OPTIMIZATION OF NON-UNIFORM RELATIONAL B-SPLINE SURFACE RECONSTRUCTION USING GROWING GRID- DIFFERENTIAL EVOLUTION

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To my beloved wife, mother and father

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ABSTRACT

Computer graphics is a fast growing field as it contributes significantly to the advancement of modern technology aimed at empowering human and nation wealth creation. Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM) and Computer-Aided Geometric Design (CAGD) are commonly used to reconstruct surfaces in order to obtain a set of limited and disorganized geometric sample values. The process of surface reconstruction consists of two main steps: parameterization and surface fitting. Various solutions have been used in previous studies to reconstruct surfaces such as Non Uniform Rational B-Spline (NURBS) and B-Spline. However, in recent years, Artificial Intelligence (AI) methods such as Advanced Neural Network and Evolutionary Algorithm (EA) have emerged and are extensively used to reconstruct and optimize complex surfaces. This study aims to optimize NURBS surfaces from unstructured 3D data points with feasible control points while preserving the shape of the objects by using Differential Evolution Algorithm (DEA). The Growing Grid Network (GGN) is implemented on a map structure, while DEA is optimally fit on to the NURBS surfaces. In this study, undefined or unstructured data points from several 2D and 3D datasets were used to validate the performance of the proposed method. An error analysis was also conducted to reconfirm the efficacy of the proposed algorithm. This is done by comparing the generated surface with the original surface using other EAs such as: Genetic Algorithm and Particle Swarm Optimization. Experimental results indicate that the proposed Growing Grid Network Differential Evolution (GGNDE) has successfully generated smoother surfaces with lesser number of control points and produced minimum feasible errors while preserving the shape of the objects.

ABSTRAK

Grafik komputer merupakan suatu bidang yang sedang berkembang pesat disebabkan sumbangannya yang ketara dalam kemajuan teknologi moden. Rekabentuk Berbantukan Komputer (CAD), Pembuatan Berbantukan Komputer (CAM) dan Reka bentuk Geometri Berbantukan Komputer (CAGD) digunakan untuk membina semula permukaan bagi mendapatkan set nilai sampel geometri yang terbatas dan tidak tersusun. Proses pembinaan semula permukaan melibatkan dua langkah utama, iaitu pemparameteran dan pemadanan permukaan. Banyak kaedah penyelesaian telah digunakan dalam kajian terdahulu untuk pembinaan semula permukaan seperti Splin-b Nisbah Tak Seragam (NURBS) dan Splin-b. Namun demikian pada masa ini kaedah kecerdasan buatan seperti Rangkaian Saraf Lanjutan dan Algoritma Evolusi telah diperkenalkan dan digunakan dengan meluas bagi membina semula dan mengoptimumkan permukaan yang rumit. Kajian ini bertujuan mengoptimumkan permukaan NURBS daripada data 3D tak berstruktur dengan bilangan titik kawalan yang tersaur dan mengekalkan rupa bentuk objek menggunakan Algoritma Evolusi Pembezaan (DEA). Rangkaian Tumbesaran Grid dilaksanakan pada struktur pemetaan manakala DEA dimuatkan secara optimum pada permukaan NURBS. Dalam kajian ini beberapa set data 2D dan 3D yang tidak tertakrif atau tidak berstruktur digunakan untuk mengesahkan prestasi kaedah cadangan. Analisis terhadap ralat juga dilakukan dengan memperbandingkan permukaan terjana dengan permukaan asal menggunakan kaedah Algoritma Evolusi yang lain seperti Algoritma Genetik dan Pengoptimuman Partikel Berkelompok. Hasil kajian mendapati bahawa kaedah cadangan, iaitu Rangkaian Tumbesaran Grid Evolusi Pembezaan telah berjaya menjana permukaan yang licin dengan bilangan titik kawalan yang kurang dan ralat minimum tersaur di samping mengekalkan rupa bentuk asal objek berkenaan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABBREVATION	DESCRIPTION
2D	(x, y)-Two dimensional plane
3D	(x, y, z)-Three dimensional plane
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CAGD	Computer Aided Geometric Design
DE	Differential Evolution
GA	Genetic Algorithm
GGN	Growing Grid Network
NFL	No Free Lunch
NURBS	Non-Uniform Rational B-Spline
PSO	Particle Swarm Optimization

LIST OF SYMBOLS

SYMBOLS		DESCRIPTION
$B_{k,n}(t)$	-	basis function for Bezier curve at parameter t.
$N_{i,k}(t)$	-	B-Spline basis function at parameter t and k^{th} degree

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Computer graphics is fast growing field due to its significant contributions to the advancement of modern technology for human and nation wealth creation. One of the major areas in computer graphics is surface reconstruction since it is widely used in industries to design the products. Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM) and Computer-Aided Geometric Design (CAGD) are commonly used in reconstructing the surfaces to obtain a set of geometric sample values (in most cases, points) which is normally limited and unorganized. Conventionally, mathematical description represents a shape of physical surface accurately and concisely. Surface reconstruction and surface representation has also an important part in the design problems such as construction of scanned 3D objects, modeling of car bodies, medical imaging and other free-form objects.

Surface representation illustrates three cases: explicit form, implicit form and parametric form. Among these, the parametric representation is the most useful and widely applied, since it is axis independent and applicable to complex surfaces (Shamsuddin, Ahmed et al. 2006). Several types of parametric curve and surface representation include Bezier, B-Spline and NURBS are the most influential methods used by the engineers. However, the common problems encountered in surface reconstruction from unstructured data is on how to acquire the control points of the surface. This is due to the parametric surface in which to obtain suitable parameterizations of data points are crucial.

Some scientists to overcome the problems of surface reconstruction from unstructured data have used variety of methods. Some of these methods used multi-quadratic functions (Franke, Hagen et al. 1994), range images (Curless 1997), discrete fairing and variation subdivision (Kobbelt 2000), dynamic base surfaces (Azariadis 2004), approximations of the unsigned distance function (Flöry and Hofer 2010), and Artificial Intelligence (AI).

Recent literatures have shown that the usage of AI in surface reconstruction can produce good results (Hoppe, DeRose et al. 1992; Ivrissimtzis, Jeong et al. 2003; Junior, Neto et al. 2004; Gálvez, Cobo et al. 2008; Tsai, Huang et al. 2009; Mendona Ernesto Rego, Araujo et al. 2010).The common AI methods in surface reconstruction include Artificial Neural Network (ANN), Kohonen Self Organizing Map (SOM), and Genetic Algorithm (GA).

1.2 Background of the Study

Surface reconstruction is view from two perspectives: mathematical aspects and Artificial Intelligence (AI). Some recent studies have shown that some AI application shave achieved remarkable results (Ivrissimtzis, Jeong et al. 2003; Junior, Neto et al. 2004; Gálvez, Cobo et al. 2008). The input data obtained from the object can be represented into two types: image mesh, and the 3D point from the scanned image with have noise and scattered. These types of data, however, yield an enormous amount of irregular and scattered digitized point that requires intensive reconstruction processing.

Surface reconstruction consists of two main steps: parameterization and surface approximation. In 3-dimensional surfaces, parameterization represents one-to-one mapping from the surface to a suitable domain. In other words, surface approximation is a procedure of determining a control polygon that generates a curve or surface from a set of known data points using a set of parameter obtained from the parameterization procedure.

Previous related studies used data points, which are noisy and scattered. However, the issue arises on how to re-arrange the scattered point data to be organized, and to deal with the algorithm's complexity as well as processing time.

(Barhak and Fischer 2001) use Self Organizing Map (SOM) for creating a 3D parametric grid. The main advantage of SOM relies on both the orientation of the grid and the position of the sub-boundaries. The neural network grid converges to the sampled shape through an adaptive learning process. However, some enhancements need to be done to create a complete envelope of a volumetric object and accuracy.

(Jalba and Roerdink 2007) have done some studies on deploying a fast convection algorithm to attract the evolving surface towards the data points. However, this method has limitation, that is, surface features are smaller than the size of the smallest grid cells; hence the reconstruction is not accurate enough.

(Gálvez, Iglesias et al. 2007)used GA to reconstruct the surface, and functional networks for the functional constraints problems. These methods are integrated with the least-squares approximation to yield suitable methods for surface fitting. However, this approach still faces the difficulty to attain global optimum due to the variation of distance error function for fitting data for different models.

(Gálvez, Cobo et al. 2008) has also used PSO to obtain a suitable parameterization of the data points on Bezier surface reconstruction. However, the results found that there was no correlation between the number of iterations and the quality of the results. In this scenario, it means that exploring the space domain of the problem is not yet optimal. Hence, adjusting PSO parameters can help solve the above problem.

(Kazhdan, Bolitho et al. 2006) has presented surface reconstruction problem as Poisson problem that allows a hierarchy of locally supported basis functions. The solution has reduced to well-conditioned sparse linear system. However, there are some limitations on this approach due to the weaknesses in handling huge data sets.

(Shamsuddin and Ahmed 2006) proposed hybrid parameterization to solve parameterization of data points on the surfaces. The method takes into consideration the maximum rational B-spline basis functions as the initial values. The centripetal method generates the parameter values of hybrid parameterization. However, some improvements are required to refine the reconstructed object to be fairer and smoother.

(Forkan and Shamsuddin 2008) proposed a method for surface reconstruction based on the hybridization of Kohonen Network and Particle Swarm Optimization (PSO). In this study, PSO probes the best control points for the data with B-Spline as surface representation. However, B-Spline surface representation is still incapable to represent accurately most of the analytically defined shape and conic sections such as Circle, Ellipse, and Hyperbola.

(Gálvez and Iglesias) in 2010 has presented recovery of a surface using PSO from scattered noisy data points. The process consists of two main phases: parameterization and surface fitting. The result is good in terms of accuracy. However, the computational time and complexity need to be reduced.

Table 1.1 shows the summary of recent study in the field of surface reconstruction

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Table 1.1: Previous Related Study on Surface Reconstruction

Author/Year	Summary	Limitation/Future Work
(Kazhdan, Bolitho et al. 2006)	surface reconstruction problem can be expressed as Poisson problem	Weak on handling huge data sets.
(Jalba and Roerdink 2007)	using a method that employs a fast convection algorithm	Surface features are smaller than the size of the smallest grid cells. Hence the surface are not accurately reconstructed
(Gálvez, Iglesias et al. 2007)	use PSO for obtaining a suitable parameterization of the data points on Bezier surface reconstruction	Only limited on bezier surface parameterization process
(Kumar et al. 2003)	Using Genetic Algorithm to optimize the parameter	Limited to B-Spline curve
(Shamsuddin, Ahmed et al. 2006)	Using hybrid parameterization, Give better accuracy	Weights value are adjusted manually
(Barhak and Fischer 2001)	use a neural network Self Organizing Map (SOM) method for creating a 3D parametric grid.	Cannot envelope the volumetric object.
(Cheng, Wang et al. 2004)	Using Squared Distance Minimization (SDM)	features like edges and corners in data sets need to be detected first, have some problem in smoothness and accuracy
(Sarfraz and Riyazuddin 2006)	Using simulated annealing to optimalize weight and knot parameter of NURBS	Good only on single segment image. Limited only on curve
(Forkan and Shamsuddin 2008)	Using Kohonen Network for mapping the data, B-Spline representation and PSO Algorithm	Further exploration by using NURBS with weight and knot vector

	for surface fitting	optimization
(Delint Ira Setyo 2010)	Solve NURBS curve approximation problem by using Particle Swarm Optimization (PSO).	Limited only on 2D data
(Gálvez and Iglesias 2010)	Using PSO for parameterization and surface fitting	The results show the algorithm can reconstruct the surface accurately, but the complexity and computation time is still need to be reduced

Based on the above issues, a comprehensive study needs to be conducted to produce an algorithm that can utilize the application of AI for surface reconstruction process. This hybridization could benefit the manufacturing and industry sectors.

1.3 Problem Statement

As mentioned previously, to solve the issues on surface reconstruction from unstructured data points, these data need to be organized. The procedure involves by obtaining suitable parameterization of data points and control point that can approximate the original surfaces. Hence, the research questions for this study include:

1. What is Growing Grid Network (GGN), and how to deal with NURBS surface reconstruction?
2. How GGN organize the unstructured data in NURBS surface reconstruction?
3. How Differential Evolution Algorithm (DEA) being implemented in optimizing the NURBS surface?
4. How the DEA obtains an optimal control point that can approximate the data point in NURBS surface reconstruction?

1.4 Research Aim

The aim of the study is to optimize NURBS surface reconstruction from unstructured 3D data points with feasible control points while preserving the shape of the objects using Evolutionary Algorithms.

1.5 Objectives

The main objectives of this research are as follows:

1. To develop NURBS surface reconstruction from unstructured data points using growing grid network (GGN).
2. To propose and develop Differential Evolution Algorithm (DEA) to optimize NURBS surface reconstruction
3. To validate and compare the proposed algorithm with the existing related methods

1.6 Research Scope

The scope of this study includes:

1. Technique to be used:
    a. The growing grid technique adopted from (Forkan and Shamsuddin 2008)are used to obtain the initial surface
    b. Differential evolution optimization are used to optimize the initial surface generated from growing grid network

c. Time consumption is not considered, more focus on the aspects of accuracy. And we also we focus on parametric approach, not on the typical graphic methods, i.e., non-parametric approach. Which is the common issue in non-parametric, such as triangulation, is difficulties in dealing with sharp corner (T-Junction).

2. Datasets
   a. Datasets in this study are open surface which noise level is minimal and unorganized. Examples of 2D and 3D data are sine, spiral, semi-sphere, ships and free-form shapes.
3. Tools and environment to be used include:
   a. Java Programming Language
   b. Graphics API and library, OpenGL and GLUT
   c. For rendering purpose, OpenGL API GLUT library will be used.
4. Experiment will be run on PC with specifications:
   a. Operating System: Windows 7 Professional
   b. Processor: 2GHz CPU
   c. Memory: 2048MB RAM

1.7 Thesis Organization

Thesis structure is given as follows:

Chapter 1: Introduction -explains an overview of the background of the study, development of techniques and methods used in surface reconstruction and the common problems that are usually encountered in surface reconstruction, also the problem statement, the aim, the objective, and the scope of this research. Finally, the thesis organization is given below.

Chapter 2: Literature review - This chapter states some existing methods of surface reconstruction. It also contains the review of the related previous works for solving surface reconstruction and approximation methods.

Chapter 3: Methodology and The Proposed Method- This chapter describes the system overview and the framework of proposed methods. It explains the details of every steps of growing grid, include the process of generating initial surface using growing grid map and differential evolution in optimizing and approximating NURBS surface reconstruction.

Chapter 4: Experimental Results and Analysis - This chapter presents the findings of the study, analysis of the results and the comparisons with other works.

Chapter 5: Conclusions and Future Work - This chapter provides the summary of the research, the contribution of the work and recommendation for future study.

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