Research Journal of Applied Sciences, Engineering and Technology 4(17): 2887-2892, 2012
ISSN: 2040-7467

Submitted: November 28, 2011 Accepted: January 04, 2012 Published: September 01, 2012

A Kinematics Significance Based Skeleton Map for Rapid Viewpoint Selection

[1,2]Zhenfeng SHI, [1]Liyang YU, [1]Ahmed A. Abd El-Latif, [1]Dan LE and [1]Xiamu NIU
[1]School of Computer Science and Technology,
[2]Department of Mathematics, Harbin Institute of Technology, Harbin 150080, China

Abstract: Viewpoint selection has become a very active area of research during the last decade. Computation of good viewpoints is important in graph drawing, scene understanding, etc. A good viewpoint can give us rich information about a scene. In this study, we present a novel Kinematics Significance based Skeleton Map (KSSM) during iterative Laplacian contraction. Inspired by salient viewpoint selection, we propose a new rapid computation method based on a few initial viewpoints for iteration. It allows us to compute the final best viewpoint via Loop subdivision stencil rapidly for iterative decision under a threshold. Experimental results demonstrate that the KSSM can describe the topology information of 3D mesh effectively. It also presents the validity and effectiveness of viewpoint selection based on KSSM.

Keywords: Kinematics significance, mesh skeleton, skeleton map, viewpoint selection

INTRODUCTION

Shape analysis and processing have been the focus of extensive research in many applications, such as animation and morphing (Oscar *et al.*, 2008; Wade and Parent, 2002), segmentation (Oscar *et al.*, 2008; Dey and Sun, 2006), shape registration and retrieval (Biasotti *et al.*, 2003; Sundar *et al.*, 2003), skeleton extraction (Oscar *et al.*, 2008; Tagliasacchi *et al.*, 2009) and surface reconstruction (Tagliasacchi *et al.*, 2009). The description of shape is a fundamental problem in computer graphics and visualization. It has received a lot of attention in recent decades. However, it is a research challenge in the definition and design of a simple and effective method for describing the shape (Oscar *et al.*, 2008).

Curve-skeleton is a 1D structure that represents a simplified version of the geometry and topology of a 3D object. It has become an effective representation for shape analysis and processing. Existing works on curve skeleton extraction almost exclusively operate on complete surface models (Dey and Sun, 2006; Hilaga *et al.*, 2001) and they can produce excellent results. Recently, skeleton extraction on point cloud data is also proposed (Cao *et al.*, 2010). However, the process is very time-expensive. Instead, some implied information during the iteration process is very useful for shape analysis, but few researches on it are presented.

The selection of a good viewpoint is also very useful for shape analysis and processing. In the last decade viewpoint selection has become a very active area of research. However, it is difficult to define precisely what a good view is. A number of papers have addressed the problem of automatically selection a viewpoint or sequence of viewpoints for looking at an object. Vázquez *et al.* (2001) used the Shannon entropy to define viewpoint entropy for quantizing the goodness of a viewpoint. Inspired by low-level human visual system cues, (Lee *et al.*, 2005) developed a computational model of perceptual importance named as mesh saliency for modeling the human visual attention mechanism. They proposed a method for viewpoint selection by maximizing the visible saliency sum from a viewpoint. Kim *et al.* (2010) introduce a normalized chance-adjusted saliency computational model by improving the previous chance-adjusted saliency measure. However, mesh saliency only can be used to describe the local important visual attention. Accordingly, saliency-based viewpoint selection or eye movement is not enough for 3D object shape analysis. Curve-skeleton provides an effective tool for describing the global shape and topology of a 3D object. It might be more useful for viewpoint selection, especially in shape analysis applications.

In this study, inspired by the kinematics in physics, we exploit a new feature based on iterative contraction for curve-skeleton extraction to describe the significance of vertex. During the contraction process, each distance series between the final skeleton and the new iteration resulted vertices is used to define the contraction displacement and velocity. We call this feature Kinematics Significance based Skeleton Map (KSSM). A new rapid viewpoint selection based on iterative optimization is also presented. The experimental results demonstrate that the best viewpoint selection based on

Corresponding Author: X. M. NIU, School of Computer Science and Technology, Harbin Institute of Technology, Harbin 150080, China, Tel.: +86 451 86402861

KSSM is effective. The efficiency of viewpoint selection is also shown in the experimental results.

The rest of the paper is organized as the following: Some related work about mesh skeleton extraction and viewpoint selection are overviewed in section II. Section III gives the definition of KSSM. In Section IV, we detail our rapid viewpoint selection algorithm based on KSSM and iterative optimization. Some experiments and results on several meshes are illustrates in section V.

LITRATURE REVIEW

Mesh skeleton extraction: The literature on skeleton extraction contains extensive research during the past decades. Curve-skeletons do not have a rigorous definition. Various applications may have different requirements on certain properties. Two main categories, volumetric and geometric, are mainly included in the existing methods (Oscar *et al.*, 2008). In the following, we review only some representative geometric methods on curve-skeleton extraction for 3D mesh, especially, the contraction based extraction methods are mainly reviewed. Other comprehensive survey of curve-skeleton extraction is presented in Cornea *et al.* (2007).

Polygon meshes or point sets are mainly used in geometric methods. Voronoi diagram based Dey and Sun (2006) and Reeb graph based methods (Hilaga *et al.*, 2001; Pascucci *et al.*, 2007) have gained much attention in recent years. Oscar *et al.* (2008) present a simple and robust geometric contraction method which works directly on the mesh domain. They apply implicit Laplacian smoothing operation and solve a sequence of constrained Laplace equations to extract a curve-skeleton. All vertices with different weights are used to constrain the iterative contraction process and allow the geometry to be contracted into an approximate zero-volume mesh. With a connectivity surgery process, all collapsed faces are removed and the shape of the contracted mesh and the key features of the original mesh are also preserved. Some valuable information about the object's geometry, such as the local thickness, is also generated from the producing process of curve-skeleton. Inspired by the work presented by Oscar *et al.* (2008) and Cao *et al.* (2010) developed a contraction operation which works on generalized discrete geometry data, especially for point cloud data. They use Laplacian-based contraction via local Delaunay triangulation and topological thinning to successfully extract a curve skeleton. Especially, the method can handle with some missing data and is robust to noise. Without explicit surface reconstruction, the skeleton-driven topology repair of point cloud data can be also performed effectively.

Curve skeleton provide an efficient tool to characterize the visual shape of 3D object. Some important information from a kinematics point of view during the iterative contraction for generation of curve-skeleton is rarely mentioned and utilized in existing published methods and applications. Selection of a good viewpoint and mesh simplification require present or keep the best visual shape and effect. These applications might be beneficial from kinematics information generating from the iterative contraction.

Viewpoint selection: During the past decade, viewpoint selection has become an emerging area in computer graphics such as scene exploration, rendering and visualization. In particular, selection of the best viewpoint is very useful to understand a scene or model a 3D object better. The minimum number of viewpoints is also important in these scenarios. A number of papers have addressed the problem. Some of them focus on the local interesting regions and others consider the global visual shape.

Weinshall and Werman (1997) show an equivalence between the most stable and most likely view of an object and show that this is the view in which an object is fattest. (Blanz *et al.*, 1999) point out that selection of a preferred view is a result of complex interactions between task, object geometry and object familiarity. In order to determine these factors they have conducted user studies. A computational model of mesh saliency is developed by Gooch *et al.* (2001) to automatically compute initial viewpoints for 3D objects. Lee *et al.* (2005) have developed a model of mesh saliency that can be considered as a perception-inspired measure of regional importance from surface curvatures using center-surround filters with Gaussian-weighted curvatures. It can capture the visually interesting regions on a mesh. They select the best viewpoint automatically by maximizing the sum of the saliency for visible regions of the object so as to visualize the most salient object features. A gradient-descent-based optimization heuristic is used to select good viewpoints instead of exhaustively computing the maximum visible saliency over all viewpoints.

Vázquez *et al.* (2001) developed a new viewpoint selection method using viewpoint entropy with information theory as a new measure. They also present how to select a set of N good views of a scene for scene understanding. Exploring automatically objects or scenes with viewpoint entropy is also shown in their experiments. The minimal set of selected viewpoints according to viewpoint entropy is also given in their experiments. Inspired by their previous work, (Feixas *et al.*, 2009) have proposed a new definition of mesh saliency based on polygonal mutual information (PMI) and have built a unified information-theoretic framework for viewpoint selection and mesh saliency. Kim *et al.* (2010) have introduced the normalized chance-adjusted

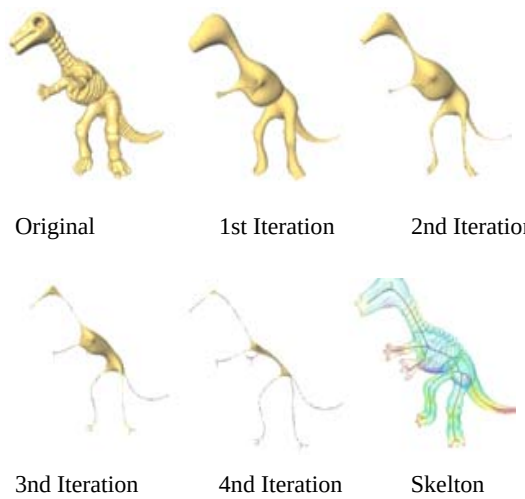


Fig. 1: Laplacian-based contraction for curve-skeleton extraction

saliency mechanism to quantify the correlation between mesh saliency and fixation locations for 3D rendering applications and proposed a new computational model of mesh saliency. The results show that their computational model can model human eye movements significantly better than curvature-based model proposed by Lee *et al.* (2005).

Although there are many methods proposed for viewpoint selection, few researches directly utilize the visual shape attributions of 3D object. As mentioned above, some important kinematics meaning information during the iterative contraction of curve-skeleton might be useful for selecting a good viewpoint and determine a set of N good viewpoints.

DEFINITION OF KINEMATICS SIGNIFICANCE BASED SKELETON MAP (KSSM)

Contraction based curve-skeleton extraction: The essential of curve skeleton of 3D mesh based on geometric contraction can be regarded as that all vertices of the original mesh are transferred to their destination step by step. Let M_0 be a 3D mesh with N vertices $V = \{v_i | v_i \in R^3\ 1 \le i \le N\}$. We use C to denote the contraction transformation and C_j to describe the jth iterative contraction. Then, each vertex v_i is contracted to new position $v_i^{(j)} = C_j(v_i)$. The mesh contraction series $\{M_j\}^K_{j=1}\{C_j(M_0)\}^K_{j=1}$ are produced after K iterative contractions, where $M_j = \{v_i^{(j)} | v_i^{(j)} = C_j(v_i), v_i \in M_0\}, 1 \le i \le N, 1 \le j \le K$.

Let the final curve-skeleton of M_0 be $S = Skel(M_0)$, then contraction based curve skeleton extraction aims to design transformation C for extracting the skeleton quickly. Laplacian-based contraction provide a rapid and effective transformation for extracting a final curve-skeleton. In this study, we use the Laplacian-based contraction described in Cao *et al.* (2010). Figure 1 shows all iterative contraction results for dinosaur object.

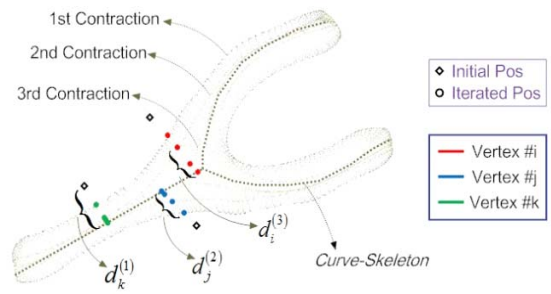


Fig. 2: Displacement between each new position and the final curve-skeleton

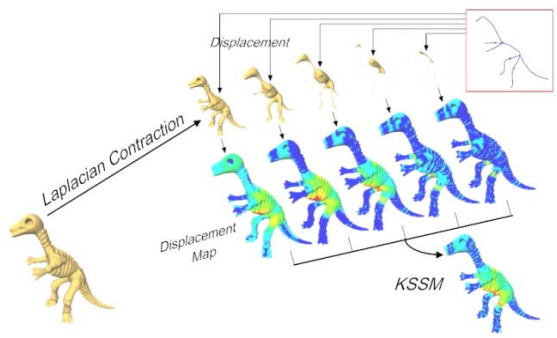


Fig. 3: Definition of kinematics significance based skeleton map

Definition of KSSM: For any vertex $v_i \in V$, we use the $d^{(j)}_i = \min\{|v^{(j)}_i - v_{skel}| v_{skel} \in S = Skel(M_0)\}$ to denote the minumum distance between the jth new contracted position $v^{(j)}_i$ and the final curve-skeleton, where j = 0, 1, 2, …. , Figure 2 shows the distance. During the extraction of curve-skeleton of 3D mesh, the distance series $\{d^{(j)}_i\}_j$ of vertex v_i can be obtained. We map$\{d^{(j)}_i\}_j$ to the cooresponding vertices of the original mesh. Then, the KSSM can be described as the following. Figure 3 shows the definition of KSSM in detail.

Firstly, for each vertex v_i, we take $d^{(j)}_i$ as the displacement relative to the initial position(original vertex position in 3D object). In a way, we also deem it as the velocity of vertex during the contraction from original position to the jth new contracted position. We call it as the j th displacement map.

Secondly, for combining the displacement map $\{d^{(j)}_i\}^N_{i=1}$ at different iterative contraction level, a non-linear suppression operation Φ similar to the one proposed by Itti *et al.* (1998) is applied to each displacement map. The non-linear suppression operator provides an efficient way of reducing some maximum displacement and smoothing some similar displacements. For each displacement map $\{d^{(j)}_i\}^N i = 1$, we linearly normalize it to

the unit interval[0,1]. Then the maximum displacement value $Max^{(j)}_{DM}$ and the average dispalcement $Avg^{(j)}_{DM}$at the iterative contraction level excluding the global maximum are computed. We multiply the displacement map $\{d^{(j)}_i\}^N_{i=1}$ by the factor $(Max^{(j)}_{DM} - Avg^{(j)}_{DM})^2$.

Finally, The total KSSM is composed of all vertices that the displacement value of vertex is:

$$DM_i = \sum_{j=0}^{K} \Phi(d_i^{(j)}) = \sum_{j=o}^{K} d_i^{(j)} * (Max_{DM}^{(j)} - Avg_{DM}^{(j)})^2 .$$

KSSM BASED VIEWPOINT SELECTION

Definition of a good viewpoint: The term *good view* in computer graphics is difficult to define precisely. Up to now, there is no consensus about what a good viewpoint is. However, it seems that the best viewpoint is the one that obtains the maximum information of a scene. Therefore, a good viewpoint must help user to capture as much as possible a high amount of information of the object or scene represented.

In this study, we develop a method for automatically selecting a good viewpoint so as to maximize the sum of features for visible regions of the object according to the kinematics significance based skeleton map. For a given viewpointbvp, supposed that F(vp) is the set of vertices visible from vp and KSSM is the map feature of 3D mesh. Then, we compute the KSSM visible from vp as: $PSSM_{sum}(vp) = \sum_{v\in F(vp)} PSSM(v)$. Finally, the best viewpoint is defined as the maximum sum of $PSSM_{sum}(vp)$, i.e. the best viewpoint vp_{best} subject to $PSSM_{sum}(vp_{best})=\text{argmax}_{vp}\{PSSM_{sum}(vp)\}$. One possible solution for obtaining the good viewpoint is to exhaustively compute the maximum visible sum of KSSM over all viewpoints. However, this could get computationally intensive as the amount and complexity of 3D object rises. We will discuss an alternative method to obtain the best viewpoint.

Rapid viewpoint selection: Considering that exhaustively computing good viewpoints is time-consuming, we design an iterative based stepwise refinement method to help us select good viewpoints.

Firstly, we sample some vertices on the surface of the bounding sphere or cube bounding box. Instead of the step, we use a discrete 3D triangular sphere M_{Sphere} with vertices set V composed of N vertices as a substitute for sampling procedure. The discrete triangular sphere or cube box is used as the initial iterative viewpoints.

Secondly, we compute the best viewpoint from the N initial viewpoints. Then, we can obtain all sum of KSSM with different viewpoint v. Supposed that the v_0

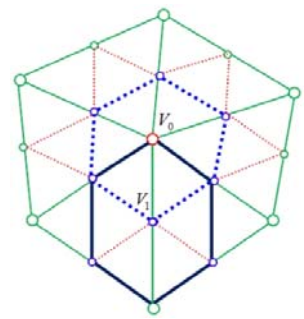


Fig. 4: Loop subdivision stencil based iterative viewpoint selection

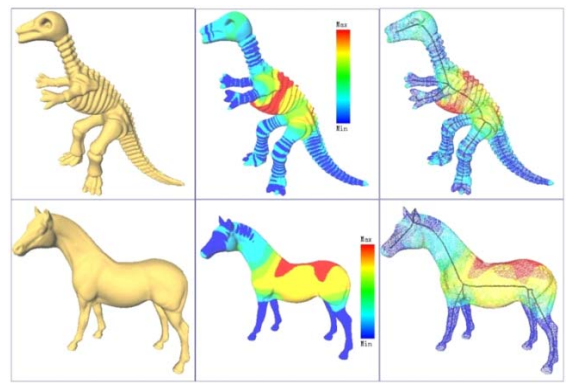
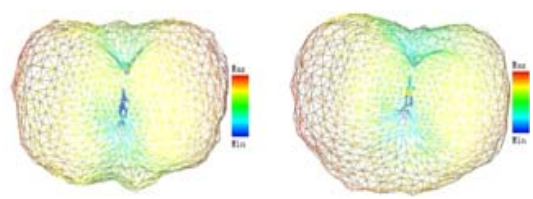


Fig. 5: KSSM and skeleton for 3D meshes: dinosaur(56194 vertices) and horse(48485vertices)



(a) Saliency based (b) KSSM bassed

Fig. 6: The wireframe mesh around the dinosaur model shows the magnitude of the visible saliency and KSSM sum when we see it from each direction

vertex is the best viewpoint for all N initial viewpoints, obviously, $PSSM_{sum}(v_0) = \arg\max_v \{PSSM_{sum}(v) | v\in V\}$. The final best viewpoint will lie around the initial best viewpoint v_0. Let N_0 be the 1-ring neighbors of v_0, then the final best viewpoint will be located in the 1-ring neighbor region.

Thirdly, considering that the viewing information is continuous over 3D space, therefore, the viewed KSSM is no sudden change when the viewpoint moves from v_0 to the final best viewpoints. Therefore, we can subdivide each of the neighbor triangles into four sub-triangles. Each new generated vertex can be achieved by using Loop subdivision stencil (Loop, 1987).

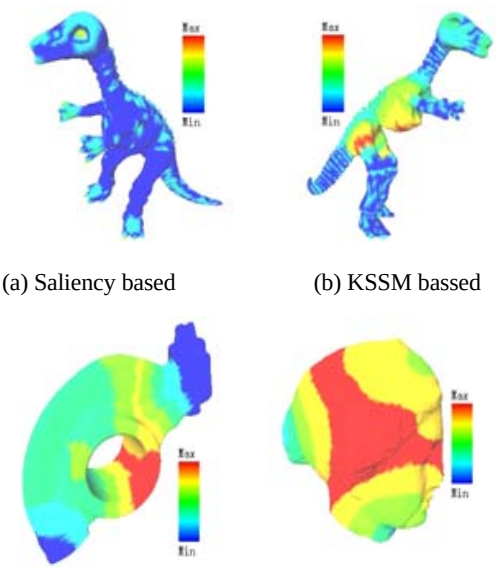
Fourthly, we use $\tilde{N}_{v0}$ to denote the new 1-ring neighbors which are composed of those new vertices. We compute KSSM value for each new vertex belong to $\tilde{N}_{v0}$. If the KSSM values of all vertices are less than v_0, we can take it as the new maximum iterative viewpoint. The third and fourth steps are carried out recursively. In otherwise cases, supposed that the viewpoint with position v has the maximum KSSM, then we take v_1 as the new viewpoint v_0 described in the second step. The procedure described in the third and fourth steps repeats successively. Figure 4 shows the subdivision rules and the iterative viewpoint selection principles used in the third and the fourth steps.

Finally, let the current best viewpoint is corresponding to vertex $vp^{(k)}$ and the next possible best viewpoint is $vp^{(k+1)}$. The final best viewpoint can be obtained and the recursive iterative subdivision operation can stop if $| PSSM_{sum}(vp^{(k)}) - PSSM_{sum}(vp^{k+1})| < \varepsilon$, where, ε is an interactive control precision. Experimental Results and Analysis.

Kinematics significance based skeleton map: Iterative contraction based skeleton map provides some important Kinematics significance for 3D mesh. It shows the importance of vertex relative to the skeleton. Figure 5 shows the KSSM and skeleton for 3D object: dinosaur and horse. The left column is the original 3D objects, the middle column is the KSSM and the last column shows the corresponding skeletons. The warmer colors(reds and yellows) in KSSM show that those vertices have high displacement relative to the skeleton and the cooler colors(greens and blues) show low displacement. We can conclude that the KSSM shown in Fig. 5 demonstrates the significance of vertex effectively according to the distance to the skeleton. Best and Worst Viewpoint Selection Using KSSM.

To validate the KSSM for viewpoint selection, we have implemented the mesh saliency and salient viewpoint selection presented in Lee *et al*. (2005). Figure 6 shows the magnitude of the visible saliency and KSSM sum when we see it from each direction.

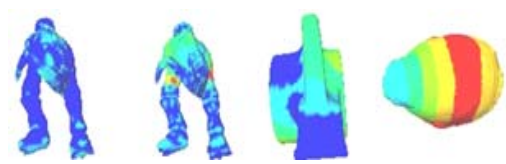
In order to further compare the saliency based and KSSM based viewpoint selection clearly, Fig. 7a and b illustrates the best viewpoint for dinosaur object with 5026 vertices. Obviously, KSSM based best viewpoint is more effective than the saliency based. In Fig. 7a, the stomach of dinosaur is occluded by the front left leg, but KSSM based best viewpoint in Fig. 7b is not the same. Figure 7b shows more topological perception for observer. Figure 7c and d also show the KSSM based best viewpoint for rocker arm and venus objects. We can also conclude that KSSM based viewpoint selection has the capability of providing more topological perception as far as possible.



(a) Saliency based (b) KSSM bassed

(c) KSSM bassed (d) KSSM bassed

Fig. 7: Selected best viewpoints of 3D object



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

Fig. 8: Selected worst viewpoints of 3D object

We also compute the worst viewpoints for 3D objects. Figure 8 show the worst viewpoint selected. Salient based and KSSM based worst viewpoint for dinosaur object is illustrated in Fig. 8a and b respectively, KSSM based worst viewpoint for rocker arm and venus objects is shown in Fig. 8 c, d. We can conclude that KSSM can provide the same result when we select the worst viewpoint. Obviously, KSSM based worst viewpoint shown in Fig. 8 b, c, d cannot provide any topological information and visual perception information. Therefore, KSSM based viewpoint is very important and effective in scene understanding. Run Time analysis for Rapid Viewpoint Selection

We conduct experiments to select the best viewpoint with Loop subdivision stencil based iterative decision in order to demonstrate the efficiency of our algorithm. One triangulated 3D cube bounding box with eight vertices is used as the initial viewpoints to be selected. Then Loop subdivision stencil is used to iteratively decide the final best viewpoint. We configure the threshold $\epsilon = 0.1$ for

Table 1: Processing time of our 3D mesh segmentation algorithm based on MRF\

3D model	Rocker-arm	Cow	Venus	Horse	Dinosaur	Armadillo
#verts	10K	29K	33K	48K	56K	172K
KSSM	5.3	14.8	17.6	28.2	36.7	102.5

stopping subdivision. Table 1 detail the processing times for the different 3D meshes. We can conclude that the proposed rapid viewpoint selection scheme is very high efficient.

CONCLUSION AND FUTURE WORK

This study presents a new Kinematics Significance based Skeleton Map (KSSM). A new rapid viewpoint selection based iterative decision using Loop subdivision stencil is also presented. Benefit from the Kinematics significance of KSSM and the rapid iterative subdivision stencil, the best and worst viewpoint are accurately selected. Experimental results demonstrate the efficiency and validity of the KSSM and viewpoint selection based on KSSM. Our proposed best viewpoint selection method with KSSM can provide rich visual perception information.

Different methods for selecting the best viewpoint and the minimum best viewpoint set will also be developed in the future. Other more applications based on viewpoint selection, such as scene understanding and scene explore, will also be developed to further show the effectiveness of our proposed scheme.

ACKNOWLEDGMENT

This study is supported by the National Natural Science Foundation of China (Project Number: 60832010, 61100187), the Fundamental Research Funds for the Central Universities (Grant No. HIT. NSRIF. 2010046), the China Postdoctoral Science Foundation (2011M500666) and the project of Heilongjiang Department of Education (Project Number: 11551513).

REFERENCES

Biasotti, S., S. Marini, M. Mortara, G. Patanè, M. Spagnuolo and B. Falcidieno, 2003. 3D shape matching through topological structures. Discrete Geometry Comp. Imagery, 2886: 194-203, DOI: 10.10071978-3-540-39966-7-18.194-203.

Blanz, V., M. Tarr and H. Bülthoff, 1999. What object attributes determine canonical views? Perception, 28: 575-599.

Cao, J., A. Tagliasacchi, M. Olson, H. Zhang and Z. Su, 2010. Point cloud skeletons via laplacian-based contraction. Proceeding. of IEEE Shape Modeling International, pp: 187-197.

Cornea, N.D., D. Silver and P. Min, 2007. Curve-skeleton properties, applications and algorithms. IEEE T. Vis. Comp. Graph., 13(3): 530-548.

Dey, T.K. and J. Sun, 2006. Defining and computing curve-skeletons with medial geodesic function. Proceedings of the Fourth Eurographic Symposion on Geometry Processing (SGP' 06), Switzerland, pp: 143-152, ISBN: 3-905673-36-3

Feixas, M., M. Sbert and F. González, 2009. A unified information-theoretic framework for viewpoint selection and mesh saliency. ACM Trans. Appl. Perception, 6(1): Article 1.

Gooch, B., E. Reinhard, C. Moulding and P. Shirley, 2001. Artistic composition for image creation. Proceedings of Eurographics Work shop on Rendering Techniques, pp: 83-88.

Hilaga, M., Y. Shinagawa, T. Kohmura and T.L. Kunii, 2001. Topology matching for fully automatic similarity estimation of 3D shapes. Proceeding. of SIGGRAPH, pp: 203-212.

Itti, L., C. Koch and E. Niebur, 1998. A model of saliency based visual attention for rapid scene analysis. IEEE T. Pattern Anal., 20(11): 1254-1259.

Kim, Y., A. Varshney, D.W. Jacobs and F. Guimbretière, 2010. Mesh saliency and human eye fixations. ACM Trans. Appl. Perception, 7(2): Article 12.

Lee, C.H., A. Varshney and D.W. Jacobs, 2005. Mesh saliency. ACM Trans. Graph, 24(3): 659-666.

Loop, C.T., 1987. Smooth subdivision surface based on triangle. MA. Thesis, University of Utah.

Oscar, K.C.A., C.L. Tai, H.K. Chu, D. Cohen-Or and T.Y. Lee, 2008. Skeleton extraction by mesh contraction. ACM Trans. Graph., 27(3): Article 44.

Pascucci, V., G. Scorzelli, P.T. Bremer and A. Mascarenhas, 2007. Robust on-line computation of Reeb graphs: Simplicity and speed. ACM Trans. Graph, 26(3): Article 58.

Sundar, H., D. Silver, N. Gagvani and S. Dickinson, 2003. Skeleton based shape matching and retrieval. Proceeding. IEEE International Conference. on Shape Modeling and Applications, pp: 130-139.

Tagliasacchi, A., H. Zhang and D. Cohen-Or, 2009. Curve skeleton extraction from incomplete point cloud. ACM Trans. Graph, 28(3): Article 71.

Vázquez, P.P., M. Feixas, M. Sbert and W. Heidrich, 2001. Viewpoint Selection Using Viewpoint Entropy. Vision, Modeling and Visualization (Stuttgart, Germany), pp: 273-280.

Wade, L. and R.E. Parent, 2002. Automated generation of control skeletons for use in animation. Visual Comp., 18: 97-110.

Weinshall, D. and M. Werman, 1997. On view likelihood and stability. IEEE Trans. Pattern Anal., 19(2).