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A New Registration Method for Scattered Point Clouds from Multi-views

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Abstract: Aiming at the multi-views scanning data of the object with complex curved surface, it is put forward that a new effective registration method from 3D armadillo range images to complete 3D model. Firstly, the coarse registration is made by using differential invariant features and ZNCC (zero-mean normalized cross-correlation coefficient), then ICS (iterative closest surface) is used to achieve accurate registration fast, final the complete 3D armadillo integrated model is got. By comparatively analyzing the registration result, registration error, number of iterations and convergence speed with numerical experiments, it is explained the validity and superiority of this method.

Key words: Cloud data registration, differential invariant features, ZNCC (zero-mean normalized cross-correlation coefficient), ICS (iterative closest surface)

INTRODUCTION

High quality, full three dimensional point data is the basis for computer vision object detection and recognition. Limited by the observation direction, the non-penetrating of laser and the shape of the object itself, it is impossible to obtain the point cloud data of all objects at once. Full three dimensional geometric modeling of objects constructed from multi-view point cloud data is gaining an increasingly wide range of applications in computer vision, virtual reality and non-contact measurement, etc (Sahillioglu and Yemez, 2010).

Many international scholars have done a lot of research on point cloud registration, a typical one is the ICP algorithm raised by Besl and McKay (1992) and its variants (Chow *et al*., 2004). So far, this algorithm has been improved significantly but because of its error metric is defined in the corresponding point or points above the surface, therefore the error metric does not exist in the corresponding points on the exact problem, making such algorithms might be seriously affected by deviation points. The document (Silva *et al*., 2005) using genetic algorithms and metrics to optimize the initial stitch position, it can get a higher accuracy but lower efficiency; In China, Gao *et al*. (2007) raised an algorithm that uses the spatial volume of the overlapping part of a depth image of volume as the error measurement precision of registration. This algorithm is not sensitive to initial parameters, it is inefficient under huge amounts of data.

This study proposes the ZNCC and ICS-based laser point clouds registration method. The method is divided into initial registration and precise registration: In initial registration phase, constructing effective matches one by one through the introduction of a new form of normalized cross correlation coefficient ZNCC similarity metrics based on neighborhood of curvature; creates a valid one by one array corresponds to the initial match point, matches are calculated on the geometry of the initial registration parameter. In precise registration phase, replace local patches with discrete points and construct the set of effective initial points involved in the recent patches ICS algorithm and replace approximate distance with a geometric distance to the corresponding patches, finally, establishment registration for non-linear least-squares optimization model and its solving strategies.

CALCULATION OF DIFFERENTIAL INVARIANTS

In 3D space, a discrete parametric surface can be expressed as follows Monge surfaces (Chen, 2006):

$$r(u,v) = \begin{bmatrix} u & v & h(u,v) \end{bmatrix}^T \quad u = 1, 2, \cdots, m, v = 1, 2, \cdots, n \tag{1}$$

U-V plane can be seen as a reference plane in 3D space R^3, then h (u, v) represents the distance between discrete surface point and the reference plane (u, v).

R (u, v) Can be expressed in two basic forms, wherein the first basic represents the intrinsic nature of the surface (Chen, 2006):

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$$
\begin{aligned}
I(d_u, d_v) &= dr.dr \\
&= (r_u d_u + r_v d_v).(r_u d_u + r_v d_v) \\
&= E d_u^2 + 2F d_u d_v + G d_v^2
\end{aligned} \tag{2}
$$

where, E, F, G are parameters for the first basic form and:

$$
E = r_u \bullet r_u,\ F = r_u \bullet r_v,\ G = r_v \bullet r_v \tag{3}
$$

The second basic represents the external nature of the surface (Chen, 2006):

$$
\begin{aligned}
II(d_u, d_v) &= -d_r \bullet d_n \\
&= (r_{uu} d_u^2 + 2r_{uv} d_u d_v + r_{vv} d_v^2) \bullet n \\
&= L d_u^2 + 2M_u d_v + N d_v^2
\end{aligned} \tag{4}
$$

were, r_{uu} is the partial derivative of r on u (the other similar). L, M, N are parameters for the first basic form and:

$$
L = r_{uu} \bullet n, M = r_{uv} \bullet n,\ N = r_{vv} \bullet n \tag{5}
$$

The Gaussian curvature K, mean curvature H and the maximum and minimum principal curvatures k_1, k_2 can also be expressed by these parameters (Sun *et al*., 1996):

$$
K = \frac{LN - M^2}{EG - F^2}, H = \frac{EN + GL - 2FM}{2(EG\text{-}F^2)} \tag{6}
$$

$$
k_1 = H + \sqrt{H^2 - K}, k_2 = H - \sqrt{H^2 - K} \tag{7}
$$

The Gaussian curvature K and mean curvature H can be expressed by surface function derivative as:

$$
K = \frac{h_{uu} h_{vv} - h_{uv}^2}{\left(1 + h_u^2 + h_v^2\right)^2} \tag{8}
$$

$$
H = \frac{1}{2} \frac{\left(1 + h_u^2\right) h_{uu} + \left(1 + h_u^2\right) h_{vv} - 2h_u h_v h_{uv}}{\left(1 + h_u^2 + h_u^2\right)^{3/2}} \tag{9}
$$

The main direction of its corresponding unit vectors respectively are:

$$
\begin{aligned}
u &= \pm \frac{(k1 \times G - N)ru + (M - k1 \times F)\mathbf{r_v}}{\left|(k1 \times G - N)\mathbf{r_u} + (M - k1 \times F)\mathbf{r_v}\right|}, \\
v &= \pm \frac{(k2 \times G - N)\mathbf{r_u} + (M - k2 \times F)\mathbf{r_v}}{\left|(k2 \times G - N)\mathbf{r_u} + (M - k2 \times F)\mathbf{r_v}\right|}
\end{aligned} \tag{10}
$$

INITIAL REGISTRATION BASED ON ZNCC

Measure of curvature similarity of isolated points: Assuming the data of point cloud to be registered in the two adjacent scanning angles is $P = \{p_i \mid p_i \in R^3\}$ and $M = \{m_i \mid m_i \in R^3,\ i=1,\ldots,N_M\}$ (M as a reference point cloud data). The random two points $p_i \in P, m_j \in M$, of P and M, first asked point neighborhood patch type must be consistent, that is, P_I and m_j are Gaussian curvature and mean curvature satisfies:

$$
\begin{cases}
\text{sign}(K(p_i)) = \text{sign}(K(m_j)) \\
\text{sign}(H(p_i)) = \text{sign}(H(m_j))
\end{cases} \tag{11}
$$

Wherein, sign (.) represents the sign function. in the surface model, the planar region feature is not obvious, it is not considered in the matching process points in the plane, that is set sufficiently small threshold δ_1, $\delta_2 > 0$ to make the Eq. 12 hold:

$$
\begin{cases}
\left|K(p_i) \bullet H(p_i)\right| \geq \delta_1 \\
\left|K(m_j) \bullet H(m_j)\right| \geq \delta_2
\end{cases} \tag{12}
$$

On this basis, t his study introduces the measure for the point-to-filter of maximum and minimum curvature similarity in reference (Sahillioglu and Yemez, 2010):

$$
\begin{cases}
\left|k_1(p_i)\text{-}k_1(m_j)\right| / \left|k_1(p_i)\text{+}k_1(m_j)\right| \leq \omega_1 \\
\left|k_2(p_i)\text{-}k_2(m_j)\right| / \left|k_2(p_i)\text{+}k_2(m_j)\right| \leq \omega_2
\end{cases} \tag{13}
$$

Measure of curvature similarity of neighborhood points: ZNCC as a two-dimensional gray-scale image matching criteria used to measure the two gray-scale pixel neighborhood similarity metric in two image. ZNCC larger value indicates higher neighborhood similarity. This article will make three-dimensional pixel point, the curvature of the point as pixel gray, which will ZNCC introducing space curvature point neighborhood similarity metric.

Let $ZNCC_1$ (p_i, m_j) measuring the principal curvatures, $ZNCC_2$ (p_i, m_j) D and E measuring the neighborhood similarity of $k_1$and k_2, respectively. The corresponding expressions are in Eq. 14:

$$
\begin{aligned}
zncc_1\left(p_i, m_j\right) &= \frac{\sum_{l=1}^{L}(k_1(p_l) - \overline{k_1^P})(k_1(m_l) - \overline{k_1^M})}{\sqrt{\sum_{l=1}^{L}(k_1(p_l) - \overline{k_1^P})^2 \sum_{l=1}^{L}(k_1(m_l) - \overline{k_1^M})^2}}, \\
zncc_2\left(p_i, m_j\right) &= \frac{\sum_{l=1}^{L}\left(k_2(p_l) - \overline{k_2^P}\right)\left(k_2(m_l) - \overline{k_2^M}\right)}{\sqrt{\sum_{l=1}^{L}\left(k_2(p_l) - \overline{k_2^P}\right)^2 \sum_{l=1}^{L}\left(k_2(m_l) - \overline{k_2^M}\right)^2}}
\end{aligned} \tag{14}
$$

Wherein, Σ represents the summation in the given neighborhood of P_i, m_j; $\overline{k_1^P}$, $\overline{k_2^P}$ and $\overline{k_1^M}$, $\overline{k_2^M}$, respectively represent the mean of the maximum principal curvature and the mean minimum principal curvatures in the neighborhood of P_i, m_j.

In the process of generating the matching point, this method not only consider the similarity of curvature and the points' curvature similarity measure of the neighborhood, as follows: assuming the threshold value $\epsilon_3>0$, the random non-planar point p_i of the first sheet of point cloud, to search and the highest similarity neighborhood curvature of p_i and select the point $p_i \in MP$ whose curvature similarity is higher than a given threshold value ϵ_3 in the point set satisfying the Eq. 12-14 constituting the set point m_j of MP as a unique match for point p_i, i.e., p_* met:

$$\begin{cases} \left(ZNCC_1(p_i, p_*) + ZNCC_2(p_i, p_*)\right)/2 \geq \omega_3 \\ ZNCC_1(p_i, p_*) + ZNCC_2(p_i, p_*) \geq ZNCC_1(p_i, m_j) + \\ ZNCC_2(p_i, m_j), \forall m_j \in MP \end{cases} \quad (15)$$

If p_* does exist, then add (p_i, p_*) to the matching points array MatchPts and add p_i to effective set PS and p_* to effective set ms.

The difficulty of calculation $ZNCC_1$ (p_i, m_j), $ZNCC_2$ (p_i, m_j) lies in constructing the sets of the corresponding points of the neighborhoods of p_I and m_j. The paper refers the method reference raised (Xue *et al*., 2011) to determine the neighborhoods of p_I and m_j.

Parameter estimation of the initial registration: In this study, a discrete feature points corresponding is used to roughly estimate the initial registration posture. The registration method based on features points is to select groups of feature point couples from the two adjacent efficient point cloud model PS and MS (N (N>3)) MS (Reference point cloud model) each couple of feature points correspond to the feature points of the same feature point real objects.

Use the Transform relations $m_i = R_0p_i+t_0(i = 1, 2, .., N)$ of the N features (p_1, p_2,...,p_N) of point cloud model PS and the N features (m_1, m_2,..., m_N) of point cloud model MS (a reference point cloud model) and four elements and linear least square method in the reference (Zhang *et al*. 2010) to work out the initial of rigid transformation (R_0t_0). Apply the transformation (R_0t_0) to the rigid transformed point cloud model PS. Thus the two point cloud models PS and MS (a reference point cloud model) can be integrated to the same coordinate system, to achieve a rough registration.

PRECISE REGISTRATION BASED ON ICS

In this study, the research is based on quadratic approximation of the effective registration algorithm ICS.

Suppose that the function f is mapped $R^3 \rightarrow R$. Approximate the neighborhood Nb_r (p) of the point p on the surface PS by the zero level set of f is:

$$f_{Pr}(x) = 0 \quad (16)$$

where, NB_r (p) is the r closed ball fields of point p at the surface PS. As is for each point m_i and NB_r (p) in target data Ms, a surface patch $f_{m,r}$ (x) = 0 can be constructed, Where, NB_r (m_i) is a closed ball field defined in pint set MS. Thus, surface PS can be approximately represented by a group of curved surfaces $f_{mj,r}(x) = 0$ (I = 1, 2,..., N).

The proximate distance (Taubin *et al*., 1994) between point Y and f (x) = 0 is:

$$\|y - x\|^2 \approx f(y)^2 \left[\nabla f(y)^T \nabla f(y)\right]^{-1} \quad (17)$$

Then: $\|y - x\| \approx |f(y)|/\|\nabla f(y)\|$ is called the first-order proximate distance. This very proximate distance is much closer than the algebraic distance |f (y) | to the geometrical distance between point y and f (x) = 0 (Taubin *et al*., 1994).

The ICS mosaic algorithm using local quadratic surface patch instead of discrete points as the flattening of the target geometry, reducing the sampling density flattening accuracy. And the curved surfaces corresponding to the point p of movement data should be nearest to the point p of all the curved-surface patches, wherein the distance is approximate to Eq. 17. Assuming the amount of curved-surface patches is P_N, then the time complexity O (P_N) of the nearest patch can be searched directly. In order to improve search efficiency, you can first search for the target data, the nearest point p, then the closest point in its neighboring points corresponding to the surface film selected from the p nearest patch.

$A = [R|t]^T$ is called state vector, representing that implementing rotation transformation R firstly and then rigid transformation translating t, Y = C (PS. MS). Represents the set of curved-surfaces of the moving points set PS corresponding targeted points MS, (a, ϵ) = PS (PS, Y) represents the calculation of the coordinate transformation when converting point set PS to corresponding patch set, wherein, ϵ is the error between corresponding points and surface matching. Initialize PS_0 = PS, The number of iterations k = 0. The initial of state vector can be estimated according to above.

The k-th iteration of the ICS algorithm is as follows:

- Calculate the most closed curved-surface set $Y_k = C(PS_K, MS)$, wherein, PS_K is the coordinate point set of the (k-1) th iteration when the coordinate transformation a_{k-1} acting on the moving-point set PS_0
- Calculate the coordinate transformation $(a_k, \varepsilon_k) = Ps(Ps_0, Y_k)$, wherein:

$$\varepsilon_k = \varepsilon(a_k) = \frac{1}{N}\sum_{i=1}^{N} f_i(p_i(a_k))^2[\nabla f_i(p_i(a_k))^T \nabla f_i(p_i(a_k))]^{-1}$$

  is the coordinate of point $p_i \in PS$ at phase a_k, f_i is the corresponding curved-surface patch of Y_K in pi (a_{k-1}). The time complexity of this step is O (NT_{LM}). Where, in T_{LM} is the average iterations number of LM algorithm in the reference (William *et al.*, 1992)
- PS_{k+1} Can be obtained by transforming the coordinates of the moving-point set P_{S0} to a_k.
- For the given errors $\tau>0$ or $N_k>0$, if $\varepsilon_k - \varepsilon_{k-1} < \tau$ end the loop; Otherwise, begin next iteration

ANALYSIS OF RESULTS

This study registers 18 perspectives of the laser scan data of Armadillo model provided by Stanford University, because of the limited space, only 4 views are showed in Fig. 1. As is for ω_1 and ω_2, it is regarded as 0.05 in the reference (Sahillioglu and Yemez, 2010); as is for ω_3, it is regarded as 0.8 as normal.

What Fig. 2a shows is the registration result using the algorithm this paper introduced; what is Fig. 2b shows is its model; what Fig. 2c shows is the registration result using the algorithm the reference (Xue *et al.*, 2011) introduced; what is Fig. 2d shows is it model.After comparing, it is obvious that the registration results using the algorithm this paper introduced are more accurate.

What showed in Fig. 3 is the comparison of convergence speed of the two registration algorithms showed in Fig. 2. it shows the error distribution of the two algorithms during they iterate 150 times. Because the

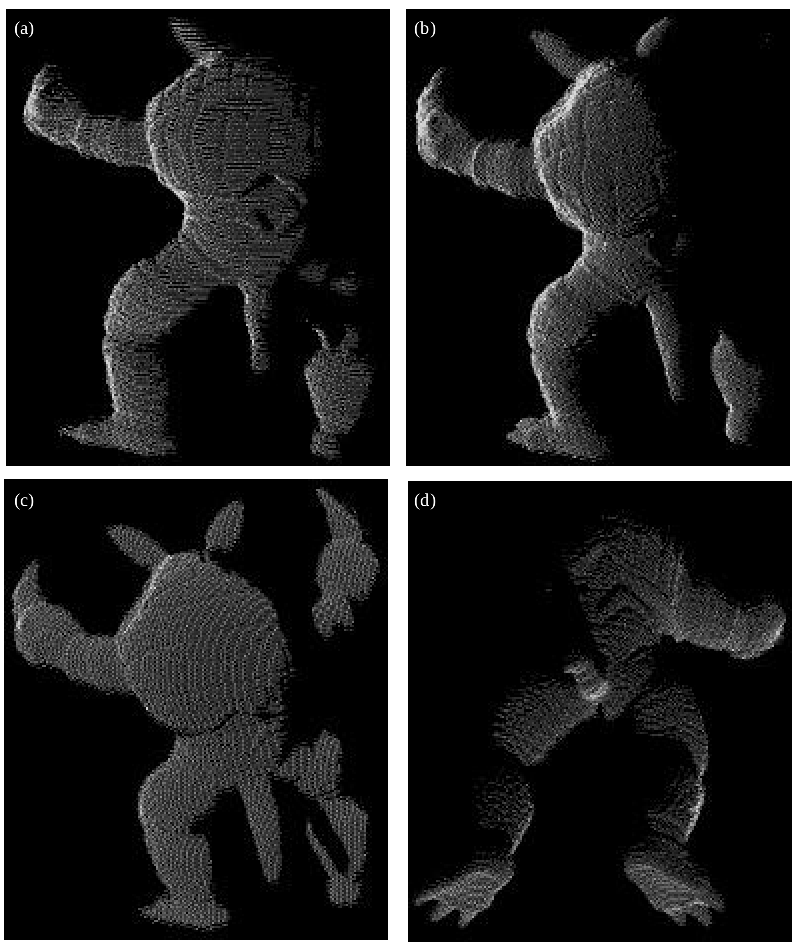

Fig. 1 (a-d): Four views point's data of Armadillo, (a) View 1, (b) View 2, (c) View 3 and (d) View 4

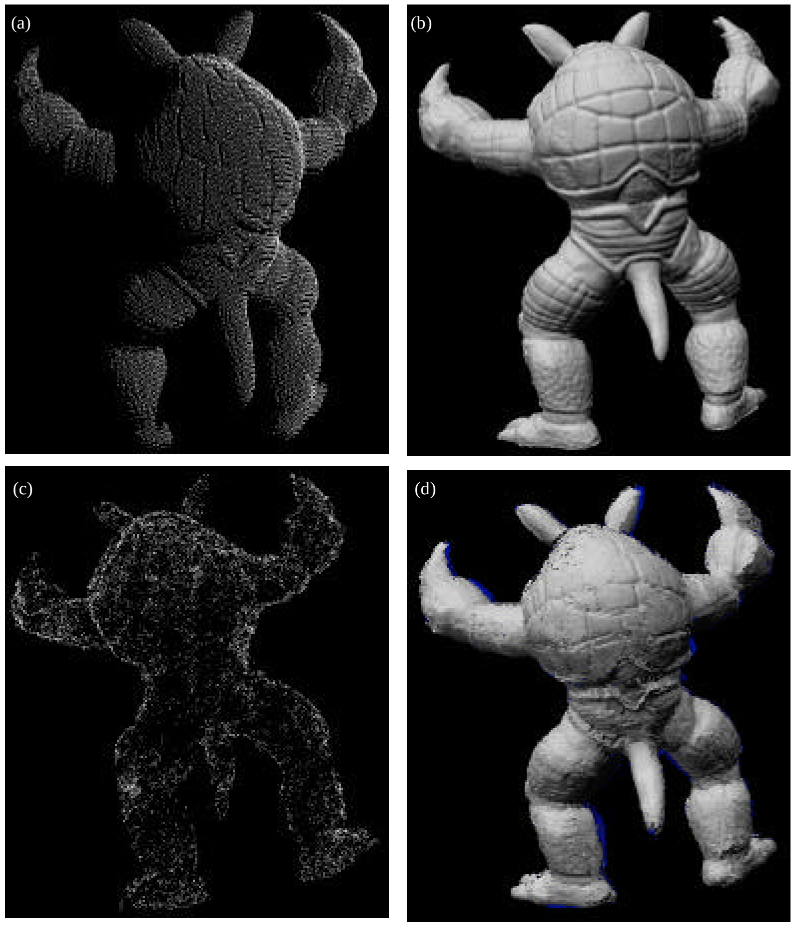

Fig. 2 (a-d) Comparison of registration results of 18 Views, (a) View 1, (b) View 2, (c) View 3 and (d) View 4

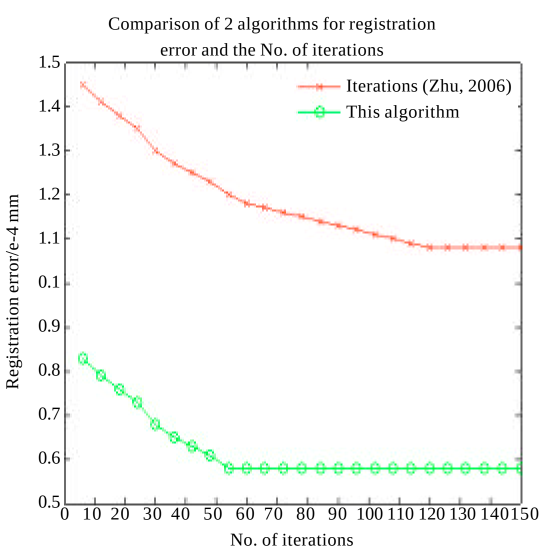

Fig. 3: Contrast of the two algorithms in Fig. 2

number of patch pairs meeting the conditions is far less than the number of the corresponding point pairs, this algorithm needs less time to calculate the space position of the new transforms, thus it can ensure the gap is not obvious of the running time of each iteration compared to the algorithm described in Literature (Xue *et al*., 2011) and consider the number of iterations, Obviously, this algorithm has a faster convergence speed.

CONCLUSIONS

This study analyzes a new matching points measurement criterion ZNCC and iterative closest patch ICS algorithm based on the existing point cloud data registration method and proposed a new laser point cloud data registration method. Compared with the existing ICP framework iterative registration method, this algorithm has two main contributions: One point is that it introduced a new point neighborhood similarity measure curvature. Another point is that, based on the integration of corresponding curved-surfaces, it proposed ICS flattening algorithm using local quadratic surface patch instead of discrete points as the flattening of the target geometry, reducing the sampling density flattening accuracy, ensure the accuracy and speed of the algorithm.

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