



AN EFFICIENT METHOD FOR SURFACE RECONSTRUCTION BASED ON LOCAL COORDINATE SYSTEM TRANSFORM AND PARTITION OF UNITY

Z. Zhou*, Y. Fu†, J. Zhao†

Abstract: Radial basis function (RBF) has been extensively applied for surface reconstruction from scattered 3D point data due to its strong ability of approximation. However, additional information, such as off-surface points, are usually required to be appended into constraints for determining the parameters, which apparently increases the computation cost and data unreliability. To avoid adding additional off surface point constraints, a novel surface reconstruction approach based on local coordinate system transform and partition of unity is proposed in this paper. Firstly, the explicit RBF functions are constructed to approximate the local surface patches, and then it is transformed into an equivalent implicit surface reconstruction form by local system coordinate transformation. Compared with the local implicit surface approximation, the proposed local explicit surface approximation method is capable of avoiding trivial solution occurred in RBF approximating, and does not increase the scale of data solution. A number of comparison experiments of the proposed method with the traditional RBF-based method and the multi-level partition of unity (MPU) method are carried out on some kinds of large dataset, non-uniformity dataset, noisy dataset. The experimental results illustrate that the proposed method is robust and effective in dealing with large-scale point clouds surface reconstruction.

Key words: *surface reconstruction, radial basis function, partition of unity, local coordinate system transform*

Received: January 5, 2019

DOI: 10.14311/NNW.2020.30.012

Revised and accepted: June 30, 2020

1. Introduction

Along with the quick development of 3D scan technology, millions of contour points on the surface of object can be obtained. These points are often used to reconstruct the watertight surface in the areas of geometry processing, scientific visualization,

*Zhenghua Zhou – Corresponding author; College of Sciences, China Jiliang University, Hangzhou, Zhejiang Province, China, 310018, E-mail: zzh@cjlu.edu.cn

†Yanqing Fu; Jianwei Zhao ; College of Sciences, China Jiliang University, Zhejiang, Hangzhou, China, 310018, E-mail: 403375883@qq.com, zhaojw@cjlu.edu.cn

and their applications [6,9,14,17,23]. In the last two decades, surface reconstruction has become one of the most significant topics in computer graphics, and substantial numbers of techniques have been developed. But it is still a challenging task for the people to build a desired surface. The main reason is that the obtained data are usually huge, non-uniform, full of noises, and even with some holes due to the inaccessibility of scan. Generally, a desirable method for surface reconstruction should include a good reconstruction accuracy, a fast reconstruction speed, a low memory cost, and a good faith to some points with the low quality as mentioned above.

According to the representation of the reconstructed surface, the existing methods for surface reconstruction are mainly classified into two categories: explicit method and implicit method. The explicit method aims to find an explicit continuous function to interpolate or approximate those scanned points [8,25], while the implicit method seeks to build an implicit continuous function whose zero-set is the reconstructed surface to interpolate or approximate those points [5]. Specifically, let $\mathcal{P} = \{p_i\}_{i=1}^N \subseteq \mathbb{R}^3$ be the set of scanned points associated with their corresponding unit normal vectors $\mathcal{N} = \{n_i\}_{i=1}^N \subseteq \mathbb{R}^3$, where \mathcal{N} forecasts the orientation of the target surface \mathcal{S} and it can be directly obtained by some scanner device or estimated with principle component analysis (PCA) or the local least-square fitting. Then the traditional explicit methods interpolate or approximate the target surface \mathcal{S} by means of a continuous bivariate function or a series of simple parametric surfaces, while the implicit methods aim at constructing a continuous function $f: \mathbb{R}^3 \rightarrow \mathbb{R}$ such that its zero-set $\{p \in \mathbb{R}^3 : f(p) = 0\}$ can approximate the target surface \mathcal{S} .

Due to the complexity and closure of the surface used for representing object, the implicit method can obviously construct a closer surface than the explicit method does. However, the existing implicit methods usually need to be appended with some additional constrains such as adding off-surface points to help determine the parameters, which increases the memory cost, computational complexity and data noises dramatically. Hermite implicit method replaces the off-surface points with the normal vectors' approximators in the additional constraint equations [16,22], so its computational complexity sometimes is still unacceptable for the large dataset. Therefore, a natural question is: Is there any implicit method that does not need off-surface points and has a satisfied computational complexity? This paper gives an affirmative answer for this question.

In this paper, we will propose a novel implicit method for the 3D surface reconstruction without adding other additional constrains by using the local coordinate system transform. First, similar to the traditional local RBF-based method, we partition the large data domain into some small subdomains. It is noted that we need ensure that each local surface sheet has an explicit expression in some new coordinate system. Then in order to avoid adding additional constraints and determine the parameters in the traditional local RBF-based method, we get a non-homogeneous linear system with a transformation between the original scanning coordinate system and the new coordinate system. Finally, the global function is obtained by blending each local approximation with some local weighed functions [19]. Therefore, our proposed method is a mixture of RBF-based and multi-level partition of unity (MPU) based method. On one hand, our proposed

method can be considered as an improved RBF-based method, but it can do more than the traditional RBF-based method does. The classical implicit RBF-based method needs to add some off-surface data, while our method avoids this process by transforming the homogeneous linear system into a non-homogeneous case with a transformation of the coordinate system. On the other hand, our proposed method can be regarded as the RBF-based MPU method. It firstly divides the dataset into a series of cells with a fixed size, then in each local coordinate system, local surface represented as an explicit a bivariate function is reconstructed. The bivariate function is taken to be the RBF.

The main contribution of the paper can be summarized as follows:

- The local coordinate system transform and partition of unity are combined to perform surface reconstruction, which does not need extra off-set points.
- The proposed approach can quickly and accurately reconstruct complex topological models.
- The bivariate function in the form of radial basis function used for approximating the local surface patches is robust to noisy data and non-uniformity datasets.

The rest of the paper is organized as follows. We first review the previous work of the surface reconstruction in Section 2. Then, we give a specific processes of our proposed method for the surface reconstruction in Section 3. In Section 4, experimental results on different shape datasets with comparison to existing methods are given. Finally, we conclude the paper in Section 5.

2. Related work

Up to now, a lot of approaches for surface reconstruction have been proposed. According to the processing techniques, these approaches are roughly classified into three groups: Delaunay triangulation (or Voronoi diagram)-based methods, parametric methods, and implicit methods.

Delaunay triangulation-based methods. Delaunay triangulation based methods generally construct the surface by exploiting the structures, such as Delaunay tetrahedral and Voronoi diagrams. That is, they usually interpolate all or most of the points by means of creating a triangle mesh. Some representative methods of this group are α -shapes [8], crust and power crust algorithms [2], tight cocone [6], and so on. The main shortcoming of these methods is that they are usually sensitive to the noise.

Parametric methods. Parametric methods aim to build the reasonable correspondence between the pairs of locations on the boundaries of the two shapes. The popular representative methods are B-spline method [10] and non-uniform rational B-spline (NURBS) surface [21]. These methods are typically faster and require less memory than Delaunay triangulation-based methods because they operate on a lower dimensional representation of an object. However, their expression ability is limited by the parametric functions.

Implicit methods. Different from the above two methods, the goal of implicit methods is to find a continuous function and uses its zero isosurface to fit those

discrete points. Most existing implicit methods for constructing the continuous function are virtually determined by the linear combination of the basis functions such as signed distance function [11,25], RBF [5,16,20], local implicit functions [19], moving least square approximation [1], indicator functions [12], and so on. Among these methods, the local RBF-based method [24] and MPU method [19] present a good performances in dealing with the large dataset. But they also have deficiency. For example, RBF-based method is powerful for the complex topology model and robust to the noises, but it requires some additional information, such as off-surface points, to determine the functions, which is apparently not reliable for the cases with noises or some closed sheets. While for the MPU method, although it can reconstruct the sharp feature for the non-uniformity or large datasets efficiently with the local quadric polynomial and the partition of unity, it is very sensitive to the noise because of the rigidity of the quadric polynomial.

3. The proposed surface reconstruction method

In this section, we will propose a new implicit surface reconstruction method based on the partition of unity (PU) and RBF for the glocal surface reconstruction. The proposed method is composed of three stages as follows: Firstly, for the given scan data, we divide the global domain into several local sub-domains based on the adaptive Octree-based subdivision method. Then we reconstruct the local surface with the proposed implicit method. Finally, the global surface is obtained by the PU method. A block schematic diagram of the proposed method is shown in Fig. 1.

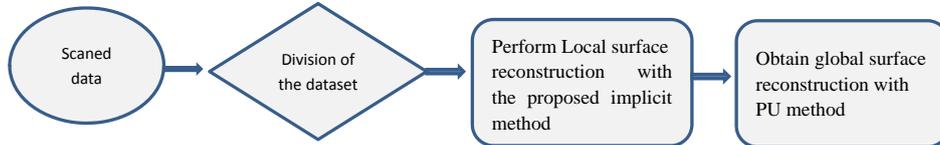


Fig. 1 Diagram of the proposed method for surface reconstruction.

3.1 Division of the dataset

Due to the complexity of the surface and the huge volume of the scanned data, we intend to reconstruct the global surface by means of reconstructing each simple local surface. Therefore, the first work is to divide the global domain into several local domains. Here, our proposed adaptive Octree-based subdivision method in [26], which is developed based on [19], is employed to achieve the data division task.

Let S_0 be the minimum bounding box which can contain the scanned dataset $\{(p_i, n_i)\}_{i=1}^N$, where $p_i \in R^3$ is the scanned position point and n_i is its corresponding unit normal vector. It is assumed that N_{\min} and N_{\max} are the minimum and maximum number of the points ensuring that each sub-domain allows to contain, respectively. If the number of points in the domain S_0 is larger than N_{\max} , then

divide S_0 into eight overlapping sub-domains. For these eight sub-domains, if their numbers of points are larger than N_{\max} , then we continue to divide these obtained sub-domains. The whole subdivision algorithm for the scanned dataset is detailed as follows:

Algorithm 1 Division of dataset.

each sub-domain S_i in the i -th layer, calculate the number n of points in the S_i ,

if $n > N_{\max}$, **then**
 divide S_i into eight sub-domains with the Octree method,
else if $N_{\min} \leq n \leq N_{\max}$, **then**
 return and input S_i into the tree;
else if $0 < n < N_{\min}$, **then**
 enlarge S_i ;
else if $n = 0$, **then**
 discard S_i .
end if

In the next step of our proposed method, we assume that each local surface to be reconstructed has an explicit expression. Therefore, we use N_{\min} and N_{\max} to adjust the structure of each local surface.

3.2 The proposed method for the local surface reconstruction

For each divided sub-domain S_j that contains point set $\{(p_i, n_i)\}_{i=1}^{N_j}$ with the division algorithm, the traditional implicit method aims to seek a smooth function $f_j : \mathbb{R}^3 \rightarrow \mathbb{R}$ from some smooth function space \mathcal{H} satisfying $f_j(p_i) = 0, i = 1, 2, \dots, N_j$. According to the approximation theory, those smooth functions in \mathcal{H} are usually taken as the form of RBF as follows:

$$f_j(p) = \sum_{i=1}^{N_j} \alpha_{ji} \phi(p, p_i) + Q_j(p), \quad (1)$$

where each $\alpha_{ji} \in \mathbb{R}$, $\phi : \mathbb{R}^3 \times \mathbb{R}^3 \rightarrow \mathbb{R}$ is the radial basis function, and Q_j is the usual polynomial with one order, i.e.

$$Q_j(p) = c_{j0} + c_{j1}x + c_{j2}y + c_{j3}z, \quad p = (x, y, z)^\top. \quad (2)$$

Therefore, we need to determine those parameters for obtaining the reconstructed surface. Usually, those parameters are determined by solving the following homogeneous linear system [5]:

$$\begin{pmatrix} \Phi & P_j^\top \\ P_j & 0 \end{pmatrix} \begin{pmatrix} \alpha_j \\ c_j \end{pmatrix} = 0, \quad (3)$$

where $\Phi = [\phi_{hk}]_{N_j \times N_j}$ with each $\phi_{hk} = \phi(p_h, p_k)$, $P_j \in \mathbb{R}^{4 \times N_j}$ with the i -th column vector being $(1, x_i, y_i, z_i)^\top$, $\alpha_j = (\alpha_{j1}, \alpha_{j2}, \dots, \alpha_{jN_j})^\top$, $c_j = (c_{j0}, c_{j1}, c_{j2}, c_{j3})^\top$.

To avoid the trivial solution of (3), many traditional methods usually introduce a number of off-surface points for increasing some constrain equations in (3). But such process of adding the off-surface points inevitably increase the scale of solving equation and the instability of system. In order to avoid adding other constraint equations, we seek to change the implicit approximation surface function into explicit bivariate surface function via transforming the homogeneous linear system into a non-homogeneous linear system. For each local surface patch, suppose that the local surface patch has the explicit expression in this coordinate plane, a local coordinate plane is established, and the projection value of the patch to the plane is taken as its local function value. Then the relation between two coordinate systems is employed to yield a nonzero vector on the right side of system (3), which needs not to add other constraint equations. In the following section, we will describe local surface reconstruction process in detail.

Suppose that the geodetic coordinate system for scanning is denoted by $O-xyz$, and the local coordinate system is represented by $P_j - n_j l_j m_j$.

According to the theory of spatial analytic geometry, there exists a unique transfer matrix $A_j \in \mathbb{R}^{3 \times 3}$ such that

$$(l_j, n_j, m_j)^\top = A_j(x, y, z)^\top. \tag{4}$$

Namely,

$$\begin{cases} l_j = a_{11}^{(j)}x + a_{12}^{(j)}y + a_{13}^{(j)}z, \\ n_j = a_{21}^{(j)}x + a_{22}^{(j)}y + a_{23}^{(j)}z, \\ m_j = a_{31}^{(j)}x + a_{32}^{(j)}y + a_{33}^{(j)}z. \end{cases} \tag{5}$$

Here the matrix A_j can be determined when the local coordinate system is chosen. Therefore, if the explicit expression for the local surface in the local coordinate system $P_j - n_j l_j m_j$ is

$$m_j = h_j(l_j, n_j), \tag{6}$$

then its implicit expression in the global geodetic coordinate system $O - xyz$ is

$$\begin{aligned} & a_{31}^{(j)}x + a_{32}^{(j)}y + a_{33}^{(j)}z \\ & = h_j(a_{11}^{(j)}x + a_{12}^{(j)}y + a_{13}^{(j)}z, a_{21}^{(j)}x + a_{22}^{(j)}y + a_{23}^{(j)}z). \end{aligned} \tag{7}$$

Let

$$g_j(x, y, z) := h_j(a_{11}^{(j)}x + a_{12}^{(j)}y + a_{13}^{(j)}z, a_{21}^{(j)}x + a_{22}^{(j)}y + a_{23}^{(j)}z) \tag{8}$$

and

$$\Pi_j(x, y, z) := a_{31}^{(j)}x + a_{32}^{(j)}y + a_{33}^{(j)}z, \tag{9}$$

then the implicit expression for the local surface in the coordinate system $O - xyz$ is

$$g_j(x, y, z) - \Pi_j(x, y, z) = 0. \tag{10}$$

Let

$$f_j(x, y, z) := g_j(x, y, z) - \Pi_j(x, y, z) \tag{11}$$

we use the RBF network

$$\sum_{i=1}^{N_j} \alpha_{ji} \phi(p, p_i) + Q_j(p) \tag{12}$$

in (1) to approximate the function g_j , then the implicit expression becomes to be

$$f_j(x, y, z) = \sum_{i=1}^{N_j} \alpha_{ji} \phi(p, p_i) + Q_j(p) - \Pi_j(x, y, z) = 0. \tag{13}$$

Now our task is to approximately determine those parameters in (13) with the scanned data. Here we obtain those parameters by solving the following non-homogeneous linear system:

$$\begin{pmatrix} \Phi & P_j^\top \\ P_j & 0 \end{pmatrix} \begin{pmatrix} \alpha_j \\ c_j \end{pmatrix} = \begin{pmatrix} d_j \\ 0 \end{pmatrix}, \tag{14}$$

where $d_j = [\Pi_j(p_1), \Pi_j(p_2), \dots, \Pi_j(p_{N_j})]^\top$.

It is noted that the left side of the equation (14) is same as (3), but the right side is a nonzero vector. Obviously, we no longer add other off-set points. Furthermore, the expression of f_j in (13) is still a form of RBF, which means that the function still have a pretty performance for a complex surface.

For the above non-homogeneous linear system (14), we add the ℓ_2 -regularization term to the optimization object function to obtain a stable solution. Therefore, parameters in (13) are finally determined by solving the following optimization problem:

$$\min_{\beta} \sum_{i=1}^{N_j} \|f_j(p_i)\|_2^2 + \lambda \|\beta\|_2^2, \tag{15}$$

where β is the vector composed of all the parameters in the non-homogeneous linear system (14). Here we will use lower upper (LU) factorization to solve the optimization problem (15).

After explaining the idea of our proposed local surface reconstruction, we give the concrete process of determining the coefficients $a_{3i}^{(j)}$ ($j = 1, 2, 3$) of the function Π_j . As we know, when $m_j = 0$, the coefficients $a_{3i}^{(j)}$ ($j = 1, 2, 3$) are the coefficients of a plane $\Pi_j = 0$ in the original global coordinate system O_{xyz} . As we have divided the global domain into some sub-domains with simple structure, each local surface has a rough orientation. The orientation can be defined by those unit normal vectors of the points in each cell, so we take the following vector ξ_j

$$\xi_j = \frac{n_h + n_k}{2} \tag{16}$$

as the normal vector of the local plane, n_h and n_k are the normal vectors of the two points with the largest angle between the normal vectors in the current surface patch.

In order to determine the local plane Π_j and avoid the intersection of plane and local surface slice as much as possible, we still need another vector η_j defined by

$$\eta_j = c_j - r_j \xi_j, \quad (17)$$

where c_j is the center vector of the cell, and r_j is the radial of the bounding sphere. For the local reconstruction cell S_j with N_j points, the implicit function expression in (13) becomes to be

$$f_j(x, y, z) = \sum_{i=1}^{N_j} \alpha_{ji} \phi(p, p_i) + Q_j(p) - \langle \xi_j, p - \eta_j \rangle = 0. \quad (18)$$

3.3 Global reconstruction surface with PU method

In this section, we use PU method to decompose the global problem into several smaller local problems, and blend the local surfaces into a global surface with the corresponding weighted functions. For each subdomain S_j , we have obtained a local implicit function f_j with our proposed local surface reconstruction method, $j = 1, 2, \dots, M$. Let w_i be the corresponding weighted function with $\sum_{i=1}^M w_i \equiv 1$ on the whole domain S . Then we can obtain the global reconstructed function f as follows:

$$f(p) = \sum_{j=1}^M w_j(p) f_j(p) = 0. \quad (19)$$

In general, the weighted functions $\{w_j\}_{j=1}^M$ can be obtained by normalizing a set of positive functions $\{W_j\}_{j=1}^M$ as follows:

$$w_j(p) = \frac{W_j(p)}{\sum_{i=1}^M W_i(p)}. \quad (20)$$

For the implicit surface reconstruction, the global approximation function should be continuous, so every W_i has to be continuous on the boundary of the sub-domains $S_i, i = 1, 2, \dots, M$. According to above analysis, we summary our algorithm for surface reconstruction as follows.

4. Experiments

In order to evaluate the performance of our proposed method, a series of experiments are designed to show the generalization ability, effectiveness and stability of the proposed surface reconstruction model. In this part, the generalization and the stability of our proposed method is verified with various models containing different features and noises. All the experiments are implemented by Microsoft Visual Studio 2010 and all results presented in this section are run on an Intel(R) 2.40GHz and Xeon (R) 2.39 GHz with 8GB RAM. The scanned database are chosen from AIM@SHAPE repository. For the visualization of the implicit surface, we adopt Bloomenthal's polygonizer method [3] to generate a polygonal mesh. The

Algorithm 2 The whole process of our proposed method for surface reconstruction.

- Start:** Input the data set $\{(p_i, n_i)\}_{i=1}^N$;
Step 1: Compute the width parameter for each point;
Step 2: Partition the domain based on the distribution of the data;
Step 3: For each sub-domain, compute the local coordinate plane;
Step 4: Solve the optimization problem (14) with LU factorization to get the parameter vector β ;
Step 5: Blending the local function into the global function;
Step 6: Extracting the isosurface to visualize the model.
End
-

parameters in the experiments are set as follows: $N_{min} = 15, N_{max} = 30$. The radial basis function $\phi(p, p_i)$ is taken as $\phi(p, p_i) = (1 - \|p - p_i\|)^4(4\|p - p_i\| + 1)$.

4.1 Generalization of our proposed method

Figs. 2-5 illustrate the performance of our proposed method for different types of objects. Fig. 2 shows the reconstruction surfaces of a blade which has some planes. It is seen from Fig. 2 that our proposed method can handle the object with the non-absolute sharp edges such like the planes. On the contrary, if the scanned object has a complex local structures, such as the absolute sharp edges, our method can still achieve good performance due to polishing effect of radial basis function. Fig. 3 shows the perfect reconstruction surfaces of some complex

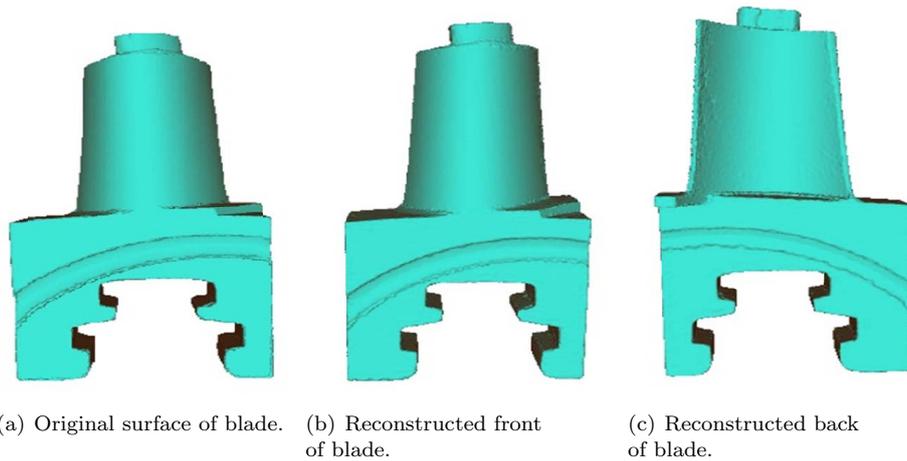
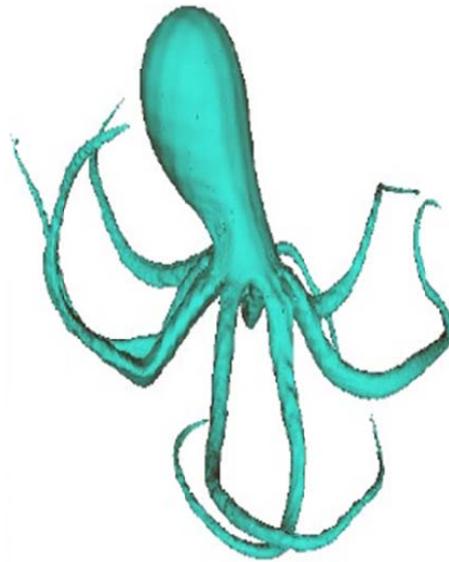


Fig. 2 Reconstruction results of blade with our proposed method with 18395 points.



(a) Reconstructed vase-lion with 200000 points.

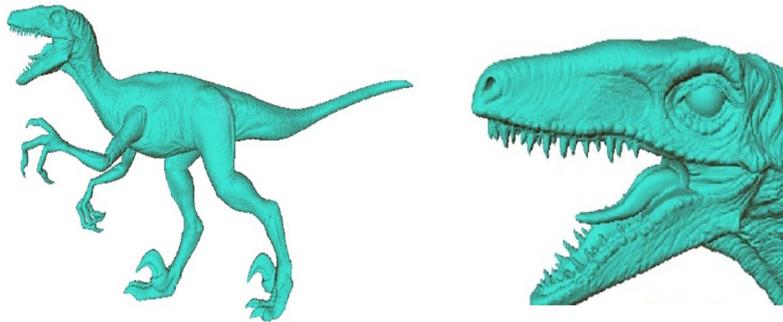
(b) Reconstructed buddha with 250000 points.



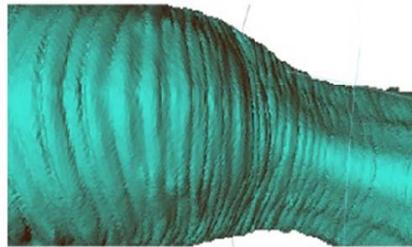
(c) Reconstructed octopus with 16944 points.

Fig. 3 *Reconstruction results of some complex models with our proposed method.*

objects with some tinny local features. Even the shallow ridges on the back of Buddha and the antennae of octopus can be vividly described. To validate the ability of disposing large and complex point set surface, we use the raptor model with 1 million sampled points to perform the reconstruction of raptor with our proposed method as seen in Fig. 4. It is observed from Fig. 4 that the fine stripes and teeth of the raptor's head are accurately reconstructed by means of the similar size of each sub-domain. In Fig. 5, the points density on the right side of Venus is lower than that of left side as shown in Fig. 5(a). It is observed from Fig. 5(b) and Fig. 5(c) that our proposed method can accurately capture the intrinsic shape feature from these non-uniformity distribution data points.



(a) Reconstructed raptor with 1000000 points (b) Reconstructed head details of raptor

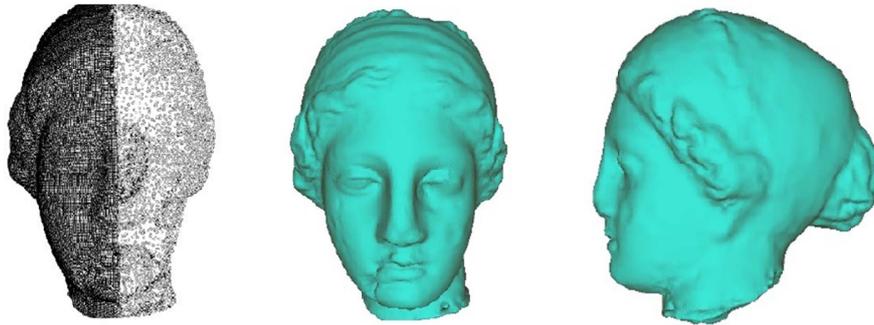


(c) Reconstructed neck ridge of raptor

Fig. 4 Reconstruction results of some complex models with our proposed method.

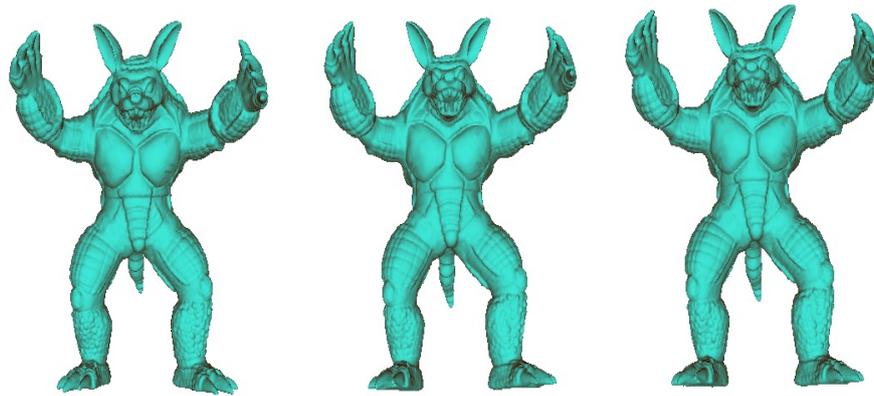
4.2 Efficiency of our proposed method compared with the traditional RBF method

To further validate the efficiency in handing large scale points surface reconstruction. Compared with the traditional RBF method for surface reconstruction, our proposed method does not need to append a large number of off-surface points, thus reducing the computational complexity. Fig. 6 shows the comparison result of Armadillo reconstruction between our proposed method and the traditional RBF method. As shown in Fig. 6, there is no obvious visual difference between the two



(a) Point representation of Venus. (b) Reconstructed Venus with our proposed method. (c) Reconstruction result of Venus's side with low density points.

Fig. 5 Reconstruction result of Venus with our proposed method for non-uniformity dataset.



(a) Original surface of Armadillo. (b) Reconstructed Armadillo with our proposed method. (c) Reconstructed Armadillo with traditional RBF method.

Fig. 6 Reconstructed Armadillo with our proposed method and the traditional RBF method.

methods, which indicates that our proposed method completely achieve the same reconstruction effect as the traditional RBF methods. Tab. I shows the comparison results of our proposed method with the traditional RBF method that requires off-surface points to prevent the occurrence of trivial solution.

In this comparison experiment, the number of partition cells and radial basis functions are same. In Tab. I, N and M are the numbers of data and the sub-domains, respectively, T_{our} and T_{RBF} denote the computational time for the coefficients of our proposed method and the RBF method, respectively. The RMS error of our proposed method and the RBF method are denoted by E_{our} and E_{RBF} ,

respectively. It is Observed from Tab. I that the computational time of the traditional RBF method is about twice that of our proposed method. In the meanwhile, the error of our proposed method is much less than that of the traditional RBF method.

Models	N	M	$T_{\text{our}}(s)$	$T_{\text{RBF}}(s)$	E_{our}	E_{RBF}
Armadillo	9679	3609	1	5	6.5×10^{-5}	4.6×10^{-2}
	36145	13173	6	19	4.3×10^{-5}	2.3×10^{-2}
	172974	57310	32	115	1.5×10^{-5}	7.2×10^{-3}
Bunny	12005	5084	2	5	6.8×10^{-5}	3.4×10^{-2}
	42399	20255	7	21	5.3×10^{-5}	3.4×10^{-2}
	139990	79430	30	68	2.6×10^{-5}	1.5×10^{-2}
Raptor	109668	62444	22	50	3.2×10^{-5}	3.2×10^{-2}
	413189	251412	94	217	1.2×10^{-5}	8.8×10^{-3}
	1000080	439985	252	707	9×10^{-6}	9.5×10^{-3}
Blade	7745	4074	1	4	2×10^{-6}	4.5×10^{-2}
	18395	8670	3	10	2×10^{-6}	4.2×10^{-2}
	29275	16798	7	18	1×10^{-6}	2.3×10^{-2}

Tab. I Time (seconds) and error comparison of our proposed method with the traditional RBF method for different models.

4.3 Stability of our proposed method compared with the MPU method

In order to show the stability of proposed method in the case of noise disturbance, we add different levels noise to the given data sampled from Stanford Bunny as shown in Fig. 7. Fig. 8 is the reconstructed Bunny from data points with different levels of noise by our proposed method. Fig. 9 exhibits the reconstructed Bunny with MPU method under various levels noise. It is seen that our proposed method is more robust to the noise than MPU method due to the strong stability of the radial basis functions. It can be seen from Fig. 9 that MPU method is completely

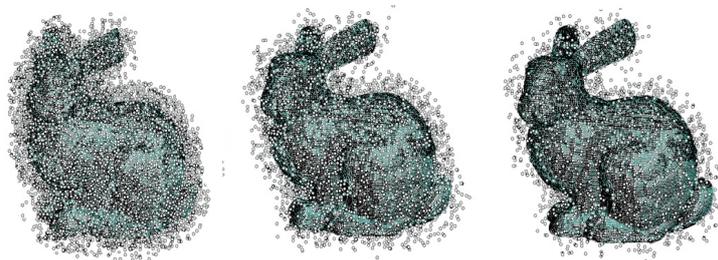


Fig. 7 Bunny data points with different levels of noise.

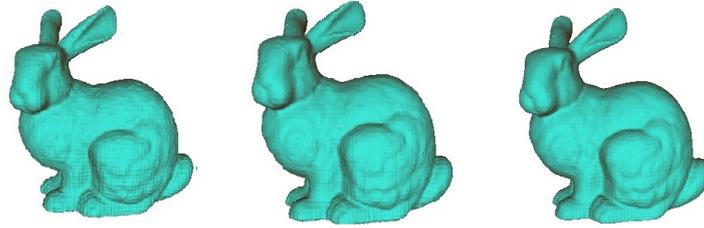


Fig. 8 Reconstructed Bunny with our proposed method from data points with different levels of noise.

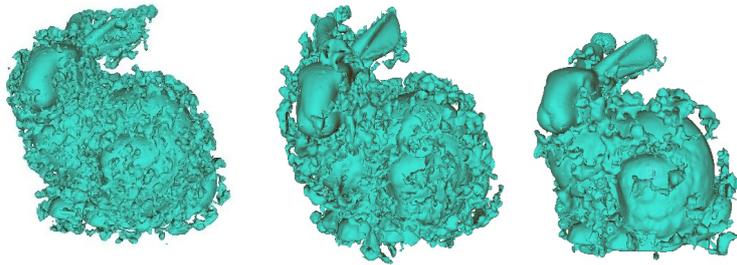


Fig. 9 Reconstructed Bunny with MPU method from data points with different levels of noise.

failed even if data is contaminated by low level of noise. Therefore, the proposed method can effectively resist noise disturbance and capture the shape of object.

5. Conclusion

This paper has presented a novel implicit surface reconstruction method based on partition of unity and local surface sheet approximation. Different to other surface reconstruction based on RBF, our proposed method does not need to add off-surface points, reducing computational complexity. Furthermore, even in the case of noisy data, non-uniform data sampling, and objects with complex topological structure, Our method is capable of achieving satisfactory reconstruction results. So our method is quite effective and efficient in reconstructing a complex surface according to the given large datasets.

Acknowledgement

This work was supported by the Natural Science Foundation of Zhejiang Province of Cina (No. LSY19F020001, LY18F020018)

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