x}{n_z} \\ Y_{q_i} = Y_{Q_i} + \left(Z_{Q_i} - Z'_P \right) \times \dfrac{n_y}{n_z} \end{cases}$$

4) Project q_i back to the first surface along Z-axis, we will get another intersection point Q_{i+1};
5) If Q_{i+1} and Q_i is sufficient close to each other, Q_{i+1} is considered to the anticipated points P, otherwise turn to Step 6);

6) Let $Q_i = Q_{i+1}$, $i = i+1$, turn to Step 3).

Usually the above procedure will give the correct intersect point P. However, it does not always work well. Therefore, some remedy for this limitation is required.

From the above procedure, the anticipated intersection point P, the series of temporal points Q_i and q_i are all in the intersection curve L, where the second surface intersects with the plane $\pi(X'P'Z')$, which is determined by the normal vector $\vec{n}$ and the Z-axis through P' (See Figure 1). Therefore, the above procedure can be simplified from 3D space to 2D space, i.e. to find the intersection point between $\vec{n}$ and L in the place $\pi(X'P'Z')$. So, we will analyze and discuss the shortcomings of the original question according to the simplified version.

As shown in Figure 2, Q_{i-1}, Q_i, Q_{i+1} are three successive temporal points, and the slope F_i^{i-1} of Q_{i-1}, Q_i in $\pi(X'P'Z')$ can be described as:

$$F_i^{i-1} = \arctan\left(\frac{\Delta Z_i^{i-1}}{d} \right) \qquad (2)$$

where ΔZ_i^{i-1} is the different between Q_{i-1} and Q_i along Z-axis, d is the distance between Q_{i-1} and Q_i along X'-axis. The slope will change with the position of Q_i. Whether the procedure convergences is determined by the relationship between F_i^{i-1} and F_n. F_n is the slope of the normal vector $\vec{n}$.

When $F_i^{i-1} < \pi - F_n$ (Figure 2-2a), Q_{i+1} is much closer to P than Q_{i-1}, the procedure will converge. When $F_i^{i-1} = \pi - F_n$ (Figure 2-2b), Q_{i+1} and Q_{i-1} are the same point, the procedure will neither converge nor diverge. When $F_i^{i-1} > \pi - F_n$ (Figure 2-2c), Q_{i+1} is much farther to P than Q_{i-1}, the procedure will diverge.

During the iteration, when $F_i^{i-1} \geq \pi - F_n$, Q_i will be replaced by Q'_i. Then continue the original procedure. With this remedy, the entire procedure will converge to the anticipated intersection point P.
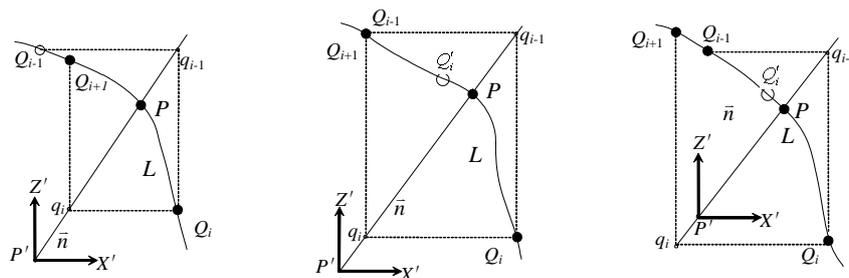
(a)convergent   (b)neither convergent nor divergent   (c)divergent

Figure 2 Finding the intersection point between $\vec{n}$ and L in the place $\pi(X'P'Z')$
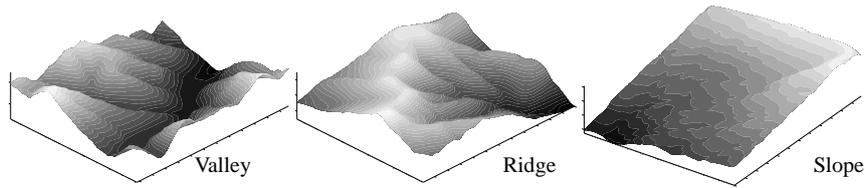
Figure 3   Data Sets

$Q_i'(X_i', Y_i', Z_i')$ is determined as follows:

$$
\begin{aligned}
X_i' &= (X_{i-1} + X_i)/2 \\
Y_i' &= (Y_{i-1} + Y_i)/2 \\
Z_i' &= S(X_i', Y_i')
\end{aligned}
\qquad (3)
$$

where X_i, Y_i is the planar coordinate, $S(X_i', Y_i')$ denotes the Z coordinate of the surface S at X_i, Y_i. Actually, $Y_i' = Y_{i-1} = Y_i$. Q_i' is much closer to P than Q_i and Q_{i-1} (See the blank circle). Specially, if the spatial Euclidean distance between Q_i and Q_{i-1} is less than a prearrange threshold, Q_i' is considered as to be the anticipated intersection point P.

3 SURFACE MATCHING WITH NDCC

The distance between the point $s \cdot \mathbf{R} P_i' + \mathbf{t}$ on the transformed second surface and its corresponding point P_i on the first surface along the normal vector $\bar{n}$ can described as:

$$
Dist_i = \left(P_i - (s \cdot \mathbf{R} P_j' + \mathbf{t}) \right) \bar{n}_0
\qquad (4)
$$

where $\bar{n}_0$ is the unit normal vector of $\bar{n}$, $\cdot$ denotes the scalar product.

Clearly $Dist$ should be zero in ideal case when the match is reached. Then, an object function that minimizes the sum of squared $Dist$ can pull the two surfaces close to each other.

$$
\min \sum w_i \cdot Dist_i^2
\qquad (5)
$$

where w_i, the weight of $Dist_i$, 0 or 1, is used to deal with the question caused by the partial overlapping(Li, Xu et al. 2001). According to the principle of least square, the surface can then be matching with an iterative behavior.

The terminated conditions of the iteration are:
1) The difference of the estimated transformation parameters between two successive iterations is less than per-arranged threshold;
2) Or reach the maximum iteration number.

This algorithm is called least normal distance algorithm (LND). Using LND, the two surfaces are pulled close to each other along the surface normal vector.

4 EXPERIMENT ANALYSES

In order to provide a better understanding of the performance of NDCC, we implemented the proposed algorithm, and the iterative closet point (ICP) algorithm with the desired rotation angle and translation are respectively less than $0.1''$ and 0.01m between two successive iterations and the maximum iteration number is 70 for a comparative study based on simulated data set (Figure 3). It is a typical landform surface. It is grided data set containing 100×120 with an interval distance equal to 10m. The second surface is derived from the first surface by firstly applying the per-arranged transformation (rotation angle is 2° and translate is 50m) to it, and then adding zero-mean Gauss noise with a standard deviation equal to 0.2m.

Both algorithms are directly applied to the data set without any pre-processing, feature extraction, and also without knowledge about the overlapping. Thus, the experimental results based on such data set are objective and they represent typical surface conditions.

The performance indices of interest in this paper are convergence and computational efficiency. Then all experimental results are given below in turn

4.1 Convergence

To give an in-depth discuss of the convergence of our algorithm, the method for computing the convergence rate will be given briefly first. The distance E between two surfaces can be measured using the mean of the distance between all corresponding points:

$$
E(n) = \frac{\sum \left\| p_i - p_j' \right\|}{N}
\qquad (6)
$$

where $n(\geq 1)$ is the number of iteration, $\left\| \cdot \right\|$ is the Euclidean distance, p_i and p_j' are corresponding points locating on the first and second surface, the sub-script i, j are the number of point, N is the total number of the corresponding pairs, $E(0)$ is the surface distance before matching. Note that the corresponding points are not construct by the matching algorithm, but the known corresponding points of two surfaces to be matched. Therefore, E is an objective value and is independent of the matching algorithm.

During the beginning phase, E is very big owing to the large error existing in the transformation parameters. With the increasing of the iterations, E reduces to a small positive number, not zero.

The convergence indicator (CI) can then be computed according

to the surface distance E, and the mean of all CIs is called the average convergence indicator (ACI). Both of them are of objective because they are based on the objective variable E, and are adopted in this paper to discuss the convergence rate in detail.

$$CI(n) = E(n)/E(n-1)$$
$$ACI = \frac{1}{n-1}\sum_{m=1}^{m=n} CI(m) \qquad (7)$$

Using CI and ACI, the convergence rate can be discussed in detailed and make comparison of different algorithms. The matching algorithm converges when CI less than 1. The less CI is, the faster it converges. ACI describes the convergence rate of the entire matching process.

ICP need about 2 times iterations more than LND in average (Figure 4). Such experimental result illustrated that LND converge faster than ICP in general. The variety of the surface distance E and convergence indicator (CI) are similar in three data sets. The experimental result on the data sets A (Figure 3) is given in Figure 5, and the variety of corresponding six transformation parameters is given in Figure 6.
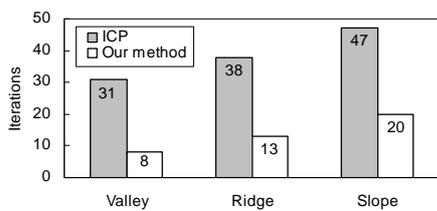
Figure 4   The iterations required by ICP and our method
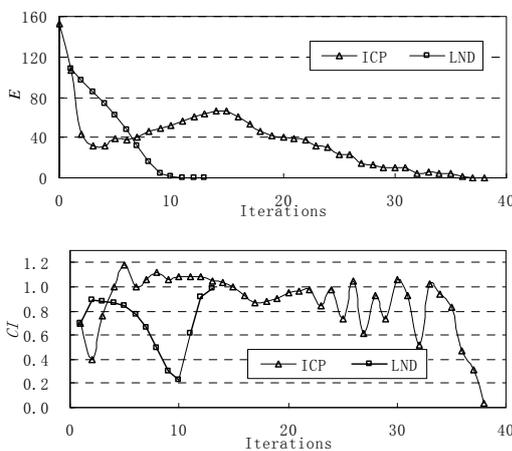
Figure 5   The surface distance and convergence indicator
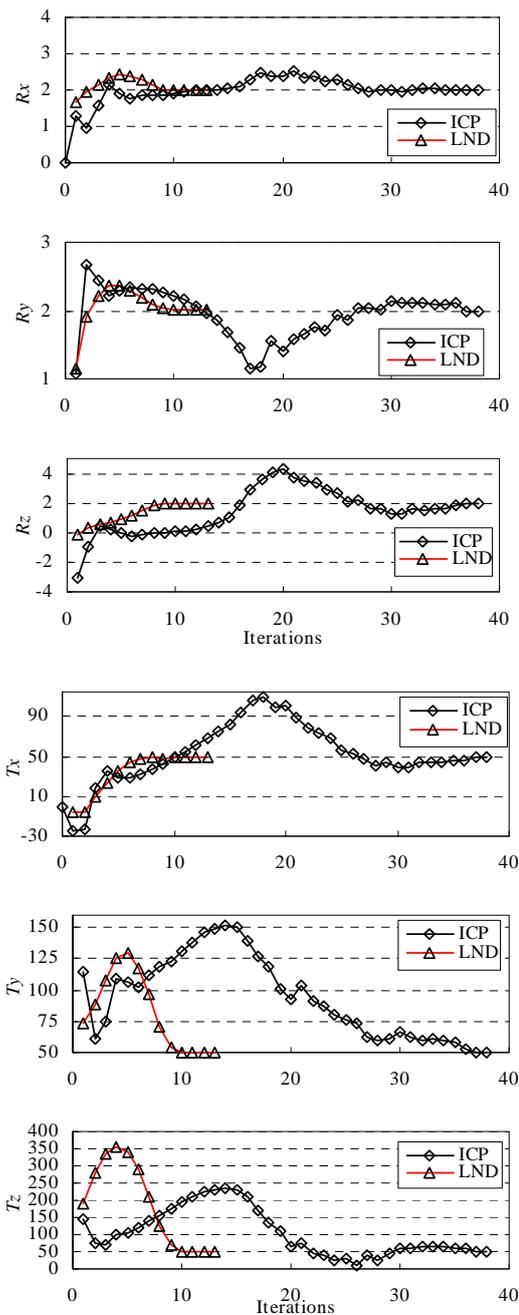
Figure 6   The six transformation parameters against iterations Rx, Ry, Rz (in degree), and Tx, Ty, Tz (in meter)

From the variety of E and CI (Figure 5), LND always converges, and the surface distance reduces monotonously. At the beginning and ending phase, CI of LND is close to 1. In these cases, LND converges slowly. In the middle phase, CI of LND is rather small. It illustrate that LND converges very faster. The ICP gives another different behavior. Some iterations are not convergence, but divergence, although it convergence to correct matching at last. The surface distance is not always reduces during the iterations. Similar conclusion is also illustrated in Figure 6. As to ICP, the variety of six parameters is much more complex than that of LND.

The ACI of LND and ICP is respectively 0.31 and 0.66. This result illustrate that LND converges faster than ICP. It is consistent with the result in Figure 4.

Taking all above three aspects into account, the convergence of LND is much better than that of ICP.

4.2 Computational Efficiency

The computational efficiency is measured by the time consumed. This experiment is performed on a computer with MS windows 2000, Intel II667Mhz, and 300M memory. All the three experiments, ICP consumes about 10 times time more than LND used. With high computational efficiency, LND can be applied to large data sets.

The reason for LND's so high computational efficiency is related on the following two aspects: 1) LND constructs the point's correspondence without exhaustive search process that used by ICP. According the statistical result from amount simulated experimental results; NDCC adopted by LND can determine one corresponding points within 6 iterations (for detail, See Section 2.2). 2) Surface moves close to each other alone the surface normal vector, which is closest route between two surfaces.

5 CONCLUSION

The correspondence criterion is the most importance step for a surface matching algorithm. In this paper, An efficient correspondence criterion, called NDCC, for 3D surface matching is proposed in this paper. Then a complete surface-matching algorithm, called LND, using NDCC is also given.

Focusing on the convergence rate and computational efficiency, a serials of experiments based on simulated data sets are performed to make an in-depth analyses of proposed method. Compared with ICP, the efficiency of LND is higher than ICP. Moreover, LND converges faster than ICP.

ACKNOWLEDGMENT

REFERENCES

Besl, P. J. and N. D. Mckay (1992). "A method of registration of 3-D shapes." IEEE Transactions on Pattern Analysis and Machine Intelligence 14(2): 239-256.

Chen, Y. and G. Medioni (1999). "Object modeling by registration of multiple range images." Image and vision computing 10(3): 145~155.

Chetverikov, D. (1991). "Fast neighborhood search in planar point sets." Pattern Recognition Letters 12(7): 409-412.

Chetverikov, D., D. Stepanov and P. Krsek (2005). "Robust Euclidean Alignment of 3D point sets: the Trimmed iterative closest point algorithm." Image and Vision Computing 23(3): 299-309.

Li, Z., Z. Xu, M. Cen and X. Ding (2001). "Robust surface matching for automated detection of local deformations using least-median-of-squares estimator." Photogrammetric Engineering and Remote Sensing 67(11): 1283-1292.

Rabbani, T., S. Dijkman, F. v. d. Heuvel and G. Vosselman (2007). "An integrated approach for modelling and global registration of point clouds." ISPRS Journal of Photogrammetry and remote sensing 61: 355-370.

Thoma, D. P., S. C. Gupta, M. E. Bauer, C. E. Kirchoff, A. da Silva Curiel, A. Wicks, M. Meerman, L. Boland and M. Sweeting (2005). "Second generation disaster-monitoring microsatellite platform." Remote Sensing of Environment 51(1-9): 191-197.

Vögtle, T. and E. Steinle (2000). "3D modelling of buildings using laser scanning and spectral information." International Archives of Photogrammetry and Remote Sensing XXXIII: 927-934.

Zhang, T., M. Cen, G. Zhou and X. Wu (2006). "A New Method for Debris-Flow Detection using Multi-Temporal DEMs Without Ground Control Points." International Journal of Remote Sensing 27(21): 4911-4921.