A surface descriptor of surface matching base on normal angle of surface data

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Abstract—**Three dimensional surface matching is an important problem in computer vision. The process of surface matching is to match similar regions or correspondences across multiple surfaces with unknown relative poses. Many surface descriptors for finding correspondences have been proposed. However, most of these approaches have been used in triangle mesh surfaces. In this paper, a local surface descriptor constituting moving least square (MLS) surface representation, differential angle calculation, and Zernike moments is proposed to find correspondences in unconstraint point set surfaces. The MLS projection is applied to generate a differential angle map described the geometric information. Then, Zernike moments are used to provide surface descriptors with rotation invariant. In addition, a congruent consistency method is proposed to find the reliable correspondences. To conclude, the experimental results show that the approach outperforms the original spin image method [2], and has slightly better performance than a modified spin image method presented in this paper. Moreover, the proposed approach has good matching performance both in terms of matching surface by using variety of descriptor size or matching surface among different resolutions.**

Keywords- surface descriptor; MLS surface; surface matching; congruent consistency analysis; Zernike moment

I. INTRODUCTION

Three dimensional (3D) surface matching is an important problem in computer vision. In recent years, the devices and the technologies for acquiring 3D surfaces have been highly developed and made the acquisition of 3D surfaces much easier. Hence, the requirements of aligning surfaces into a consistent coordinate frame have increased enormously. To achieve this goal, a surface matching algorithm is needed to find the matching parts and the rigid transformation among multiple 3D surfaces. The process of surface matching is to match similar regions or correspondences across multiple surfaces. While the relative position and pose are unknown, the process estimates the corresponding rigid transform to align the surfaces to each other. Many approaches have been proposed to address the matching problem by using the correspondence framework. Thus, the surface matching problem can be treated as to find reliable correspondences among surfaces.

Generally, the algorithm of finding correspondences is as follows. Correspondence is created between two surfaces. Then the correspondence is used to calculate a plausible transformation to align two surfaces. Finally, a measurement is applied to verify the goodness of surfaces alignment. However, it is difficult to create good correspondence because of the complex geometry and various representations of surfaces. An unsuitable correspondence would result in an ambiguous transformation. Therefore, a growing body of research about surface matching attempts to handle such a problem.

The correspondence is created by matching specific local surface features. Spin image [1] proposed by Johnson is a classic method to describe the geometric information of a surface by using a 2D distance histogram. Although the spin image is a highly descriptive feature, it needs a lot of storage space. In addition, a compressed spin image [2] based on principal component analysis (PCA) is proposed to cope with the shortcoming. Ashbrook et al. proposed the Geometric histogram matching (GHM) [3]. It is very like spin image that use a histogram to extract the geometric information. Differing from spin image, GHM extracts angles between normals and distance from the local surface; however, it requires accurate surface normals to generate a good feature. Similarly, mutual angle-distance histogram [4] is another method to calculate a histogram image as the surface feature. Additionally, multiple-value surface features, such as surface signature matching (SSM) [5] and curvature maps [6], are some of the better surface features.

However, most surface features mentioned above are proposed for 3D mesh models of mesh surfaces. Some of them have innate limitations, and cannot be adopted for point set data directly. Thus, M. Alexa [7] proposed a point feature used the curvature and normal of the surface defined by point set data. E. Akagunduz [8] proposed a point feature based on Gaussian curvature map to represent the peaks, pits and saddles on the surface, and applied to face detection and pose estimation. Also, 3D point features extended from greatly robust 2D image features. For example, THRIFT was proposed in [9] based on SURF [10] and SIFT [11] for describing and recognizing local 3D structures. Skelly [12] proposed a rotation invariant 3D descriptor based on SIFT, and demonstrated a result compared with spin image.

Besides surface descriptors and point features, another important step for finding the correspondence is the matching algorithm. A single point may be matched to more than one point during the matching process. This causes ambiguity for calculating the transformation matrix between two surfaces. To overcome this problem, a geometric consistency method was represented in [2]. However, the grouping of the geometric consistency method uses an exhausted computation, and it is a serious problem when the number of groups is large.

In this paper, a surface descriptor based on MLS surface projection and differential angle features is proposed for matching point set surfaces. The proposed descriptor is attempt to overcome not only to describe the geometric information about point set surfaces, but also to have the ability to handle different resolutions of point set data. This approach uses a geometric descriptor calculated form the differential angle between normals to match among point set surfaces. Furthermore, the descriptor is generated by extracting the Zernike moments as a rotation invariant feature. These methods lead to the proposed approach, which is robust against translation, rotation, and various resolutions for point set surface matching. Moreover, using the Zernike moments for the local surface descriptor decreases the dimension of features, and increases the efficiency of surface matching. Additionally, a congruent consistency analysis is bought to match the correspondences and estimate the possible transformation. The experimental results show that the approach outperforms the original spin image method, and has slightly better performance than a modified spin image method represented in this paper. Moreover, the proposed approach has good matching performance both in terms of matching surface by using variety of descriptor size or matching surface among different resolutions.

The organization of the rest of this paper is as follows. The local surface descriptor is discussed in Section II. The proposed surface matching methods is described in Section III. In Section IV, the experimental results with discussions are presented. Finally, Section V concludes this paper.

II. Proposed Surface Descriptor

This section mainly discusses the surface descriptor extraction of a point set surface. First, this paper uses moving-least-squares (MLS) surfaces to represent the surface from the unconstructed point set. After that, a point descriptor based on the differential angle between normals is proposed to describe the local surface. Finally, a rotation invariant process is adopted to generate the pose-independent surface descriptor called DAD. The surface matching algorithm which employs DAD will be discussed in the next section.

A. Surface Representation

Levin [13][14] has proposed MLS surfaces, and introduced in computer graphics for rendering. Furthermore, many variants and extensions have been presented [14]-[21] and widely used in various scenarios. Although MLS surfaces have the ability to handle the noisy input, most of them do not preserve the details of the surfaces. To keep the information of sharp surface, this paper adopts robust implicit MLS (RIMLS) surface proposed by Öztireli et al. [21] as the definition of point set surfaces, which is briefly discussed as follows.

The RIMLS algorithm is derived from the implicit MLS definition (IMLS) [19] and a robust local kernel regression approach. Given the sampled point set $P=\{p_i \in \mathbb{R}^3\}$, $i=1,\ldots,n$, with the normal vector n_i at point p_i, the iterative minimization of RIMLS definition at k-th iteration is shown as:

$$f^k(x)=\frac{\sum n_i^T(x-p_i)\phi_i(x)w(r_i^{k-1})w_n(\Delta n_i^{k-1})}{\sum \phi_i(x)w(r_i^{k-1})w_n(\Delta n_i^{k-1})}, \tag{1}$$

with the residuals:

$$r_i^{k-1}=f^{k-1}(x)-(x-p_i)^T n_i, \tag{2}$$

where x is an input point near the surface, and $\phi_i(\cdot)$ is a spatial weight function approximated to a Gaussian:

$$\phi_i(x) = \left(1 - \frac{\|x - p_i\|^2}{h_i^2}\right)^4, \tag{3}$$

where h_i is the kernel bandwidth related to the radii of the sampled points. The refitting weight term in Eq. (1) is defined as:

$$w(r_i) = \exp\left(-\frac{r_i^2}{(\sigma_r h_i)^2}\right), \tag{4}$$

where σ_r is a scale term and can be set to a constant. The last weight function in Eq. (1) is the normal refitting weight defined as:

$$w_n(\Delta n_i^{\,k}) = \exp\left(-\frac{(\Delta n_i^{\,k})^2}{\sigma_n^{\,2}}\right), \tag{5}$$

where σ_n is a width of the filter to control the sharpness of surfaces, and $\Delta n_i^{\,k}$ is the distance between the current gradient and an input normal, which is given by:

$$\Delta n_i^{\,k} = \left\|\nabla f^k(x) - n_i\right\|. \tag{6}$$

The gradient ∇f^k can be calculated by:

$$\nabla f^k(x) = \frac{\sum w_i \phi_i(x) n_i + \sum w_i \nabla \phi_i(x)\left(n_i^{\,T}(x - p_i) - f^k(x)\right)}{\sum w_i \phi_i(x)} \tag{7}$$

with $w_i = w(r_i^{k-1}) w_n(\Delta n_i^{k-1})$. To project an input point onto the RIMLS surface, the Eq. (1) is computed iteratively until it is converged or the termination criteria are reached. In short, the projected point is calculated by:

$$x^{k+1} = x^k - f^k(x)\nabla f^k(x). \tag{8}$$

Since MLS algorithms depend on normals significantly, the initial normals are calculated approximately by using principal component analysis. The principal axis with the smallest eigenvalue of the covariance matrix is treated as the normal. However, the orientation of the yielded normal is not determined. To deal with this problem, the minimum spanning tree (MST) algorithm [22] is always employed to maintain the consistent orientation of normals.

B. Point Descriptor Extraction

A local surface is described by the geometry information. Two main issues should be addressed for point set data. First, the point set provides only low-level primitives, such as positions and normal directions. It is hard to extract features from the original representation directly. Second, point sets may be generated from various sampling densities. It is difficult to describe the detail of surfaces with lower sampling density. To solve these two issues, a surface descriptor based on projection map is proposed. Furthermore, the geometry information described in the map is the differential angle between normals. While the information is stored in a 2D map, the point descriptor is called differential angle map (DAM).

The proposed descriptor extraction employs the sampling point lattices on the tangent plane to represent a map. For a base point selected from the query surface, a tangent plane can be defined by its Darboux frame. Given two principal directions denoted as e_1 and e_2, a point $t(u,v)$ on the tangent plane is shown as:

$$t(u,v) = ue_1 + ve_2. \tag{9}$$

Hence, the point p_t on the tangent plane referred to the frame of the query surface is represented as follows:

$$p_t(u,v) = t(u,v) + p_b, \tag{10}$$

where p_b is the base point referred to the frame of the query surface. According to Eq. (9) and Eq. (10), point lattices P_t on the tangent plane can be calculated as:

$$P_t = \left\{ p_t(u,v) \middle| u = \frac{r}{\delta u}, v = \frac{r}{\delta v} \right\}, \tag{11}$$

where r denotes the radius of the extracting range, and δu and δv indicate the spacing between lattices along the principal direction e_1 and e_2, respectively.

A large radius means that a large region of surface is described. Moreover, the spacing between lattices decides the level of details on the local surface. However, a tiny value of the spacing could cause high computational load. The appropriate combination of radius and spacing should make the map handle enough details of local surface. A recommended radius is at least four times the average point set resolution. Also, a typical spacing is from one-tenth to half the average point set resolution. For example, suppose the average point set resolution is 0.2, the suitable radius is 0.8 and the maximal spacing should be 0.1.

To calculate the differential angle between normals, the lattice point is projected to the MLS surface. The differential angle θ is computed by the following:

$$\theta = \cos^{-1}\left({n_p}^T n_b \right), \tag{12}$$

where n_p means the normal of the projected point, and n_b is the normal of the base point. Eq. (12) is applied to all projected points, and differential angles are stored in a DAM. Since the DAM is generated from the points referred to a local coordinate, orientations of DAMs of a surface are not consistent, and limit the matching procedure. To make DAM rotation invariant, an advanced rotation invariant process is proposed.

C. Rotation Invariant Point Feature

As mentioned above, a 2D map, DAM, is extracted for representing a local surface. However, DAM is oriented because it is generated by referencing the principal directions. To achieve rotation invariant, this paper adopts Zernike moments to represent the rotation invariant feature.

Zernike moments, which are constructed using a set of complex polynomials that form a complete orthogonal basis set defined on the unit disc, are widely used as a region-based image retrieval tool or selected as a feature extractor. Zhang and Lu [23] suggested that it has better performance than Fourier descriptors in 2D image retrieval. Zernike moments have translation, scale, and rotation invariance.

Complex Zernike moments are derived from Zernike polynomials, and they are expressed as a 2D Zernike moment:

$$Z_{mn} = \frac{m+1}{\pi} \int_x \int_y f(x,y) \cdot [V_{mn}(x,y)]^* \, dxdy, \tag{13}$$

where $(\cdot)^*$ denotes the complex conjugate. Eq. (13) is rewritten in polar coordinate form as:

$$Z_{mn} = \frac{m+1}{\pi} \int_0^{2\pi} \int_0^{1} f(r,\theta) \cdot V_{mn}(r,\theta) dr d\theta. \tag{14}$$

For easy computation, the set Zernike moments must follow polynomials:

$$V_{mn}(r,\theta) = R_{mn}(r) \exp(jn\theta), \tag{15}$$

and $R_{mn}(r)$ is defined as:

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}} (-1)^2 \frac{(m-s)!}{s!(\frac{m+|n|}{2}-s)!(\frac{m-|n|}{2}-s)!} r^{m-2s}, \tag{16}$$

where n and m are subject to $|m|-n$ is even and $|n| \le m$. Zernike polynomials are a complete set of complex-valued function orthogonal over the unit disc. For $f(x,y)$ is real and discrete, the complex Zernike moments of order n with repetition m can be derived from modifying Eq. (13):

$$Z_{mn} = \frac{m+1}{\pi} \sum_x \sum_y f(x,y) \left[VR_{mn}(x,y) + jVI_{nm}(x,y) \right], \tag{17}$$

where $VR_{mn}(x,y)$ is the real part of $V_{mn}(r,\theta)$, and $VI_{mn}(x,y)$ is the imaginary part of $V_{mn}(r,\theta)$.

This paper chooses the magnitude of the Zernike moments to keep the rotation invariant. Thus, the representation can be shown as follows:

$$\left[|Z_{00}|,|Z_{11}|,|Z_{20}|,|Z_{22}|,\ldots,|Z_{\infty\infty}|\right]^T . \tag{18}$$

It is clear that after Zernike moments are applied to DAM, it yields a one-dimension feature vector with rotation invariant. The precision of content representation depends on the number of moments truncated from the expansion, and the first 36 moments up to order 10 are used in this paper. Since that, the number of feature dimensions decreases dramatically about two orders of magnitude compared to DAM. In summary, a rotation invariant point feature, differential angle descriptor (DAD), is proposed. The steps of extracting DAD for a point set surface are as follows:

1. For an input point set, apply the RIMLS procedure mentioned in section III.A. This procedure also calculates normals and principal curvatures for the point set.
2. For a base point selected in the point set, find the tangent plane and generate sampling points by referencing its principal directions.
3. Project the sampling points to the MLS surface, and then calculate the differential angles. After that, the angles are stored as a 2D map, DAM.
4. Apply Zernike moments calculation to DAM. The rotation invariant descriptor, DAD, is obtained, and it is associated with the base point.
5. Repeat steps 2 to 4 until all points in the point set have been calculated.

III. Surface Matching

This section introduces a surface matching approach that uses the correspondence framework. The main idea of the correspondence framework is to find the point correspondences between two surfaces, and then the geometric transformation is computed. Once the transformation is defined, the matching error can be evaluated. Furthermore, to reduce the computation cost, this approach selects salient points based on curvature estimates for establishing correspondences. These parts will be explained in detail as follows.

A. Salient Points Selection

A salient point is a point which is in the edge or the sharp corner. It means that the salient point lies on the sharp surface and has details around it. Like an interest point extracted by corner detection in image processing, a salient point on the surface can be detected analogically.

To decide which point is a salient point, some features associated with the point are considered. In image processing, for example, a pixel with a local intensity extremum or a local maximal magnitude of gradient will be considered an interest point. However, the point set data only provide low-level geometric data, such as the position in a 3D coordinate. Since we have MLS surface, other local properties can be determined by the underlying MLS function. In this paper, the principal curvatures are employed to select salient points.

The principal curvatures at a base point can be derived as follows. Given the neighborhood of a base point and its normal n_b, the matrix $\nabla {n_b}^T$ is calculated as:

$$\nabla {n_b}^T = -\frac{1}{|g|}\left(I - n_b {n_b}^T\right)H , \tag{19}$$

where g is the gradient at base point, I is the identity matrix, and H is the Hessian matrix. Two principal curvatures, κ_1 and κ_2, are the first two eigenvalues of the matrix $\nabla {n_b}^T$, while the third eigenvalues is zero. In addition, the eigenvectors associated with κ_1 and κ_2 are the principal directions.

Koenderink [24] has defined a curvature representation for shape classification. This representation is show as:

$$s = \frac{2}{\pi}\tan^{-1}\left(\frac{\kappa_1+\kappa_2}{\kappa_1-\kappa_2}\right), c = \sqrt{\frac{{\kappa_1}^2+{\kappa_2}^2}{2}} , \tag{20}$$

where s is a shape index indicated the type of the shape, and c is described the magnitude of the curvedness at a point. For the salient point selection, the shape index is not a major concern. Therefore, a threshold of the deviation from flatness is applied to decide the salient point. A larger threshold yields points selected from sharper surfaces. For a query point set, the surface descriptors are computed only for salient points. This not only ensures the importance of the surface descriptors, but also increases the processing efficiency.

B. Finding Correspondences

To find out whether the two surfaces match each other, the correspondence framework which consists of two main steps is applied. The first is similarity measure, and the other is potential transformation between two surfaces.

The similarity measure performs a local matching to establish point correspondences. The similarity measure of a query point q for a matching point m is defined as the 2-norm distance between two DAD:

$$d = \left\| DAD_q - DAD_m \right\| . \tag{21}$$

After the similarity measures of each matching point are calculated, a distance histogram is yielded for choosing possible corresponding points. This procedure repeats until all salient points are computed. Moreover, possible corresponding matching points are chosen by finding the bin with the smallest distance in the histogram of similarity measures for each salient point. Another criterion is appended to increase the reliability of the correspondences:

$$c_1 > \lambda c_2 , \tag{22}$$

where c_1 and c_2 are the centers of the adjacent histogram bins with values, and λ is a distance weight. A large weight means that the distance between the adjacent bins is far. This brings reliable correspondences. As mentioned above, all salient points on the query surface calculate the similarity and find the correspondences. After that, a possible correspondence list is generated to estimate transformations.

A single point may be matched to more than one point. This causes ambiguity for calculating the transformation matrix between two surfaces. The primary reason is that spatially close points may have similar surface descriptors. In addition, surface descriptors generated from very small regions may result in similar to each other. To overcome this problem, a congruent consistency technique is proposed. This approach consists of geometric consistency and congruent consistency analysis.

The geometric consistency is a filter measuring the likelihood of two correspondences. Two correspondences are consistent means that they have similar geometric forms, and can be grouped together to calculate a transformation of two surfaces. If a correspondence is not geometric consistent with other correspondences, it should be eliminated from the possible corresponding list. Further details of the geometric consistency are described in [2].

A unique 3D transformation matrix at least needs four point correspondences to calculate it. Since there are a huge amount of combinations from the possible corresponding list for calculating transformation matrices, a grouping approach, namely congruent consistency analysis, is used to determine a group of correspondences resulting in a more robust transformation.

The congruent consistency analysis is based on the concept of a congruent triangle, as shown in Fig. 1. It assumes that if two surfaces are similar, then at least three correspondences are geometric consistent. The condition of the triangle congruence can be defined as:

$$\sum_{i=1}^{3} \frac{\left| e_i^{(Q)} - e_i^{(M)} \right|}{e_i^{(Q)} + e_i^{(M)}} < \varepsilon , \tag{23}$$

where $e_i^{(Q)}$ and $e_i^{(M)}$ denote the *i*-th length of the side of the triangle on surface Q and M , respectively. The distance error ε controls how congruent is. A small value gives the strict congruency.

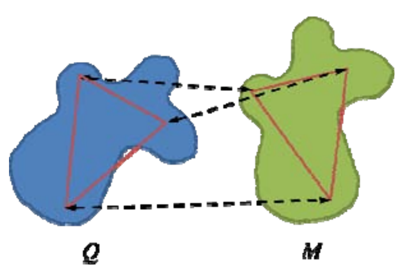

Figure 1. An example of the congruent consistency analysis. The triangles on both surfaces are congruent

The congruent consistency analysis gives corresponding groups with more reliable geometric consistency. The grouping procedure applied in the possible corresponding list is as follows: Each three correspondences satisfying Eq. (23) are considered as a basis of the congruent group; others in the possible corresponding list are examined the congruency with respect to the basis group. The correspondence is added into the congruent group if it satisfies the congruent condition. As the result, each congruent group is calculated candidate transformation $\hat{T}$ from model to query surface by minimizing:

$$\sum_i \left\| q_i - \hat{T} m_i \right\|^2 , \tag{24}$$

where $[q_i, m_i]$ is the i-th correspondence in the congruent group. Finally, the candidate transformations and associated congruent groups are then input into a verification procedure.

C. Varification and Calculating Matching Error

The purpose of verification is determining the best transformation from model to query surface. The transformation with minimal matching error which calculates for all points of the query surface comparing to all points of the model will be treated as the best one. The verification approach is based on the iterative closest point (ICP) algorithm [25][26] which can handle partial data of point sets and arbitrary transformations. After applying the verification, a fine-tuned transformation is computed. Moreover, the matching error can be calculated to evaluate the goodness of matching.

In this paper, the goodness of matching R_{gom} is defined as:

$$R_{gom} = \frac{\varphi^2}{E_{icp}} , \tag{25}$$

where φ is the ratio of the overlapping points aligned by ICP between query surface and model, and E_{icp} is the mean-square-error calculated from data set aligned by ICP. To consider variant sampling densities of surfaces, φ is defined as the sum of the areas of overlapping surface. Additionally, for N correspondences, E_{icp} is shown as:

$$E_{icp} = \frac{1}{N} \sum_i^N \left\| q_i - T m_i \right\|^2 , \tag{26}$$

where $[q_i, m_i]$ is the i-th correspondence aligned by ICP.

Consequently, the goodness of matching is used to find the best matching model for a query surface. The larger value represents better match between two surfaces. Moreover, the transformation matrix associated with the largest R_{gom} is the best post estimation as the matching result.

IV. Discussions And Experimental Results

To demonstrate the proposed surface descriptor, we have performed several surface matching experiments. A database containing 25 complete object models is created. The database consists of two groups, one is the vehicle group including 16 vehicles, and the other is the common group including 9 models. All these models are collected from the internet, and they are all triangle mesh models.

To extract the surface points of these models as point set models, a process which simulates a range finder is applied to models. This process scans each model from multiple viewpoints by calculating the intersection of the ray with the surface. Additionally, a variety of different resolutions of the point set models can be obtained by adjusting parameters. Hence, as shown in TABLE I. , six different resolutions of the point set data are acquired for test in experiments. The point set models with the highest resolution (High II) are the ground-truth data, and others are the test data. Also, the last column of TABLE I. shows the average radius of a point for each level of the model resolution. All models are scaled to a unity bounding box.

TABLE I. The overall matching performance

Level of the model resolution	**Low I**	**Low II**	**Medium I**	**Medium II**	**High I**	**High II**
Avg. number of points of a model	220	536	1066	2173	4185	8281
Avg. radius of a point	0.0756	0.0523	0.0375	0.0263	0.0188	0.0150

Figure 2. The models in the common group.

To evaluate the performance of surface matching is illustrated as the following. Since the proposed surface descriptor handles local features, input surfaces as test data are chosen partial surfaces took from the predefined viewpoints for each model. Therefore, the correctness of surface matching C is defined as:

$$C = \frac{N_c}{N_{vp}} \tag{27}$$

where N_c is the number of the correct matching poses and N_{vp} is the number of the predefined viewpoints. In our experiments, 164 predefined viewpoints are selected as shown in Fig. 3.

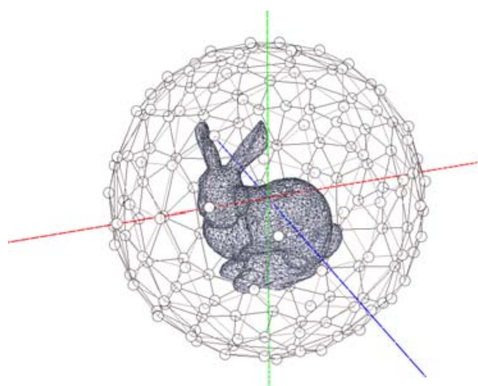

Figure 3. The predefined viewpoints denoted as the circle unform distributed on the sphere.

Besides, the spin image method [2] as a competing method is selected to verify the performance of the proposed DAD method. The original spin image method is applied to mesh models; nevertheless, it computes only the vertices on the mesh as the points sampled from the surface. Thus, the spin image method is suitable to describe local features. In addition, two approaches to generate spin images form point set surfaces are introduced. One is directly computing spin images form point set data (DSI); another is computing spin images form the points which are interpolated by using Eq. (11), namely interpolated spin images (ISI).

The results presented in the following are divided into two parts. The first is the performance of partial surface matching. And the second is the capability of matching across different resolutions of point set surfaces.

A. Surface Matching Performance

Fig. 4 shows some examples of input point set surfaces. TABLE II. gives the overall matching performances of three methods including the proposed DAD method in High I and High II resolutions, where the radius of the descriptor is 0.2. It shows that our method achieve the best results in the tests of both two resolutions. The ISI also carries out good performance which is close to DAD. The original spin image method, DSI, reaches worse performance than ISI. The major cause is that ISI uses the interpolated points to compute spin images, while DSI uses only points on surfaces. Since the resolutions of models are decreasing, ISI can keep more complete surface information than DSI.

(a) (b) (c) (d)

Figure 4. The examples of some test point set surfaces. (a) A bunny, (b) a cow, (c) a Audi A4 sedan, and (d) a BMW X5 SUV vehicle.

TABLE II. THE OVERALL MATCHING PERFORMANCE

Model resolution	Correctness of matching (%)		
	DAD	***DSI***	***ISI***
High I	**83.58**	77.27	79.58
High II	**84.48**	79.73	81.48

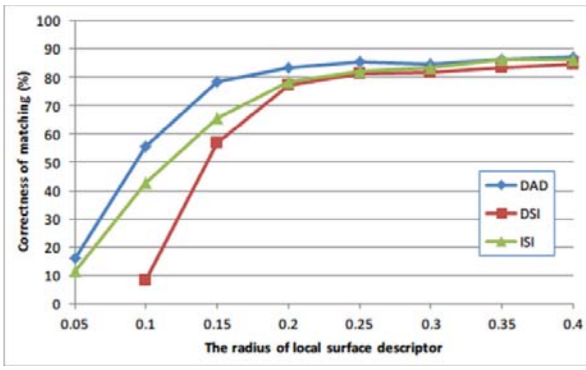

Figure 5. The different radius of the effect on the correctness of matching.

Another important factor affecting the matching performance is the radius of the local surface descriptor. A higher value of the radius means that the descriptor covers larger area of the surface; on the other hand, a smaller value of the radius represents a more local descriptor. For a unity-scale model, the radius of a value 1 can generate descriptors which are similar to global features.

The Fig. 5 illustrates the different radius producing effect on the correctness of matching at High I resolution. When the radius is greater than 0.2, all methods achieve good performances similarly. However, as the radius is small than 0.15, the performances for three methods are decrease dramatically, because the descriptor is too local to find correct correspondences. It can be observed that DAD method keeps better performance than other two methods, even though the radius is small than 0.15. The major cause of this phenomenon is that a differential angles map likely describes more precise geometric information than a histogram does. Besides, DAD derived from DAM, which has less redundant data than spin image. As a result, the DAD method could match surfaces by using descriptors generated from smaller regions.

B. Matching in Different Resolutions

A further experiment is carried out to demonstrate the ability of matching surface among different resolutions. The Fig. 6 depicts the results provided by comparing surfaces with various resolutions to the ground-truth data. Since DSI uses only point data, it is obvious that DSI has worse matching performance than DAD and ISI. In brief, the methods with interpolation have better ability against the different resolution problem.

To match point set surfaces among different resolutions, DAD method could provide more robust results than ISI method. However, DAD produces unsatisfactory results under an extreme difference between resolutions, for example, matching surfaces between Low I resolution and High II resolution. This limitation is because the details are lost at low-resolution point set surfaces. For such case, it is hard to improve the result even the descriptors are computed by using an interpolation technique.

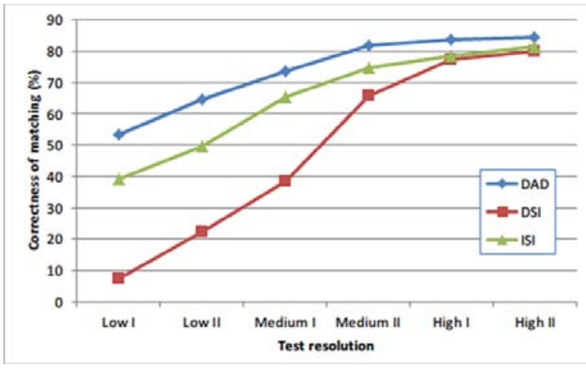

Figure 6. The results of matching among different resolutions.

In summary, the proposed DAD method has good matching performance compared with other methods both in terms of matching surface by using variety of descriptor size or matching surface among different resolutions.

V. CONCLUSIONS AND FUTURE WORK

In this paper, an approach called DAD based on MLS surface projection and differential angle features is proposed for matching point set surfaces. The approach uses a geometric descriptor calculated form the differential angle between normals to match among point set surfaces. Furthermore, the descriptor is generated by extracting the Zernike moments as a rotation invariant feature. These methods lead to the proposed approach, which is robust against translation, rotation, and various resolutions for point set surface matching. Using the Zernike moments for the local surface descriptor decreases the dimension of features, and increases the efficiency of surface matching. In summary, the experimental results show that our approach outperforms the original spin image method, and has slightly better performance than interpolated spin image method. Additionally, a congruent consistency analysis is bought to match the correspondences and estimate the possible transformation.

Future research could be conducted on labeling point set data or point set classification. In addition, this work might be extended to retrieve 3D models, or detect complete and partial models in point set data.

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