



Compact implicit surface reconstruction via low-rank tensor approximation[☆]



Maodong Pan, Weihua Tong, Falai Chen^{*}

School of Mathematical Sciences, University of Science and Technology of China, Hefei, Anhui, 230026, PR China

ARTICLE INFO

Keywords:

Compact representation
Implicit surface
Surface reconstruction
Low-rank approximation
Tensor

ABSTRACT

Implicit representations have gained an increasing popularity in geometric modeling and computer graphics due to their ability to represent shapes with complicated geometry and topology. However, the storage requirement, e.g. memory or disk usage, for implicit representations of complex models is relatively large. In this paper, we propose a compact representation for multilevel rational algebraic spline (MRAS) surfaces using low-rank tensor approximation technique, and exploit its applications in surface reconstruction. Given a set of 3D points equipped with oriented normals, we first fit them with an algebraic spline surface defined on a box that bounds the point cloud. We split the bounding box into eight sub-cells if the fitting error is greater than a given threshold. Then for each sub-cell over which the fitting error is greater than the threshold, an offset function represented by an algebraic spline function of low rank is computed by locally solving a convex optimization problem. An algorithm is presented to solve the optimization problem based on the alternating direction method of multipliers (ADMM) and the CANDECOMP/PARAFAC (CP) decomposition of tensors. The procedure is recursively performed until a certain accuracy is achieved. To ensure the global continuity of the MRAS surface, quadratic B-spline weight functions are used to blend the offset functions. Numerous experiments show that our approach can greatly reduce the storage of the reconstructed implicit surface while preserve the fitting accuracy compared with the state-of-the-art methods. Furthermore, our method has good adaptability and is able to produce reconstruction results with high quality.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Over the past two decades there has been an immense amount of efforts dedicated to obtain digital representations of objects in the real world. Techniques for digitizing objects include optical laser-based range scanners, structured light scanners, LiDAR scanners, multi-view stereo and so on. A recent trend has seen the massive proliferation of point clouds from commodity real-time scanners such as the Microsoft Kinect. As a result of the ability to acquire point cloud data, the need for the development of surface reconstruction techniques continues to increase. Moreover, since acquisition methods tend to produce point clouds containing a variety of properties and imperfections, e.g., the presence of geometric features or missing data, noise or outliers, etc., surface

reconstruction is a challenging task. A good survey can be found in [1].

Existing surface reconstruction methods can be broadly categorized as polygonal mesh approaches and implicit surface approaches [2]. The methods in former class typically generate a triangular mesh by interpolating a subset of the input points as vertices. Although these approaches produce mesh representation directly, they are difficult to handle non-uniform, incomplete or noisy data. Please refer to [3,4] for details.

Implicit surface approaches usually create an implicit function or an indicator function for the underlying surface the point cloud is sampled from, and perform iso-surfacing to extract a triangular mesh for rendering. Implicit representations greatly facilitate the classification problem of whether a given point is on, inside or outside a surface. They are able to represent shapes with complicated topology and geometry, even with dynamic topology [5,6]. Implicit representations are more suitable for reconstructing surfaces from datasets that are noisy, incomplete or non-uniformly distributed. As a result, they are widely used in surface reconstruction. Many representations of implicit surfaces have been proposed, e.g. the Blobby model, the signed distance

[☆] This paper has been recommended for acceptance by Scott Schaefer and Charlie C.L. Wang.

^{*} Corresponding author.

E-mail addresses: mdpan@mail.ustc.edu.cn (M. Pan), tongwh@ustc.edu.cn (W. Tong), chenfl@ustc.edu.cn (F. Chen).

fields, the radial basis functions (RBFs), the moving least squares (MLS) surfaces, the algebraic spline (AS) surfaces, the multilevel partition of unity (MPU) and so on. However, no matter which implicit representation is used, the storage requirement for state-of-the-art reconstruction methods is usually large for complex models [7]. To our knowledge, little work has been done on compact representations in implicit surface reconstruction.

In this paper, we propose an algorithm for creating compact representations for Multilevel Rational Algebraic Spline (MRAS) surfaces using low-rank tensor approximation technique, and exploit its applications in surface reconstruction. MRAS surfaces have an analytic spline representation which is advantageous over mesh representation in problems such as point classification, and in subsequent computations such as function/derivative evaluation, boolean operations, shape blending, etc. An MRAS surface can be conveniently stored by its control coefficients. However, for complex models the storage requirement for the control coefficients can be very large, ranging from several hundred megabytes to tens of hundred megabytes [7]. Large storage requirement is a big burden for memory costs in the computation with the implicit surface and in the transition of the implicit surface on the internet. Thus how to reduce the number of control coefficients in MRAS representation is an important research problem. Our approach is outlined as follows.

Given a point cloud with oriented normals, our aim is to build a MRAS surface that approximates the scanned surface as much as possible while uses less storage space. We start with fitting an algebraic spline surface defined on a box that bounds the given point set. We split the box into eight sub-cells if the fitting error is greater than a given threshold. For each cell over which the fitting error is larger than the given threshold, a local offset function represented by an algebraic spline function is computed to reduce the fitting error. In order to obtain a compact representation, a low-rank regularization term is introduced in the fitting model, and the optimization problem is solved locally based on the alternating direction method of multipliers together with the CP decomposition of tensors. The above procedure terminates when the fitting error over each cell is less than a user-specified threshold or the maximum subdivision level reaches.

The remainder of this paper is organized as follows. Section 2 reviews some related work. Section 3 presents some preliminary knowledge about algebraic spline surfaces and tensor decompositions. In Section 4, we introduce a new implicit representation, i.e., the MRAS surface. Section 5 describes our adaptive surface reconstruction algorithm in detail. To achieve compact representations, a convex optimization model equipped with a low-rank regularization term and a corresponding algorithm based on the alternating direction method of multipliers and the CP decomposition are proposed. Section 6 demonstrates some experimental results and performance of our algorithm. Comparisons on the storage requirement with the state-of-the-art methods are also included. Finally, we conclude the paper with proposals for future work.

2. Related work

Since surface reconstruction has been well studied in the past several decades, there is a large body of related work. For the sake of clarity, we shall focus on the approaches that are most related to ours.

2.1. Surface reconstruction

Most implicit surface reconstruction methods are based on Blinn's idea of blending local implicit primitives [8], called *blobs*. Fitting scattered data with algebraic surfaces was discussed by

Pratt [9]. Muraki [10] combined the above two ideas and proposed the Blobby model for fitting an implicit surface to a given point set.

Hoppe et al. [11] proposed a reconstruction algorithm based on the signed distance function, which is locally defined. Curless and Levoy [12] used the volumetric representation consisting of a cumulative weighted signed distance function. Kazhdan et al. [13] presented the Poisson surface reconstruction by approximating the indicator function of the underlying surface. To avoid over-smoothing of the data, they further introduced positional constraints into the optimization, resulting in a screened Poisson problem [2]. The work of Manson et al. [14] solved the Poisson equation using a wavelet basis, which provided a localized, multi-resolution representation of functions.

Using projection moving least squares (PMLS) to reconstruct a C^∞ surface from the point cloud (i.e., point-set surface) was originally proposed by Levin [15], and was used by Alexa et al. [16] in point-based graphics. An explicit definition of point-set surface as the set of local minima of an energy function was given by Amenta and Kil [17]. An implicit MLS (IMLS) approach proposed by Shen et al. [18] based on the classical MLS method, has been used to build interpolating or approximating implicit surfaces from polygonal data. Fleishman et al. [19] devised the robust MLS fitting technique, which could deal with noise and sharp features simultaneously. To separate mixed scanning points received from a thin-wall object, Feng et al. [20] proposed a model called moving multiple curves/surfaces approximation that is an second-order extension of PMLS.

Although the signed or unsigned distance function and the MLS surface have some desirable properties, the absence of analytical expression limits their usage in many applications. Radial basis functions (RBFs) interpolant is a linear combination of radially symmetric functions with distinct centers. The early surface reconstruction algorithms based on RBF interpolants are usually credited to Carr et al. [21], and Turk and O'Brien [22]. To reconstruct surfaces from large datasets, Morse et al. [23] proposed to use the compactly supported RBFs. A thorough treatment of the RBFs is given by Buhmann [24].

Another family of implicit surface reconstruction algorithms is the partition of unity. Ohtake et al. [25] used the multilevel partition of unity (MPU) together with three types of local approximation quadratic functions to reconstruct implicit surfaces from very large sets of points, including surfaces with sharp features. Furthermore, Ohtake et al. [26] combined RBFs and the partition of unity as a mean for large, non-uniform datasets. Piecewise algebraic surface patches defined within a tetrahedral lattice of control points were firstly introduced by Sederberg [27]. Its successor A-patch proposed by Bajaj et al. [28] was used to reconstruct a C^1 continuous surface and a scalar field defined over it. To have some desirable properties from both global and local representations, Jüttler and Felis [29] applied algebraic spline surfaces into fitting scattered data. By extending the geometric distance minimization and using the trust region technique, Yang et al. [30] proposed to use active implicit B-spline curves for fitting unorganized point clouds. Rouhani and Sappa [31] presented an extension of the 3L algorithm to the implicit tensor-product B-spline solution space. Recently, they [32] further developed a reconstruction algorithm using the partition of unity technique. The applications of algebraic spline surfaces in approximate implicitization can be found in [33]. Polynomial splines over hierarchical T-meshes (PHT-splines) [34] are a useful generalization of B-splines over T-meshes. Wang et al. [7] proposed an adaptive surface reconstruction algorithm based on implicit PHT-splines, which can produce high quality reconstruction surfaces very efficiently at the cost of large storage requirement.

Download English Version:

<https://daneshyari.com/en/article/440672>

Download Persian Version:

<https://daneshyari.com/article/440672>

[Daneshyari.com](https://daneshyari.com)