MULTIPLE 2D SELF ORGANISING MAP NETWORK FOR SURFACE RECONSTRUCTION OF 3D UNSTRUCTURED DATA

LIM SENG POH

UNIVERSITI TEKNOLOGI MALAYSIA

MULTIPLE 2D SELF ORGANISING MAP NETWORK FOR SURFACE RECONSTRUCTION OF 3D UNSTRUCTURED DATA

LIM SENG POH

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

JANUARY 2015

To my beloved mother, Ooi So Ngo, father, Lim Sam Huat,

dearest sister, Lim Shin Phey and dearest brother, Lim Seng Kaei,

cousin, Ooi Zane,

brother-in-law, Tan Guan How, nephew, Tan Yee Xuan,

and all my relatives,

thanks for their continuous support, love and care.

To all my friends,

thanks for their valuable guidances, understanding and encouragement.

ACKNOWLEDGEMENTS

I want to thank Buddha for guiding me in my life and towards the research. I would like to take this opportunity to say a big thank you to my respectful supervisor, Professor Dr. Habibollah Bin Haron for his continuous guidance, care and support. Without his guidance, I believe I cannot prepare and finish this thesis. Once again, thanks for all your efforts.

Special thanks to Universiti Teknologi Malaysia for providing me financial support during the period of this research work. I am also very thankful to my department lecturers, without their continued support, I cannot successfully complete this thesis.

My appreciation also extends to all my undergraduate and postgraduate friends who have helped me in doing the research. Their feedbacks and views are very useful to me in preparing this thesis.

Last but not least, I am very grateful to my lovely parent, Ooi So Ngo and Lim Sam Huat, dearest sister, Lim Shin Phey, dearest brother, Lim Seng Kaei, cousin, Ooi Zane, brother-in-law, Tan Guan How, nephew, Tan Yee Xuan, and all my relatives for their love and persistent support, I cannot finish this thesis successfully without you all. I love you guys so much.

ABSTRACT

Surface reconstruction is a challenging task in reverse engineering because it must represent the surface which is similar to the original object based on the data obtained. The data obtained are mostly in unstructured type whereby there is not enough information and incorrect surface will be obtained. Therefore, the data should be reorganised by finding the correct topology with minimum surface error. Previous studies showed that Self Organising Map (SOM) model, the conventional surface approximation approach with Non Uniform Rational B-Splines (NURBS) surfaces, and optimisation methods such as Genetic Algorithm (GA), Differential Evolution (DE) and Particle Swarm Optimisation (PSO) methods are widely implemented in solving the surface reconstruction. However, the model, approach and optimisation methods are still suffer from the unstructured data and accuracy problems. Therefore, the aims of this research are to propose Cube SOM (CSOM) model with multiple 2D SOM network in organising the unstructured surface data, and to propose optimised surface approximation approach in generating the NURBS surfaces. GA, DE and PSO methods are implemented to minimise the surface error by adjusting the NURBS control points. In order to test and validate the proposed model and approach, four primitive objects data and one medical image data are used. As to evaluate the performance of the proposed model and approach, three performance measurements have been used: Average Quantisation Error (AQE) and Number Of Vertices (NOV) for the CSOM model while surface error for the proposed optimised surface approximation approach. The accuracy of AQE for CSOM model has been improved to 64% and 66% when compared to 2D and 3D SOM respectively. The NOV for CSOM model has been reduced from 8000 to 2168 as compared to 3D SOM. The accuracy of surface error for the optimised surface approximation approach has been improved to 7% compared to the conventional approach. The proposed CSOM model and optimised surface approximation approach have successfully reconstructed surface of all five data with better performance based on three performance measurements used in the evaluation.

ABSTRAK

Pembinaan semula permukaan adalah tugas yang mencabar dalam kejuruteraan kebelakang kerana ia mestilah mewakili permukaan yang sama dengan objek asal berdasarkan data yang diperolehi. Data yang diperolehi kebanyakannya adalah dalam jenis tidak berstruktur di mana tiada maklumat yang cukup dan permukaan yang tidak tepat akan diperolehi. Oleh itu, data perlu disusun semula dengan mencari topologi yang betul serta ralat permukaan yang minimum. Kajian terdahulu menunjukkan bahawa model Peta Swa-Organisasi (SOM), pendekatan penghampiran permukaan konvensional dengan permukaan Splin-B Nisbah Tak Seragam (NURBS), dan kaedah pengoptimuman seperti kaedah Algoritma Genetik (GA), Evolusi Pembezaan (DE) dan Pengoptimuman Partikel Berkelompok (PSO) dilaksanakan secara meluas dalam menyelesaikan pembinaan semula permukaan. Tetapi, model, pendekatan dan kaedah pengoptimuman masih mengalami masalah-masalah data tidak berstruktur dan ketepatan. Oleh itu, matlamat penyelidikan ini adalah untuk mencadangkan model Kubus SOM (CSOM) dengan rangkaian SOM 2D berganda untuk menyusun data permukaan yang tidak berstruktur, dan untuk mencadangkan pendekatan penghampiran permukaan optimum untuk menjana permukaan NURBS. Kaedah GA, DE dan PSO dilaksanakan bagi mengurangkan ralat permukaan dengan melaraskan titik kawalan NURBS. Bagi menguji dan mengesah model dan pendekatan yang dicadangkan, empat data objek primitif dan satu data imej perubatan digunakan. Bagi menilai pencapaian model dan pendekatan yang dicadangkan, tiga pengukuran pencapaian digunakan: Purata Ralat Pengkuantuman (AQE) dan Bilangan Bucu (NOV) untuk model CSOM manakala ralat permukaan untuk pendekatan penghampiran permukaan optimum yang dicadangkan. Ketepatan AQE bagi model CSOM telah meningkat kepada 64% dan 66% berbanding dengan model SOM 2D dan 3D. NOV bagi model CSOM telah dikurangkan daripada 8000 kepada 2168 berbanding dengan model SOM 3D. Ketepatan ralat permukaan bagi pendekatan penghampiran permukaan optimum telah meningkat kepada 7% berbanding dengan pendekatan konvensional. Model CSOM dan pendekatan penghampiran permukaan optimum yang dicadangkan telah berjaya membina semula permukaan untuk kelima-lima imej ujian dengan pencapaian yang lebih baik berdasarkan ketiga-tiga pengukuran pencapaian yang diguna dalam penilaian.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

Surface reconstruction towards data points has become the popular topic in the field of computer graphics and computational geometry (Studholme, 2001; Ni and Ma, 2010) in the recent years. In addition, surface reconstruction is a challenging task in the reverse engineering (Elmidany *et al.*, 2011; Gálvez *et al.*, 2012) because it will reconstruct the surface of the model based on the data obtained (Guo *et al.*, 2010; Zhou, 2011; DalleMole *et al.*, 2010). The studies of surface reconstruction has become the important aspects for different scientific areas and variety of applications, such as medical imaging, mechanical and virtual reality (Montes and Penedo, 2004; Forkan, 2009). It is very useful especially for those objects which are damaged and do not have any model that can be used to represent the original surface (Forkan, 2009). It can also be used to reproduce the spare part for the component that is no longer available and the design for that particular part can be modified or redesigned (Várady *et al.*, 1997).

Basically, surface reconstruction can be performed after the data have been collected. Data collection is very important in surface reconstruction because the methods and surface representation will be selected based on the data available. As stated by Goldenthal and Bercovier (2004), the initial data collected are not the exact surface of an object. It only roughly represents the shape of surface based on some measuring points. In addition, the data collected can be in the structured or unstructured type. As stated by DalleMole *et al.* (2010), connectivity on the data is important in surface reconstruction because normally unstructured data are obtained. The shape of the surface can be affected by the data type. Hence, the organising process should be performed if the data obtained are in unstructured type.

Generally, surface representation can be categorised into three categories, which are explicit, implicit and parametric form. As stated by Iglesias and Gálvez (2014), parametric form such as Non Uniform Rational B-Spline (NURBS) is usually used as the mathematical entities in representing the curves and surfaces. This is also suggested by Farin (2002) and Gálvez *et al.* (2007) because the representation is flexible by simply modifying certain parameters (Iglesias and Gálvez, 2014) and better shape can be obtained.

In addition, the traditional reverse engineering procedures contain a lot of disadvantages due to complicated procedures are required with a large amount of time for the manual operations (Zhou, 2011). Therefore, the Artificial Intelligence (AI) methods which contain the heuristic characteristics have attracted the attention of researchers to implement in solving the surface reconstruction case studies (Forkan, 2009; Pandunata, 2011). This is because the AI methods are able to provide several results for the same case studies and the most optimised results can be obtained. The AI methods such as the Self Organising Map (SOM) model is used to organise the unstructured data in Do Rêgo and Araújo (2010) and Iglesias and Gálvez (2014) while Genetic Algorithm (GA), Differential Evolution (DE) and Particle Swarm Optimisation (PSO) methods are used to solve the fitting and optimisation problems in Safari *et al.* (2013), Gálvez *et al.* (2012), Dehmollaian (2011) and Gálvez *et al.* (2010).

This chapter demonstrates the introduction for this research. The problem background based on the previous works is discussed in the first section and the problem statement in the second section is derived based on the issues stated in the problem background. The topic of discussion is continued with the objectives and scopes for this research and the thesis organisation is elaborated in the last section.

1.2 Problem Background

There are two main issues in the surface reconstruction will be discussed in this research. The first issue is related to the unstructured data and the second issue is related to the accuracy of the results. Both of the issues are connected and should be noticed when the methods are implemented. Basically, unstructured data are frequently obtained after data collection has been performed (Kazhdan *et al.*, 2006; Iglesias and Gálvez, 2014) and there is no any connectivity information for the unstructured data (DalleMole *et al.*, 2010). So, surface reconstruction will be difficult to perform when it is implemented with this kind of data (Gálvez *et al.*, 2007) because it needs to find the correct connectivity for the data (Yu, 1999; Yan *et al.*, 2004; Boudjemaï *et al.*, 2003; DalleMole *et al.*, 2010). As stated by Knopf and Sangole (2004), the connectivity of the surface is very important and it must be established in the beginning in order to reconstruct and represent the surface correctly.

As stated by Zhou (2011), the traditional reverse engineering procedures are suffered from many disadvantages and required to handle a lot of complicated procedures. Hence, the AI methods such SOM model is usually used to handle the topological and connectivity of unstructured data in surface reconstruction case studies (Forkan, 2009; Pandunata, 2011). This is because SOM model is able to cluster the data accordingly based on the topological arrangement (Hoffmann, 1999; Iglesias and Gálvez, 2014; Jiang *et al.*, 2010; DalleMole *et al.*, 2010). However, the 2D SOM model is unable to cover the whole surface of the closed surface object (Boudjemaï *et al.*, 2003) and gaps are appeared on the results produced. Although the authors have proposed the spherical with triangle topology to represent the closed surface object, but the results can only be used for visualisation without providing any performance measurement on the approximation. In addition, the SOM model has been enhanced with the growing abilities (Montes and Penedo, 2004; Andreakis *et al.*, 2009; DalleMole *et al.*, 2010; DalleMole *et al.*, 2011; Holz and Behnke, 2013). However, extra processes are needed to handle the problem caused by the growing criteria. This is because if unnecessary vertices are removed, it will destroy the connectivity of the polygon and overlapping triangle faces and gaps will be appeared. Hence, the proposed method leads to even complicated calculation and procedures.

In addition, dense dataset must be used by most of the existing methods in calculating the connectivity for the data in order to avoid gaps appeared that can cause the shape incomplete (Gálvez *et al.*, 2007; Júnior *et al.*, 2004; Júnior *et al.*, 2008). Furthermore, some of the current methods also contain topological problems (Gálvez *et al.*, 2008) which lead to produce incorrect surface and final results based on the data used. Hence, multiple curves and surfaces are used to avoid the gaps appeared as shown in Kumar *et al.* (2001), Tai *et al.* (2003), Yin (2004) and Chen and Wang (2010) in solving the surface reconstruction case studies. However, more procedures are required to handle the problems occurred in their proposed methods such as eliminating the unacceptable polygons, dividing the edges to avoid concavity, formation of triangulation and knot adjustment. The edges for the adjacent curves and surfaces must be connected (Soni *et al.*, 2009) in order to produce the correct surface. This concept is good to be applied and should be adapted with fewer procedures. Basically, the flow of organising unstructured data using SOM model which is used in Boudjemaï *et al.* (2003), Forkan (2009), and Pandunata (2011) with the conventional surface approximation approach based on NURBS that is used in Elmidany *et al.* (2011) and Pandunata and Shamsuddin (2013) can only be applied to reconstruct a single curve and surface. If multiple surfaces need to be reconstructed, this approach needs to perform the reconstruction of the surfaces separately, which leads the methods to be manually performed.

As stated by Gálvez *et al.* (2012), the parametric surface reconstruction is still a difficult problem because many data are unable to be properly reconstructed. This is due to higher accuracy is considered as the best result in surface reconstruction. Based on Elmidany *et al.* (2011), the NURBS surface error for the generated surface can be affected by the parameterisation and knot vector generation. As stated by Gálvez *et al.* (2008), AI methods show good results in handling the parameterisation problems. Basically, the initial parameters and knot vectors will be determined and optimisation-based method such as GA, DE and PSO can be used to improve the accuracy of the surface error (Owen, 1998; Elmidany *et al.*, 2011) through iteration procedures. This can be shown in the work of Forkan and Shamsuddin (2008), Forkan (2009) and Pandunata and Shamsuddin (2013). The limitation of the authors works is comparison between the parameterisation methods are not discussed. As stated by Wulamu *et al.* (2005), parameterisation on the data points will affect the performance of the surface approximation. In addition, GA, DE and PSO methods are used in Safari *et al.* (2013) to determine the optimum number of a NURBS control points for airfoil profiles and the authors also proved that the methods are able to handle the case study. Hence, the GA, DE and PSO methods can be used to optimise the surface error for NURBS by adjusting the control points coordinates, as shown in Pandunata (2011) and Safari *et al.* (2013). However, the parameters used for all the population in AI methods as shown in their works are not the same. So, the results are unable to correctly prove the accuracy of each method.

Also, the recent research works in surface reconstruction are still focused in organising the unstructured data and minimising the surface error. This can be shown in Iglesias and Gálvez (2014), Kavita and Rajpal (2014) and Deng and Lin (2014). Their works are still focused in solving the approximation of curve and surface towards the data by minimising the error of curve and surface. Hence, the issues as discussed in this section should be solved in the suitable way using the models and methods.

1.3 Problem Statement

As stated in the previous section, basically the problem in surface reconstruction is related to the unstructured surface data and the accuracy of the surface. In order to produce the surface which is similar to the original object, hence the unstructured surface data should be reorganised in the appropriate way so that correct surface and connectivity of the data can be obtained. In addition, the accuracy of the surface should be concerned in order to represent the surface with minimum surface error. Therefore, the methods selected should be correctly implemented in order to organise the unstructured surface data with minimum surface error.

1.4 Research Objectives

Based on the on the problem background and statement, the objectives for this research are as follows:

i. To propose Cube Self Organising Map (CSOM) model in organising the unstructured surface data.
ii. To propose surface approximation approach based on the CSOM model in generating and representing the NURBS surfaces.
iii. To optimise the surface approximation approach by incorporating with Genetic Algorithm, Differential Evolution and Particle Swarm Optimisation methods.

1.5 Research Scopes

The scopes for this research are as follows:

i. The dataset used for this research are four set of primitive objects (Cube, Oiltank, Sphere, Spindle).
ii. For additional testing, one set of medical image data (Talus bone) is used.
iii. This study only considers three parameterisation methods (Uniform, Centripetal, Chord Length) which will be used to determine the minimum surface error for each data.
iv. This study only considers three optimisation methods (GA, DE, PSO) which will be used to optimise the surface error.
v. Visualisation on the side view will be used for demonstration on the surface produced and validation purposes.

1.6 Thesis Organisation

This thesis is divided into seven chapters. Chapter 1 begins with the introduction by demonstrating the overview of this thesis. This chapter explains the problem background, problem statement, research objectives and scopes for this research. Chapter 2 discusses the literature review which includes the background study, theories and previous works that are related to surface reconstruction. The characteristics of the methods will be discussed in deep in this chapter. Research methodology is demonstrated in Chapter 3. In this chapter, a thorough discussion on the research framework in conducting the research work will be clearly presented.

Chapter 4 illustrates the framework for Cube SOM (CSOM) model in organising the unstructured surface data. This chapter explains the structure of CSOM model and equations involved in organising the unstructured surface data. Discussion on the result based on the average quantisation error and validation on the images will also be presented at the end of this chapter. Chapter 5 presents the proposed framework for surface approximation. This chapter demonstrates the flow of obtaining the control points, basis functions and NURBS surfaces in representing the surfaces using the proposed surface approximation approach. Discussion on the result based on the surface error and validation on the images will be demonstrated in this chapter.

Chapter 6 explains the framework in optimising the NURBS surfaces. The optimisation will be performed using Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimisation (PSO) methods. The details of each optimisation method in minimising the surface error of the proposed surface approximation approach for NURBS surfaces are presented in this chapter. Discussion on the result based on the surface error and validation on the images will be presented at the end of this chapter. Finally in Chapter 7, conclusion and future works are presented which briefly explains the overall results obtained and summarises the research works. In addition, contributions and limitation of the research will also be demonstrated in this chapter.

REFERENCES

Adi, D. I. S. (2011). Evolutionary Algorithm for Ship Hull Skinning Approximation. Master, Universiti Teknologi Malaysia, Skudai.

Adi, D. I. S., Shamsuddin, S. M. and Ali, A. (2009). Particle Swarm Optimization for NURBS Curve Fitting. *6th International Conference on Computer Graphics, Imaging and Visualization*. 259 – 263.

Adi, D. I. S., Shamsuddin, S. M. and Hashim, S. Z. M. (2010). NURBS Curve Approximation using Particle Swarm Optimization. *7th International Conference on Computer Graphics, Imaging and Visualization*. 73 – 79.

Aganj, E., Keriven, R. and Pons, J. P. (2009). Photo–Consistent Surface Reconstruction from Noisy Point Clouds. *IEEE International Conference on Image Processing*. 505 – 508.

Andreakis, A., Huene, N. V. H. and Beetz, M. (2009). Incremental Unsupervised Time Series Analysis Using Merge Growing Neural Gas. *Lecture Notes in Computer Science.* 5629, 10 – 18.

Astudillo, C. A. and Oommen, B, J. (2014). Self-Organizing Maps Whose Topologies Can Be Learned with Adaptive Binary Search Trees Using Conditional Rotations. *Pattern Recognition*. 47, 96 – 113.

Babaeizadeh, S., Brooks, D. H. and Isaacson, D. (2005). A Deformable-Radius B-Spline Method for Shape-based Inverse Problems, As Applied to Electrical Impedance Tomography. *IEEE International Conference on Acoustics, Speech, and Signal Processing.* 485 – 488.

Bae, E. and Weickert, J. (2010). Partial Differential Equations for Interpolation and Compression of Surfaces. *Lecture Notes in Computer Science.* 5862, 1 – 14.

Bai, Q. (2010). Analysis of Particle Swarm Optimization Algorithm. *Computer and Information Science.* 3 (1), 180 – 184.

Barhak, J. and Fischer, A. (2001a). Adaptive Reconstruction of Freeform Objects with 3D SOM Neural Network Grids. *IEEE Proceedings of Pacific Conference on Computer Graphics and Applications*. 97 – 105.

Barhak, J. and Fischer, A. (2001b). Parameterization and Reconstruction from 3D Scattered Points Based on Neural Network and PDE Techniques. *IEEE Transactions on Visualization and Computer Graphics.* 7 (1), 1 – 16.

Bauer, H. U. and Villmann, T. (1997). Growing A Hypercubical Output Space in A Self-Organizing Feature Map. *IEEE Transactions on Neural Networks*. 8 (2), 218 – 226.

Becker, G., Schäfer, M. and Jameson, A. (2011). An advanced NURBS fitting procedure for post-processing of grid-based shape optimizations. *49^{th} AIAA Aerospace Science Meeting*. 1 – 19.

Bevilacqua, V., Mastronardi, G. and Marinelli, M. (2006). A Neural Network Approach to Medical Image Segmentation and Three-Dimensional Reconstruction. *International Conference on Intelligent Computing*. (1), 22 – 31.

Boudjemaï, F., Enberg, P. B. and Postaire, J. G. (2003). Surface Modeling By Using Self Organizing Maps of Kohonen. *IEEE International Conference on Systems, Man and Cybernetics.* 3, 2418 – 2423.

Boudjemaï, F., Enberg, P. B. and Postaire, J. G. (2005). Dynamic Adaptation and Subdivision in 3D–SOM Application to Surface Reconstruction. *IEEE International Conference on Tools with Artificial Intelligence*. 1 – 6.

Boyer, D. O., Martínez, C. H. and Pedrajas, N. C. (2005). A Crossover Operator for Evolutionary Algorithms Based on Population Features. *Journal of Artificial Intelligence Research*. 24, 1 – 48.

Brujic, D., Ainsworth, I. and Ristic, M. (2011). Fast and Accurate NURBS Fitting for Reverse Engineering. *International Journal Advance Manufacturing Technology*. 54, 691 – 700.

Busch, C. and Groß, M. H. (1993). Interactive Neural Network Texture Analysis and Visualization for Surface Reconstruction in Medical Imaging. *Eurographics*. 12 (3), 49 – 60.

Cappello, F. and Mancuso, A. (2004). Curve and Surface Fitting via Optimisation Technique. *International CAD Conference and Exhibition*. 1 – 9.

Capulin, C. H. G., Cuevas, F. J., Caballero, G. T. and Gonzalez, H. R. (2014). Hierarchical Genetic Algorithm for B-Spline Surface Approximation of Smooth Explicit Data. *Mathematical Problems in Engineering*. 2014, 1 – 11.

Chandrasekaran, M., Muralidhar, M., Murali Krishna, C. and Dixit, U. S. (2009). Application of Soft Computing Techniques in Machining Performance Prediction and Optimization: A Literature Review. *International Journal Advance Manufacturing Technology*. 46, 445 – 464.

Chao, J., Minowa, K. and Tsujii, S. (1992). Unsupervised Learning of 3D Objects Conserving Global Topological Order. *IEEE International Conference on Systems Engineering*. 24 – 27.

Chen, J. and Wang, G. J. (2010). Approximate Merging of B-Spline Curves and Surfaces. *Appl. Math. J. Chinese Univ.* 25(4), 429 – 436.

Chen, S., Zhang, J., Zhang, H., Guan, Q., Du, Y., Yao, C. and Zhang, J. (2010). Myocardial Motion Analysis for Determination of Tei–Index of Human Heart. *Sensors*. 10 (12), 11428 – 11439.

Cheng, X., Wang, J. and Wang, Q. (2007). Leak–mending and Recruitment of Incomplete Points Data in 3D Reconstruction Based on Genetic Algorithm. *International Conference on Natural Computation*. 259 – 263.

Chivate, P. N. and Jablokow, A. G. (1995). Review of Surface Representations and Fitting for Reverse Engineering. *Computer Integrated Manufacturing Systems*. 8 (3), 193 – 204.

Cong, V. and Linh, H. Q. (2002). *3D Medical Image Reconstruction*. Technical Report. Biomedical Engineering Department, Faculty of Applied Science, HCMC University of Technology.

DalleMole, V. L. and Araújo, A. F. R. (2011). Growing Topology Learning Self-Organizing Map. *Self Organizing Maps - Applications and Novel Algorithm Design*. 627 – 642.

DalleMole, V. L., Do Rêgo, R. L. M. E. and Araújo, A. F. R. (2010). The Self-Organizing Approach for Surface Reconstruction from Unstructured Point Clouds. *Self-Organizing Maps*. 167 – 188.

Dalmasso, P. and Nerino, R. (2004). Hierarchical 3D Surface Reconstruction Based on Radial Basis Functions. *2nd International Symposium on 3D Data Processing, Visualization, and Transmission*. 574 – 579.

Daud, R., Abdul Kadir, M. R., Izman, S., Md Saad, A. P., Lee, M. H. and Che Ahmad, A. (2013). Three-Dimensional Morphometric Study of the Trapezium Shape of the Trochlea Tali. *Journal of Foot & Ankle Surgery*. 52, 426 – 431.

Das, S. and Suganthan, P. N. (2011). Differential Evolution: A Survey of the State-of-the-Art. *IEEE Transactions on Evolutionary Computation*. 15 (1), 4 – 31.

Dehmollaian, M. (2011). Through–Wall Shape Reconstruction and Wall Parameters Estimation Using Differential Evolution. *IEEE Geoscience and Remote Sensing Letters*. 8 (2), 201 – 205.

Deng, C. and Lin, H. (2014). Progressive and Iterative Approximation for Least Squares B-Spline Curve and Surface Fitting. *Computer-Aided Design*. 47, 32 – 44.

Dimas, E. and Briassoulis, D. (1999). 3D Geometric Modelling Based on NURBS: A Review. *Advances in Engineering Software*. 30, 741 – 751.

Do Rêgo, R. L. M. E. and Araújo, A. F. R. (2010). A Surface Reconstruction Method Based on Self–organizing Maps and Intrinsic Delaunay Triangulation. *International Joint Conference on Neural Networks*. 1 – 8.

Dong, X. L., Liu, S. Q., Tao, T., Li, S. P. and Xin, K. L. (2012). A Comparative Study of Differential Evolution and Genetic Algorithms for Optimizing the Design of Water Distribution Systems. *Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)*. 674 – 686.

Elmidany, T., Elkeran, A., Galal, A. and Elkhateeb, M. (2011). NURBS Surface Reconstruction Using Rational B-Spline Neural Networks. *Journal of Control Engineering and Technology*. 34 – 38.

Engelbrecht, A. P. (2002). *Computational Intelligence*. John Wiley & Sons, Ltd.

Esmin, A. A. A., Lambert-Torres, G. and Alvarenga, G. B. (2006). Hybrid Evolutionary Algorithm Based on PSO and GA Mutation. *International Conference on Hybrid Intelligent Systems*. 57 – 60.

Fang, M., Chen, D. and Zhu, B. (1997). Model Reconstruction of Existing Poducts Using NN for Reverse Engineering. *IEEE International Conference on Intelligent Processing Systems*. 396 – 400.

Farin, G. (2002). *Curves and Surfaces for CAGD, A Practical Guide, Fifth Edition*. Morgan Kaufmann Publishers.

Floater, M. S. and Surazhsky, T. (2005). Parameterization for Curve Interpolation. *Topics in Multivariate Approximation and Interpolation*. 101 – 115.

Flöry, S. (2009). Fitting Curves and Surfaces to Point Clouds in the Presence of Obstacles. *Computer Aided Geometric Design*. 26, 192 – 202.

Forkan, F. (2009). *Algoritma Rangkaian Kohonen-Swarm Bagi Penjanaan Permukaan*. Master, Universiti Teknologi Malaysia, Skudai.

Forkan, F. and Shamsuddin, S. M. (2008). Kohonen–Swarm Algorithm for Unstructured Data in Surface Reconstruction. *5th International Conference on Computer Graphics, Imaging and Visualization*. 5 – 11.

Fritzke, B. (1994). Growing Cell Structures - A Self-Organizing Network for Unsupervised and Supervised Learning. *Neural Networks*. 7 (9), 1441 – 1460.

Fritzke, B. (1995). Growing Grid – A Self–Organizing Network with Constant. *Neural Processing Letters*. 2 (5), 9 – 13.

Ganegedara, H. and Alahakoon, D. (2012). Redundancy Reduction in Self-Organising Map Merging for Scalable Data Clustering. *International Joint Conference on Neural Networks*. 1 – 8.

Gálvez, A. and Iglesias, A. (2010). Particle Swarm Optimization for Non-uniform Rational B-spline Surface Reconstruction from Clouds of 3D Data Points. *Information Science*. 192, 174 – 192.

Gálvez, A., Cobo, A., Puig–Pey, J. and Iglesias, A. (2008). Particle Swarm Optimization for Bézier Surface Reconstruction. *Lecture Notes in Computer Science*. 5102, 116 – 125.

Gálvez, A., Iglesias, A. and Pey, J. P. (2012). Iterative Two-Step Genetic-Algorithm-Based Method for Efficient Polynomial B-Spline Surface Reconstruction. *Information Sciences*. 182, 56 – 76.

Gálvez, A., Iglesias, A., Cobo, A., Puig–Pey, J. and Espinola, J. (2007). Bézier Curve and Surface Fitting of 3D Point Clouds Through Genetic Algorithms, Functional Networks and Least–Squares Approximation. *Lecture Notes in Computer Science.* 4706 (2), 680 – 693.

Goldenthal, R. and Bercovier, M. (2004). *Design of Curves and Surfaces Using Multi–Objective Optimization*. Retrieved on August 19, 2011 from http://leibniz.cs.huji.ac.il/tr/741.pdf.

Guo, G., Wu, X., Wang, M. Y. and Wu, J. (2010). Fast Implicit Surface Reconstruction Method Based on Normal Constraints. *IEEE International Conference on Mechatronics and Automation*. 1783 – 1788.

Guthikonda, S. M. (2005). *Kohonen Self-Organizing Maps*. Technical Report. Weittenberg University.

Hamann, B., Jean, B. A. and Radzan, A. (1998). Computer Aided Geometric Design Techniques for Surface Grid Generation. *Handbook of Grid Generation*. 29-1 – 29-36.

He, Y. and Qin, H. (2004). Surface Reconstruction with Triangular B–splines. *Proceedings of the Geometric Modeling and Processing*. 279 – 287.

Hoffmann, M. (1999). Modified Kohonen Neural Network for Surface Reconstruction. *Publ. Math*. 54, 857 – 864.

Hoffmann, M. (2005). Numerical Control of Kohonen Neural Network for Scattered Data Approximation. *Numerical Algorithm.* 39, 175 – 186.

Holland, J. (1992). *Adaptation of Natural and Artificial Systems*. MIT Press.

Holz, D. and Behnke, S. (2013). Fast Range Image Segmentation and Smoothing Using Approximate Surface Reconstruction and Region Growing. *Intelligent Autonomous Systems.* 12, 61 – 73.

Höllig, K., Reif, U. and Wipper, J. (2001). B–Spline Approximation of Neumann Problems. *Mathematics Subject Classification*. 1 – 13.

Iglesias, A. and Gálvez, A. (2014). Hybrid Functional-Neural Approach for Surface Reconstruction. *Mathematical Problems in Engineering.* 2014, 1 – 13.

Igwe, P. C. and Knopf, G. K. (2006). 3D Object Reconstruction Using Geometric Computing. *IEEE Proceedings of the Geometric Modeling and Imaging.* 9 – 14.

Islam, K., Dobbe, A., Adeeb, S. M., Rich, M. E., Duke, K. and Jomha, N. M. (2012). Computer Methods for Designing Artificial Talus Bone in the Ankle Joint. *American Society Biomechanics*. 525-1 – 525-2.

Ivrissimtzis, I. P., Jeong, W. K. and Seidel, H. P. (2003). Using Growing Cell Structures for Surface Reconstruction. *Proceedings of the Shape Modeling International*. 78 – 86.

Jiang, J., Trundle, P. and Ren, J. (2010). Medical Image Analysis with Artificial Neural Networks. *Computerized Medical Imaging and Graphics.* 34, 617 – 631.

Ju, H., Wang, W., Xie, J. and Chen, Z. (2004). Neural Network Approach for Modification and Fitting of Digitized Data in Reverse Engineering. *Journal of Zhejiag University Science*. 5 (1), 75 – 80.

Júnior, A. d. M. B., Neto, A. D. D. and de Melo, J. D. (2004). Surface Reconstruction Using Neural Networks And Adaptive Geometry Meshes. *IEEE International Joint Conference on Neural Networks*. 1, 803 – 807.

Júnior, A. d. M. B., Neto, A. D. D., Melo, J. D. d. and Gonçalves, L. M. G. (2008). An Adaptive Learning Approach for 3–D Surface Reconstruction from Point Clouds. *IEEE Transactions on Neural Networks*. 1 – 11.

Kanimozhi, M. and Bindu, C. H. H. (2013). Brain MR Image Segmentation Using Self Organizing Map. *International Journal of Advanced Research in Computer and Communication Engineering*. 2 (10), 3968 – 3973.

Kavita and Rajpal, N. (2014). Comparative Analysis of Feed Forward and Radial Basis Function Neural Networks for the Reconstruction of Noisy Curves. *International Conference on Reliability, Optimization and Information Technology*. 353 – 358.

Kazhdan, M., Bolitho, M. and Hoppe, H. (2006). Poisson Surface Reconstruction. *Eurographics Symposium on Geometry Processing*. 61 – 70.

Kennedy, J. and Eberhart, R. (1995). Particle Swarm Optimization. *IEEE International Conference on Neural Networks.* 1942 – 1948.

Kipp, A. (1998). *Spline Galerkin Approximation*. Doctor Philosophy, University of Stuttgart.

Knopf, G. K. and Sangole, A. (2004). Interpolating Scattered Data Using 2D Self-Organizing Feature Maps. *Graphical Models*. 66, 50 – 69.

Kohonen, T. (1990). The Self–Organizing Map. *Proceedings of the IEEE*. 78 (9), 1464 – 1480.

Kohonen, T. and Honkela, T. (2007). *Kohonen Network*. Retrieved on August 19, 2011 from http://www.scholarpedia.org/article/Kohonen_network.

Koivunen, V. and Vezieu, J. M. (1994). Multiple Representation Approach to Geometric Model Construction From Range Data. *Proceedings of Second CAD-Based Vision Workshop*. 132 – 139.

Kumar, G.S., Kalra, P. K. and Dhande, S. G. (2003). Parameter Optimization for B–spline Curve Fitting using Genetic Algorithms. *Congress on Evolutionary Computation*. 1871 – 1878.

Kumar, G. V. V. R., Srinivasan, P., Shastry, K. G. and Prakash, B. G. (2001). Geometry based triangulation of multiple trimmed NURBS surfaces. *Computer-Aided Design.* 33, 439 – 454.

Lan, H. C., Chang, T. R., Liao, W. C., Chung, Y. N. and Chung, P. C. (2009). Knee MR Image Segmentation Combining Contextual Constrained Neural Network and Level Set Evolution. *IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology*. 271 – 277.

Leal, N., Leal, E. and Branch, J. W. (2010). Simple Method for Constructing NURBS Surfaces from Unorganized Points. *19th International Meshing Roundtable*. 161 – 175.

Lee, E. T. (1989). Choosing Nodes in Parametric Curve Interpolation. *Computer Aided Design*. 21, 363 – 370.

Li, Y. and Chi, Z. (2005). MR Brain Image Segmentation Based on Self-Organizing Map Network. *International Journal of Information Technology*. 11 (8), 45 – 53.

Li, Y., Rao, L., He, R., Xu, G., Wu, Q., Ge, M. and Yan, W. (2003). Image Reconstruction of EIT Using Differential Evolution Algorithm. *25th Annual International Conference of the IEEE EMBS*. 1011 – 1014.

Lin, C. T., Cheng, W. C. and Liang, S. F. (2005). Neural–Network–Based Adaptive Hybrid–Reflectance Model for 3–D Surface Reconstruction. *IEEE Transactions on Neural Networks*. 16 (6), 1601 – 1615.

Lin, H. (2008). Staged Self-Organizing Map Surface Modeling of Complex and Multiple Bone Objects. *5th International Conference on Information Technology and Application in Biomedicine, in conjunction with 2nd International Symposium & Summer School on Biomedical and Health Engineering.* 430 – 433.

Liu, X. M., Huang, H. K., Xu, W. X. and Chen, J. (2004). Research on the Reconstruction Method of B–Spline Surface Based on Radius Basis Function Neural Networks. *IEEE Conference on Cybernetics and Intelligent Systems.* 1123 – 1127.

Liu, Y. (2003). *Effect of Knot Vectors on B-Spline Curves and Surfaces*. Technical Report. Department of Mechanical Engineering, State University of New York.

Liu, Y., Yang, H. and Wang, W. (2005). Reconstructing B–Spline Curves from Point Clouds – A Tangential Flow Approach Using Least Squares Minimization. *International Conference on Shape Modeling and Applications*. 4 – 12.

Luger, G. F. (2005). *Artificial Intelligence Structures and Strategies for Complex Problem Solving Fifth Edition*. Pearson Education Limited.

Ma, W. and Kruth, J. P. (1998). NURBS Curve and Surface Fitting for Reverse Engineering. *International Journal of Advance Manufacturing Technology*. 14, 918 – 927.

Mallipeddi, R. and Suganthan, P. N. (2008). Empirical Study on the Effect of Population Size on Differential Evolution Algorithm. *IEEE World Congress on Computational Intelligence*. 3663 – 3670.

Mansour, N., Awad, M. and El-Fakih, K. (2006). Incremental Genetic Algorithm. *International Arab Journal of Information Technology*. 3 (1), 42 – 47.

Manura, D. (2005). *Areas, Volumes, Surface Areas*. Retrieved on June 18, 2014 from http://math2.org/math/geometry/areasvols.htm.

Martišek, D., Procházková, J. and Brno.(2010). Relation between Algebraic and Geometric View on NURBS Tensor Product Surfaces. *Applications of Mathematics*. 55 (5), 419 – 430.

Meng, A., Li, B., Holstein, H. and Liu, Y. (2013). Parameterization of Point-Cloud Freeform Surfaces Using Adaptive Sequential Learning RBF Networks. *Pattern Recognition*. 46, 2361 – 2375.

Meng, F., Wu, L. and Luo, L. (2010). 3D Point Clouds Processing and Precise Surface Reconstruction of the Face. *International Conference on Image Analysis and Signal Processing.* 104 – 107.

Menyhárt, N. F. and Hernyák, Z. (2012). Implementing the GSOSM algorithm. *Annales Mathematicae et Informaticae*. 40, 77 – 92.

Miléř, V. and Miléř, J. (2005). *NURBS Curves and Surfaces*. Retrieved on August 19, 2011 from http://www.rw–designer.com/NURBS.

Montes, C. A. and Penedo, M. F. G. (2004). 3D Object Surface Reconstruction Using Growing Self-Organised Networks. *Lecture Notes in Computer Science.* 3287, 163 – 170.

Motavalli, S. (1998). Review of Reverse Engineering Approaches. *23rd International Conference on Computers and Industrial Engineering.* 35(1-2), 25 – 28.

Müller, H. (1999). Surface Reconstruction – An Introduction. *IEEE Scientific Visualization*. 239 – 242.

Natsheh, A. R., Ponnapalli, P. V. S., Anani, N., Benchebra, D. and Kholy, A. E. (2010). Neural Networks-Based Tool for Diagnosis of Paranasal Sinuses Conditions. *7th International Symposium on Communication Systems Networks and Digital Signal Processing*. 780 – 784.

Natsheh, A. R., Ponnapalli, P. V. S., Anani, N., Benchebra, D., Kholy, A. E. and Norburn, P. (2010). Segmentation of Bone Structure in Sinus CT Images Using Self-Organizing Maps. *IEEE International Conference on Imaging Systems and Techniques*. 294 – 299.

Nechaeva, O. (2010). Using Self Organizing Maps for 3D Surface and Volume Adaptive Mesh Generation. *Self-Organizing Maps*. 123 – 144.

Ngan, S. C., Yacoub, E. S., Auffermann, W. F. and Hu. X. (2002). Node Merging in Kohonen's Self-Organizing Mapping of fMRI Data. *Artificial Intelligence in Medicine.* 19 – 33.

Ni, T. and Ma, Z. (2010). A Fast Surface Reconstruction Algorithm for 3D Unorganized Points. *2nd International Conference on Computer Engineering and Technology*. 7, 15 – 18.

Owen, S. J. (1998). A Survey of Unstructured Mesh Generation Technology. *7th International Meshing Roundtable, Sandia National Lab*. 239 – 267.

Pandunata, P. (2011). *Optimization of Non-Uniform Relational B-Spline Surface Reconstruction Using Growing Grid-Differential Evolution*. Master, Universiti Teknologi Malaysia, Skudai.

Pandunata, P. and Shamsuddin, S. M. (2010). Differential Evolution Optimization for Bezier Curve Fitting. *7th International Conference on Computer Graphics, Imaging and Visualization.* 68 – 72.

Pandunata, P. and Shamsuddin, S. M. (2013). Growing Grid-Evolutionary Algorithm for Surface Reconstruction. *10th International Conference Computer Graphics, Imaging and Visualization*. 68 – 74.

Panduro, M. A. and Brizuela, C. A. A. (2009). A Comparative Analysis of the Performance of GA, PSO and DE for Circular Antenna Arrays. *IEEE Antennas and Propagation Society International Symposium*. 1 – 4.

Panduro, M. A., Brizuela, C. A., Balderas, L. I. and Acosta, L. I. (2009). A Comparison of Genetic Algorithms, Particle Swarm Optimization and the

Differential Evolution Method for the Design of Scannable Circular Antenna Arrays. *Progress in Electromagnetics Research B.* 13, 171 – 186.

Park, H., Kim, K. and Lee, S. C. (2000). A Method for Approximate NURBS Curve Compatibility Based on Multiple Curve Refitting. *Computer-Aided Design*. 32, 237 – 252.

Perez, L. L., Lemaitre, J., Alfiansyah, A. and Bellemare, M. E. (2008). Bone Surface Reconstruction Using Localized Freehand Ultrasound Imaging. *30th Annual International IEEE EMBS Conference Vancouver*. 2964 – 2967.

Piegl, L. (1991). On NURBS: A Survey. *IEEE Computer Graphics and Application*. 55 – 71.

Piegl, L. and Tiller, W. (1997). *The NURBS Book (2nd Edition).* Springer-Verlag New York, Inc.

Premalatha, K. and Natarajan, A. M. (2009). Hybrid PSO and GA for Global Optimization. *International Journal Open Problems Computer Mathematics.* 2 (4), 598 – 608.

Price, K. V., Storn, R. M. and Lampinen, J. A. (2005). *Differential Evolution A Practical Approach to Global Optimization*. Springer.

Rajasekaran, S. and Pai, G. A. V. (2007). *Neural Networks, Fuzzy Logic, and Genetic Algorithms Systhesis and Applications*. Prentice-Hall of India Private Limited.

Randrianarivony, M. and Brunnett, G. (2002). Approximation by NURBS Curves with Free Knots. *Proceedings in Vision, Modeling, and Visualization*. 195 – 201.

Rekanos, I. T. (2008). Shape Reconstruction of a Perfectly Conducting Scatterer Using Differential Evolution and Particle Swarm Optimization. *IEEE Transactions on Geoscience and Remote Sensing*. 46 (7), 1967 – 1974.

Renner, G. and Weiß, V. (2004). Exact and Approximate Computation of B-Spline Curves on Surfaces. *Computer-Aided Design*. 36, 351 – 362.

Robinson, J., Sinton, S. and Rahmat-Samii, Y. (2002). Particle Swarm, Genetic Algorithm, and their Hybrids Optimization of A Profiled Corrugated Horn Antenna. *IEEE Antennas and Propagation Society International Symposium.* 1, 314 – 317.

Rogers, D. F. (2001). *An Introduction to NURBS with Historical Perspective*. Morgan Kaufmann Publishers.

Rubio, E. L. and Ramos, A. D. (2014). Grid Topologies for the Self-Organizing Map. *Neural Networks*. 35 – 48.

Saeedfar, A. and Barkeshli, K. (2006). Shape Reconstruction of Three–Dimensional Conducting Curved Plates Using Physical Optics, NURBS Modeling, and Genetic Algorithm. *IEEE Transactions on Antennas And Propagation*. 54 (9), 2497 – 2507.

Safari, A., Lemu, H. G., Jafari, S. and Assadi, M. (2013). A Comparative Analysis of Nature-Inspired Optimization Approaches to 2D Geometric Modelling for Turbomachinery Applications. *Mathematical Problems in Engineering.* 2013, 1 – 15.

Sarkar, B. and Menq, C. H. (1991). Smooth-Surface Approximation and Reverse Engineering. *Computer-Aided Design*. 23 (9), 623 – 628.

Shene, C. K. (2005). *Parameters and Knot Vectors for Surfaces*. Retrieved on May 17, 2012 from http://www.cs.mtu.edu/~shene/COURSES/cs3621/NOTES/INTAPP/PARA-surface.html.

Shene, C. K. (2011). *B-Spline Curves: Important Properties*. Retrieved on June 18, 2014 from http://www.cs.mtu.edu/~shene/COURSES/cs3621/NOTES/spline/B-spline/bspline-curve-prop.html.

Shi, Y. H. and Eberhart, R. (1998). A Modified Particle Swarm Optimizer. *IEEE International Conference on Evolutionary Computation.* 69 – 73.

Sivanandam, S. N. and Deepa, S. N. (2008). *Introduction to Genetic Algorithm*. Springer.

Soni, K., Chen, D. and Lerch, T. (2009). Parameterization of Prismatic Shapes and Reconstruction of Free-Form Shapes in Reverse Engineering. *International Journal of Advance Manufacturing Technology*. 41, 948 – 959.

Söderkvist, I. (1999). *Introductory Overview of Surface Reconstruction Methods*. Technical Report. Department of Mathematics, Luleå University of Technology, Luleå, Sweden.

Spotfire (2012). *Normalization by Scaling Between 0 and 1*. Retrieved on July 30, 2014 from http://stn.spotfire.com/spotfire_client_help/norm/norm_scale_between_0_and_1.htm.

Storn, R. and Price, K. (1997). Differential Evolution - A Simple and Efficient Heuristic for Global Optimization Over Continuous Spaces. *Journal of Global Optimization.* 11, 341 – 359.

Strickerta, M. and Hammer, B. (2005). Merge SOM for Temporal Data. *Neurocomputing*. 64, 39 – 71.

Studholme, C. (2001). *Deriving Camera and Point Location from A Series of Photos Using Numerical Optimization*. Retrieved on August 19, 2011 from http://www.cs.toronto.edu/~cvs/geometry/GeometryProject.pdf.

Sun, S., Lin, H. and Zheng, L. (2013). A Study on Adaptive NURBS Interpolation Points Calculation with Jerk-limited Acceleration. *IEEE International Conference on Information and Automation*. 510 – 515.

Tai, C. L., Hu, S. M. and Huang, Q. X. (2003). Approximate Merging of B-Spline Curves Via Knot Adjustment and Constrained Optimization. *Computer-Aided Design*. 35, 893 – 899.

Tsai, J. H. and Wang, J. H. (1999). Using Self-Creating Neural Network for Surface Reconstruction. *IEEE International Conference on Systems, Man, and Cybernetics*. 4, 886 – 890.

Tsai, Y. C., Huang, C. Y., Lin, K. Y., Lai, J. Y. and Ueng, W. Y. (2008). Development of Automatic Surface Reconstruction Technique in Reverse Engineering. *International Journal Advance Manufacturing Technology.* 42, 152 – 167.

Tseng, J. (2009). Shape–Sensitive Surface Reconstruction for Low–Resolution Point–Cloud Models. *International Conference on Computational Science and Its Applications*. 198 – 207.

Ueng, W. D. and Lai, J. Y. (1998). A Sweep-Surface Fitting Algorithm for Reverse Engineering. *Computers in Industry*. 35, 261 – 273.

Uriarte, E. A. and Martn, F. D. (2005). Topology Preservation in SOM. *International Journal of Applied Mathematics and Computer Sciences*. 1 (1), 19 – 22.

Üstündağ, E. and Çelebi, M. S. (2005). A B-Spline Curve Fitting Approach by Implementing the Parameter Correction Terms. *International Conference on Computational Science and Engineering*. 1 – 5.

Vavak, F. and Fogarty, T. C. (1996). A Comparative Study of Steady State and Generational Genetic Algorithms for Use in Nonstationary Environments. *Lecture Notes in Computer Science*. 1143, 297 – 304.

Várady, T., Martin, R. R. and Cox, J. (1997). Special Issue: Reverse engineering of Geometric Models. *Computer-Aided Design*. 29 (4), 253 – 254.

Wahab, M. S. A., Hussein, A. S. and Gaber, M. S. (2005). An Enhanced Algorithm for Surface Reconstruction from A Cloud Of Points. *International Conference on Graphics, Vision and Image Processing*. 181 – 188.

Wang, J., Gu, D., Yu, Z., Tan, C. and Zhou, L. (2012). A Framework for 3D Model Reconstruction in Reverse Engineering. *Computers & Industrial Engineering*. 63, 1189 – 1200.

Wang, S. and Dhawan, A. P. (2007). Shape–Based Reconstruction of Skin Lesion for Multispectral Nevoscope Using Genetic Algorithm Optimization. *4th IEEE International Symposium on Biomedical Imaging*. 488 – 491.

Weise, T. (2009). *Global Optimization Algorithms – Theory and Application 2nd Ed*. Retrieved on August 19, 2011 from http://www.it–weise.de/.

Weiss, V., Andor, L., Renner, G. and Várady, T. (2002). Advanced Surface Fitting Techniques. *Computer Aided Geometric Design.* 19 (1), 19 – 42.

Woodward, C. D. (1987). Cross-Sectional Design of B-Spline Surfaces. *Computers and Graphics*. 11 (2), 193 – 201.

Wulamu, A., Marc, G. and Dirk, Z. (2005). Approximation of NURBS Curves and Surfaces Using Adaptive Equidistant Parameterizations. *Tsinghua Science and Technology*. 10 (3), 316 – 322.

Xu, J., Zhang, H., Zhu, X., Li, L. and Ding, P. (2013). Curve Surface Fitting Based on an Improved Genetic Algorithm. *IEEE 6th International Congress on Image and Signal Processing*. 747 – 752.

Yan, L., Yuan, Y. and Zeng, X. (2004). Adaptive 3D Mesh Reconstruction from Dense Unorganized Weighted Points Using Neural Network. *3rd International Conference on Machine Leaning and Cybernetics*. 3238 – 3242.

Yi, S. (2007). *3D Free-form Surface Representation and Its Applications*. Doctor Philosophy, University of Nottingham.

Yin, Z. (2004). Reverse Engineering of A NURBS Surface from Digitized Points Subject to Boundary Conditions. *Computers and Graphics*. 28, 207 – 212.

Yoo, D. J. (2011). Three-dimensional Surface Reconstruction of Human Bone Using A B-Spline Based Interpolation Approach. *Computer-Aided Design*. 43 (8), 934 – 947.

Yu, Y. (1999). Surface Reconstruction from Unorganized Points Using Self–Organizing Neural Networks. *IEEE Proceedings of Conference Visualization.* 61 – 64.

Zhao, H. K., Osher, S. and Fedkiw, R. (2001). Fast Surface Reconstruction Using the Level Set Method. *IEEE Workshop on Variational and Level Set Methods*. 194 – 201.

Zheng, L., Li, G. and Sha, J. (2007). The Survey of Medical Image 3D Reconstruction. *5th International Conference on Photonics and Imaging in Biology and Medicine*. 6534, 1 – 6.

Zhou, M. (2011). A New Approach of Composite Surface Reconstruction Based on Reverse Engineering. *Procedia Engineering.* 23, 594 – 599.