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Surface reconstruction techniques: a review

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Abstract Surface reconstruction means that retrieve the data by scanning an object using a device such as laser scanner and construct it using the computer to gain back the soft copy of data on that particular object. It is a reverse process and is very useful especially when that particular object original data is missing without doing any backup. Hence, by doing so, the data can be recollected and can be stored for future purposes. The type of data can be in the form of structure or unstructured points. The accuracy of the reconstructed result should be concerned because if the result is incorrect, hence it will not exactly same like the original shape of the object. Therefore, suitable methods should be chosen based on the data used. Soft computing methods also have been used in the reconstruction field. This papers highlights the previous researches and methods that has been used in the surface reconstruction field.

Keywords Surface reconstruction · Soft computing methods · Unstructured points

1 Introduction

Data collection is important for surface reconstruction because the collected data will determine the type of techniques and approaches that going to be used in reconstructing the surface of the object. Besides that, surface representation also important because it will be used to represent the topology and shape of the collected data. After the reconstruction technique is chosen, maybe there will be some pre-processing steps need to be done, such as simplification towards the data before begin the reconstructing process. It depends on the technique used because sometimes some techniques cannot deal with the large amount of data. Hence, some assumptions need to be done and limitations need to specify in the results.

Surface fitting and optimization can be carried out to modify the results of previous stage and produce a better solution. When the process is done, it will be continued by visualization.

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This process is to test the results and it will use third party software to deal with it in terms of validate the result produced. To summarize, type of input data, representation scheme, reconstruction techniques, fitting and visualization of reconstructed surface are stages require in surface reconstruction.

This paper is structured as follow. In Sect. 2, we review the surface reconstruction data since the problems will be based on the type of the input data. Besides that, we also mentioned the data sources for the researches used. Section 3 describes the surface reconstruction and representation techniques used in previous researches. For Sect. 4, soft computing as surface reconstruction technique such as neural network (NN), genetic algorithm (GA), particle swarm optimisation (PSO) will be discussed. Section 5 presented the analysis based on the techniques reviewed. Conclusions, future work and future direction are presented in the last section.

2 Surface reconstruction data

Data collection in surface reconstruction is very important. Guo et al. (2010) mentioned that surface reconstruction can be referred as recover back the data points into a shape. Different kind of data can deal with different kind of methods and the results produced by the algorithm is highly depends on the types of data. This section discusses the types of data, steps involved in the preprocessing stage and sources to obtain the data set in surface reconstruction.

2.1 Data set and the problems arise

A set of points or point cloud is one type of input data set for surface reconstruction process. It can be in the form of coordinates which used x_i, y_i and z_i to represent the location of the points in three dimensions (3D). Besides that, the data can be categorized into structured and unstructured types. For the structured type, the data contain the connectivity information for the input point while unstructured do not contains this kind of information (do Rêgo and Araújo 2010).

Surface reconstruction will be more difficult to implement if it deals with the data which is unorganized or scattered (Gálvez et al. 2007). As mentioned by Kazhdan et al. (2006), the point sampling is mostly non-uniform because the points which are obtained from scanned objects are often unstructured. Since the data is unstructured, it needs a considerable time to render a complex 3D virtual prototype, producing less accurate representation, and very much dependent on the need to have high computational requirements. The most difficult in reconstructing unorganized points is to get the correct connectivity for the sample points because there is no information related to the connectivity (Yu 1999; Yang et al. 2004; Boudjemaï et al. 2003).

Lot of techniques usually used dense data set to calculate the connectivity to avoid holes appear which can cause the shape incomplete and not perfect (Gálvez et al. 2007). Because after the data is undergoing the reconstruction process and the data distribution is not dense or uniform, the output produced will present the results which contain outliers or holes on the surface (Júnior et al. 2004, 2007).

After data scanning, maybe there will exist some data redundancy problems too. This will let the surface reconstruction steps difficult to carry out because it will affect the speed of reconstruction (Cheng et al. 2007). So, some assumptions will be made to deal with the problems faced. As mentioned by Aganj et al. (2009), some of the methods consider the sample is free from noise and outliers because no scanning device will provide correct data.

While for those data set which have problems such as sparse, missing data or incomplete, they must be identified before the reconstruction process is performed because they will lead to errors in the results produced. Hence, one more step will be performed, which is simplification in the preprocessing stage by removing unrelated, damage or incomplete data (Cheng et al. 2007). But, sometimes this will lead to difficulty in surface reconstruction due to the point distribution was destroyed because of simplification process (Tseng 2009).

If the amount or size of data is too large, some reconstruction methods cannot deal with it because it will take longer time, slower speed, larger memory usage and higher costs in producing the results. Therefore, before begin the reconstruction process, data compression is suitable to be applied by decreasing the amount of data (Cheng et al. 2007; Bae and Weickert 2010) so that the reconstruction process can run smoother. Since an accurate and good quality shape is preferred in reconstructing the surface, hence if possible, the algorithm used must be able to handle the problems as mentioned above.

2.2 Data set sources

There are several kind of data set used in testing the reconstruction methods. Sample sets can be obtained from different sources such as medical imagery, laser range scanner and mathematical models (Amenta et al. 1998). Some researchers used their own data by scanning the shape of the object using the laser scanner or by measuring using mechanical probe (Liu et al. 2008). While for those who do not have this kind of scanning devices or materials, free data source can be used such as the Stanford University data set in testing and validating the reconstruction process. Previous researches data such as Master or PhD project data set can be used in doing the researches and hence comparison can be done toward the results produced.

Examples of data set used by Stanford University in their research work are Stanford Bunny, Happy Buddha, Armadillo and Dragon. This is easier for all the researchers because when they used the same data set, then comparison with previous research results can be done by them.

3 Surface reconstruction and representation

Surface reconstruction means that retrieving the data by scanning an object using a device such as laser scanner and constructing it using the computer to gain back the soft copy of data on that particular object. It is a reverse process and is very useful especially when that particular object original soft copy data is missing without doing any backup. Hence, by doing so, the data can be recollected and can be stored for future purposes. At the same time, the accuracy of the reconstructed result should be concerned because if the result is incorrect, hence it will not exactly same like the original shape of the object. While for surface representation, it means that the method used is able to represent the collected data in the form of shape which is roughly same as the original object.

Lot of review or research papers mentioned that surface reconstruction based on the unorganized points was a challenging tasks, no matter it is in three dimensions of maybe even higher dimension (Zhao et al. 2001; do Rêgo and Araújo 2010; Dalmasso and Nerino 2004). This is due to it involves several processes such as curve net construction and surface fitting (Tsai et al. 2008). One of the problems for unorganized points is to obtain correct connectivity among the points (Yu 1999; Yang et al. 2004; Boudjemaï et al. 2003). Hence, accurate and precise results will be the main aim in designing an algorithm by choosing suitable methods to overcome the drawback of the problems.

Numerous methods have been proposed in reconstructing the surface of a model or objects because it involve in a lot of area such as medical, engineering, manufacturing and geoinformatics. After data collection is done, then will proceed by selecting suitable approaches to deal with the data. But before choosing the method to do the reconstruction, surface representation must be identified and considered. This is very important because the method used in designing the algorithm may have several limitations based on the data collected. If the data set is in unorganized type, then just used the collected data to build a coherent mesh structure which can display as same as the original shape of the object (Boudjemaï et al. 2005). As mentioned by Júnior et al. (2004), (2007), the topology recovery is the main problems in surface reconstruction. So, the basis in developing the algorithm used in reconstructing the data must be able represent the topology and geometry by fitting the data correctly so that the surface produced will be similar as the original shape of the object.

As mentioned by Zhao et al. (2001), there are two type of surface representation, explicit and implicit. Some reviews mentioned that the surface reconstruction techniques can be categorized into surface interpolation or approximation (Yang et al. 2004; Wahab et al. 2005). But at the same time, parameterization and surface fitting are also considered as the stages involved in the surface reconstruction process as mentioned by Barhak and Fischer (2001). For parameterization stages, actually it is used to determine the topology, shape and boundary of the surface (Barhak and Fischer 2001) or assign parameter values to each point by making some assumptions (Hoffmann 2005).

As general for surface reconstruction process flows, after the data collection is completed, the next step is to represent the topology of the data and is continued by pre-processing steps such as compression and simplification. Depending on the type of data and after completing these steps, it will proceed to construct the data by fitting it to get as same as the shape of the object. Optimization may involve in the fitting process where it will deal with the iterative steps in producing accurate and better results. Next step, sometimes involve some beautification works on the result produced such as adding in data points to overcome some holes produced by the algorithm. The last steps will be the visualization by validating the results produced using third party software. Processing time taken to produce an accurate and optimal result without affect the quality of the surface are the main focus and aim in designing surface reconstruction framework. Surface reconstruction methods will be discussed generally in this section.

3.1 Explicit surface

This section will discuss methods in the category of Explicit Surfaces. For Parametric Surfaces, a general theory on B-Spline and Non Uniform Rational B-Spline (NURBS) will be explained whereas for Triangulated Surfaces, explanation on Voronoi Diagram and its dual, Delaunay Triangulation are discusses. As mentioned by Zhao et al. (2001), explicit surfaces denote the exact location of a surface.

3.1.1 Parametric surfaces

Parametric surfaces methods such as B-Spline and NURBS are the earliest techniques used in solving the surface reconstruction problems by fitting with local surface patches. Some information related to parametric surfaces methods is discussed below.

3.1.1.1 B-spline surfaces Due to Bezier curves cannot be modified locally and the movement of the control points will affect the whole curve shape, hence research should be conducted to solve the problems. Finally, B-Spline method has been generalised from Bezier method to overcome the problems faced and it can up to C^2 continuity. B-Spline curve with parameter u can be defined as:

$$P(u) = \sum_{i=0}^{n} P_i N_{i,k}(u) \quad 0 \leq u \leq u_{max} \tag{1}$$

and the basis function of order k (degree $k-1$) are recursive function and is defined as (Rogers 2001),

$$N_{i,k}(u) = \frac{u - u_i}{u_{i+k-1} - u_i} N_{i,k-1}(u) + \frac{u_{i+k} - u}{u_{i+k} - u_{i+1}} N_{i+1,k-1}(u) \tag{2}$$

$$N_{i,0}(u) = \begin{cases} 1 & \text{if } u_i \leq u \leq u_{i+1} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where,

P_i are the control points, eg: $P_0, \ldots, P_n$
$N_{i,k}$ are the normalized B-Spline basis function
u is the knot vector with the range $U = \{0, \ldots, u_{max}\}$

As mentioned by Rogers (2001), B-spline curve can be defined as a polynomial spline function of order k (degree $k-1$) and composed of $n-k+2$ when it satisfies below conditions:

i. $P(u)$ with degree $k-1$ polynomial on each interval $u_i \leq u \leq u_{i+1}$.
ii. $P(u)$ with the order of $1, \ldots \mathrm{k} - 2$ derivaties are continuously on the curve.

For B-Spline surface at parameter (u, v) with $n+1$ and $m+1$ control point can be defined as

$$P(u, v) = \sum_{i=0}^{n} \sum_{j=0}^{m} B_{i,j} N_{i,k}(u) M_{j,l}(v) \tag{4}$$

where $B_{i,j}$ are the vertices of a polygonal control net, with i in the range between 0 to n, while j in the range between 0 to m. $N_{i,k}(u)$ and $M_{j,l}(v)$ are the B-Spline basis functions previously given in the Eq. (2).

Based on Liu et al. (2004), B-Splines method contains two advantages where a B-Splines polynomial degree can be set independently of the number of control points, but with certain limitations and local control can be done on the shape of a spline curve or surface. Besides that, when degree is lower, the closer the curve follows the control polyline. Some previous works has been studied on the topic related to B-Spline. In Chen et al. (2010), they used B-Spline to build several models of left ventricular (LV) inside-wall. The models were calculated by B-Spline integral and the curves were fitted in the cadiac cycle. Mean while, Höllig et al. (1991) maintained the B-Spline basis and retaining full approximation power of it at the same time. For Liu et al. (2005), their algorithm is applied in the least square sense by generating suitable control points of the fitting B-Spline curve.

In Tsai et al. (2008), they developed the integrated procedure for automatic reconstruction of B-Spline surfaces. As mentioned by Wang and Dhawan (2007), B-Spline curve can adequately represent the complex shape although given a few control points. For example, He and Qin (2004) specifies triangular B-Spline surface with n-degree and fitting error tolerance, ϵ. Nonuniform B-Spline surface is used by Fang et al. (1997) to generate samples for the network training used.

3.1.1.2 NURBS surfaces NURBS actually refers to Non-uniform Rational B-Spline and it is a generalization of both Bézier and B-splines surfaces. NURBS has been developed because Bézier and B-splines methods contain limitations such as more complicated shapes require higher order Bézier curves and cannot accurately represent conic curve. Currently, NURBS models are industrial standards for surface representation which are used widely in reverse engineering field (Tsai et al. 2008; Rogers 2001; He and Qin 2004). Besides that, NURBS can be used as a method for approximation or interpolation of scattered data and it is also incorporated with most of the current geometric modeling systems (Hoffmann 2005; Rogers 2001). In addition, by using NURBS, the reconstructed surface is smoother and it can deal with non-uniform data set (Zhao et al. 2001).

Since NURBS is a generalization of Bézier and B-splines, hence degree, control points, weights and knot vector is needed to specify a NURBS curve. For knot vector, it is used to define the information on how much should be shared by neighbour curves (segments) (Miléř and Miléř 2005). For NURBS, although the data can be non-uniform, but it is difficult to deal with noisy data. Below shows the NURBS equation, $P(t)$:

$$P(t) = \frac{\sum_{i=1}^{n+1} N_{i,k}(t) P_i h_i}{\sum_{i=1}^{n+1} N_{i,k}(t) h_i} \tag{5}$$

It is customary to write as

$$P(t) = \sum_{i=1}^{n+1} P_i R_{i,k}(t) \tag{6}$$

and

$$R_{i,k}(t) = \frac{h_i N_{i,k}(t)}{\sum_{i=1}^{n+1} h_i N_{i,k}(t)} \tag{7}$$

where,

P_i	is the control points (Eg: P_0, P_1, P_2)
h_i	is weight (Eg: h_0, h_1, h_2)
t	is the knot vector
$N_{i,k}$	is the normalized B-Spline basis function (Eg: $N_{1,1}$, $N_{1,2}$, $N_{1,3}$)
i and n	is the number of control points P_i

Based on the equation, NURBS surface at parameter (u, v) is defined as $P(u, v)$:

$$P(u, v) = \sum_{i=1}^{n+1} \sum_{j=1}^{m+1} B_{i,j} S_{i,j}(u, v) \tag{8}$$

where $B_{i,j}$s are the 3D control net points and $S_{i,j}(u, v)$ are the rational B-Spline surface basis function as defined:

$$S_{i,j}(u, v) = \frac{h_{i,j} N_{i,k}(u) M_{j,l}(v)}{\sum_{i=1}^{n+1} \sum_{j=1}^{m+1} h_{i,j} N_{i,k}(u) M_{j,l}(v)} \tag{9}$$

where $N_{i,k}(u)$ and $M_{j,l}(v)$ are the nonrational B-Spline basis functions previously given in the Eq. (2).

NURBS surface reconstruction can be done in many ways. For example, Goldenthal and Bercovier (2004) solved the optimisation of NURBS surfaces using linear least squares fitting. Saeedfar and Barkeshli (2006) used NURBS modelling to solve the shape reconstruction of 3D conducting curved plates. While for Meng et al. (2010), NURBS is used to detect the curvature, generate the rectangle meshes and also build UV parameter lines.

3.1.2 Triangulated surfaces

3.1.2.1 Voronoi diagram and delaunay triangulation Voronoi diagram (VD) and its dual, delaunay triangulation (DT) can also refer as computational geometry methods (Bolitho et al. 2009). Zhou et al. (2011) mentioned that for VD and DT methods, the data is assumed to be dense and free of noise. It using the sample points to generate the vertices of triangle meshes which call *crust* for a set of triangles (Amenta et al. 1998). It can deal with general data set (Zhao et al. 2001) and the triangle mesh can cover most of the points (Kazhdan et al. 2006). In addition, this method is very hard to overcome the noisy and non-uniform data problems and the quality of the output surface rely on the quality of the inputs (Zhao et al. 2001). Refer to Floriani (1987) for more details on VD and DT explanations.

For most of these methods, researchers try to use or apply the method to build the mesh by forming the nearest connectivity among the nearest points. It is good by doing so but there are some obstacles such as it may appear sparse set of sample points (Boudjemaï et al. 2005).

DT were used because it able to maximizes the minimum angles and evade the skinny triangles in many meshing algorithm (do Rêgo and Araújo 2010). Allègre et al. (2006) mixes the kd-tree and the selected points of Dalaunay triangulation and enriched the less sample points area.

There are lot of techniques derived from Delaunay and VD such as Alpha shape, Crust algorithm and Cocone algorithm. For example, Chaine's geometric convection algorithm in Allègre et al. (2005) works, the output produced were 3D DT. Below will discussed about the algorithms.

Alpha (α) shape is a heuristic approach and performs well in uniform sampling. However, the optimal value of alpha relies on the sampling density which keeps on changing at different parts of surface (Yu 1999). As mentioned by Xu and Harada (2003), once α change, different shapes can be obtained from the same point sets. The shape of this technique is derived from DT and every shape is a well defined polytope (Edelsbrunner and Mücke 1994). In Xu and Harada (2003), they want to reconstruct the surface automatically by applying this method. They find the triangle with minimum area by keeping α value and then just adjust it based on the point density.

Crust algorithm is naturally in 2D (Amenta et al. 1998) and is based on the Delaunay complex of the sample points. For Crust algorithm, if the sampling density is dense, hence the "crust" is correct. Otherwise, it will be incorrect (Yu 1999). Besides that, Power Curst is an improvement and extension for Crust algorithm. As mentioned by Ni and Ma (2010), if the sample is dense enough or the data is too large, then this technique is not suitable to be used because the running time is too long and hence make it slow. As the improvement is done toward existing technique, so the expected benefits from the new technique sure will overcome the problems faced in the existing techniques. Ni and Ma (2010) proposed a non-uniform down sampling method based on Power Crust algorithm.

Cocone algorithm is an improvement and extension from VD too. The Cocone calculates the input set of Delanay triangulation and choose the triangles to construct the surface. The algorithm is performed by choosing Voronoi edges subset from the dual simplices and forming the reconstructed surface. Besides that, it is straight forward compared to Crust algorithm due to the calculation only need to be done once from the original sample points. Tight cocone algorithm was introduced by Dey and Goswami (2003). As mentioned by Wahab et al. (2005), this algorithm is faster than Crust algorithm and Power crust in practice and comparison to other methods has been discussed.

3.2 Implicit surface

Some of the researchers refer the implicit surfaces as Volumetric Representation or function fitting approaches. For Zhao et al. (2001), they mentioned that implicit surfaces represent the surface as a particular isocontour of a scalar function. The methods in this group can be categorized into global or local fitting (Bolitho et al. 2009). Zhou et al. (2011) mentioned that signed distance function, radial basis function, moving least square and indicator function are the techniques used in reconstructing surface which represented in implicit forms. As Ni and Ma (2010) mentioned, this approach used different standard to fit the implicit surfaces toward inputs point by minimizing the energy that represent different distance functions. As mentioned by Xie et al. (2004), implicit surfaces can provide a better topology and can fill up the holes automatically.

3.2.1 Least square

Least square method is one of the most common fitting methods and it have been used in works of Wen et al. (2009) and Goldenthal and Bercovier (2004). The least square method is an approximation method to find a solution that close to the real solution of undetermined problem. The least square method defines the error as the difference between the data and the value provided by the model. Commonly, the least square method is combined with one of optimisation method.

In Wen et al. (2009) work, they combined least square method with radial basis function. Based on the combination, they can use less centers in reconstruction and remove the numerical ill-condition. While for Gálvez et al. (2007), this method is used in solving surface fitting problems by merging with Genetic Algorithm. Besides that, they also applied this method by combining with functional network in fitting the curve.

3.2.2 Poisson surface reconstruction

Poisson surface reconstruction algorithm is an implicit function which merges global and local fitting schemes (Bolitho et al. 2009; Li et al. 2010). Based on Kazhdan et al. (2006); Li et al. (2010), they mentioned that Poisson reconstruction algorithm considers all data at once and hence it is a global solution. Besides that, it can create very smooth surfaces just like radial basis function. At the same time, it able to do data fitting, cover the surface hole by filling and remeshs the existing model (Kazhdan et al. 2006).

For Bolitho et al. (2009) work, they applied this algorithm by reconstructing the indicator function where the function contains the value of one for inside surface and zero at the outside surface. As discussed by Li et al. (2010), they improved this algorithm by using linear interpolation to make the reconstructed surface closer to the curves and reduce the time by using quick search method. In work (Xiong et al. 2011), this method is applied in making 3D points gridded. For Zhou et al. (2011), they used Poisson algorithm to calculate the implicit function over the volume spanned by the octree nodes.

3.2.3 Partial differential equation

Based on Bae and Weickert (2010), Partial differential equation (PDE) had illustrated very good results in the field of image interpolation and compression. In Zhao et al. (2001), they construct the continuous models by using PDE and differential geometry. In addition, they can overcome the changes of topological by solving the PDE on a simple rectangular grid. For Barhak and Fischer (2001), they developed the parameterization method by using PDE to construct a 2D parameterization grid. In Ostrov (1999) work, the result shows that PDE is able to decrease the time taken to calculate the solution.

PDE method is also able to perform well in biomedical image analysis research too. For example in Osechinskiy and Kruggel (2010) work, they had presented an automatic reconstruction method using several PDE modelling stages. Eulerian framework PDE is used in calculating the geodesic distance from white matter and level set PDE is used to reconstruct the outer cortical surface. PDE based method is applied twice in Bae and Weickert (2010) work on surface interpolation from less unorganized point sets and for lossy compression of triangulated surfaces.

3.2.4 Level set method

Level set method was introduced by Osher and Sethian (Zhao et al. 2001). It is a numerical and theoretical method for implicit surfaces as mentioned by Liu et al. (2008). Besides that, it can be used to deal with the complex topology and noisy data easily as mentioned in Zhao et al. (2001).

For Zhao et al. (2001), they used the level set method as a numerical technique merged with implicit surfaces to form a general framework for surface modelling and many other applications. In Liu et al. (2008), the steepest descent of the energy functional is gained from the energy minimization techniques and performed in the level set space.

3.3 Computer vision techniques

Shape from shading (SFS) and Photometric stereo (PMS) is mentioned as classic reconstruction techniques in Petrovic et al. (2001). The techniques in this category were using photographs from several viewpoints or lighting condition to generate the point samples or in short, recover a shape from images of an object under different lighting condition (Petrovic et al. 2001). Mapping from surface gradients to image intensity is the idea for SFS and PMS. Mapping here actually is the reflectance map which merges the information related to light source, surface material and viewing geometry (Petrovic et al. 2001). Non-linear relationship among image intensity and surface gradients is formed using the information from mapping. Long time is needed to solve this method due to nonlinear optimization problems and also difficult to obtain optimum solution (Cho and Chow 2001).

PMS was introduced by Woodham (1980) and this method used some images to reverse the reflectance map (Petrovic et al. 2001). As mentioned by them, without using the global constraints, PMS can locally estimate the surface gradients for each pixel. As mentioned in Cheng (2006), this technique can use some images of the same surface to predict the local surface orientation.

For Cheng (2006), they solved the PMS based on Lambertian model by firstly know the locations of light sources. Kuparinen and Kyrki (2009) used this method to deal with the optimal reconstruction of approximately planar surfaces. Kobayashi et al. (2011) discussed the error in the surface normals estimated by this method and proposed method to deal with it. While Thiele and Klette (1998) merge the shape from occluding contour with PMS approach.

3.4 Other methods

This section discusses other methods used in surface reconstruction. For Lecrivain et al. (2008), Hybrid surfacing shows that the results produced were balance in terms of quality, time and accuracy compare to rapid surfacing (RS) and classical surfacing (CS). RS is a fast modeling method compare to CS by forming a three or four side patches using intersecting curve. However, CS can produced higher quality surfaces compare to RS which is based on free form modeling (Lecrivain et al. 2008). While in Nie et al. (2007), they detect simulated brain atrophy by using the central cortical surface reconstruction method with hybrid cortical surface registration method. Xie et al. (2006) used image fusion method for the 3D surface reconstruction on microparts by providing the 3D information of "in focus" pixels. Multi-level Partition of Unity method is improved in Xie et al. (2004) where it can accommodate with general data sets.

For support vector machine, it can decrease the sample data noise and repair holes but the speed is slow if deal with large data set based on Zhang et al. (2008). They applied this algorithm by simplifying and reconstructing the data set. Same goes to robust estimation method which is used by Schenk and Castheó (2007) because they want to remove useless point from the fitted surface. Tseng (2009) extended projection-based reconstruction method to solve the problems. Normal constraints method is used in Guo et al. (2010) to minimize the energy function and solve as linear system equations. Variational implicit function method is used in work (Deng et al. 2011) which is based on the method presented by Greg Turk. As for ball-pivoting algorithm, it is used by Bernardini et al. (1999) to calculate a triangle mesh interpolating a given point cloud in their work.

4 Soft computing methods in surface reconstruction and optimization

Mostly, soft computing techniques will deal with the optimization problems in surface reconstruction such as fitting problems. This is because most of the soft computing methods contain the iteration steps which can be used to improve the results from the reconstruction techniques and hence produced better surface. This section will discuss the soft computing methods that were used by previous works in surface reconstruction problems.

4.1 Neural network

Artificial neural network (ANN) is inspired by the way biological nervous systems works where artificial neuron is the basis of Neural Network (Luger 2005). Based on Luger (2005), an artificial neuron consists of input signal, a set of real valued weight, activation level and a threshold function. In addition to the properties, neural network is characterised by global properties such as the network topology, learning algorithm used and the encoding scheme.

Besides that, Neural Network contains input layer, output layer and hidden layer. For input layer, it used to present data for the network whereas it used to produce the results based on ANN response for output layer. Neural Network sometimes consists more than one hidden layer (Chandrasekaran et al. 2009). As mentioned in Jaganathan et al. (2011), neural network is a modeling tool that can represent complex multi-input and output nonlinear systems by training it.

In surface reconstruction, there are lots of researches using Neural Network to design their model. For Yu (1999), he applied neural network learning algorithm to obtain the 3D coordinates at each vertex correctly. While for Wu (2008), some sample points to construct the generalize regression neural network (GRNN) is used. After the noise has been eliminated, GRNN is reconstructed again using the measured points.

For Wu et al. (2008a, b,c), they used back propagation neural network to evaluate the information for ore grade unknown area. The same idea is used by Arie and Nandy (1998) in their work for learning brightness patches. For Yang et al. (2004), they applied it in multilayer perception (MLP) training technique since it is the most popular technique used. Two layered self-organization neural network model is applied in Tang et al. (2002) work to simulate the interaction of binocular neurons. Besides that, they also add in two cooperative terms into the Neural Network equation to extend collaboration from neigbouring region. In Cheng (2006) work, the pixel values were the inputs for neural network to reconstruct the 2D images. While in Yu (1999), they used Neural Network to obtain each vertex 3D coordinates. In Hoffmann (2005), Neural Network is used for scattered data fitting. For Hwang and Li (1991), Neural Network was used for representation and reconstruction of 2D curves and 3D surfaces of complex objects. Three neural network with back-propagation algorithm is used to identify the correspondent points in Fang et al. (1997).

ANN is also used to recognise the model parameter in Xu et al. (2010) work. Two symmetric structures neural networks were used by Liu et al. (2005) in their work to compute separately two reflection components and merge every points on the object surface with adaptive ratio. ANN is also used by Yang et al. (2004) by combining it with virtual laser 3D automatic optical inspection to raise the inspection speed and accuracy and at the same time decrease the implementation cost. As mentioned by Chen et al. (1992); Chen and Jain (1994), robust BP algorithm is able to remove outliers for surface reconstruction.

Apart of that, due to the characteristics and abilities of Neural Network, some approaches and methods were further derived from this method. Below will discuss the based on associated methods used in surface reconstruction case study which derived from Neural Network theories.

4.1.1 Kohonen network

Kohonen Network, or known as self organizing map (SOM) is used to analyse high-dimensional data and visualization method which introduced by Kohonen (1982); Hoffmann (2005); Kohonen and Honkela (2007). It is a two-layer unsupervised continuous valued Neural Network (Hoffmann 2005; Luger 2005). Kohonen Network contains *n* input and *m* output nodes in its training steps and there is a weight associated to the connection from the input nodes to the output nodes. The minimum output node will be the winning node and the weights of this connection and their neighbours will be updated in a well-defined way (Hoffmann 2005). The algorithm often used by SOM is the competitive hebbian learning (CHL) (do Rêgo and Araújo 2010). For Kohonen Network theory, please refer to Kohonen (1990).

SOM can be used to define some standard to modulate the function of a data set (Júnior et al. 2008). In Yu (1999), Kohonen training algorithm is applied to improve the overall performance at multiple resolution of the mesh. As discussed in Jaganathan et al. (2011), Kohonen Self Organizing Feature Map is used to estimate the parameter for permanent magnet synchronous motor (PMSM) drive. While for Hoffmann (2005), he had created different kind of B-spline surfaces continuously by using Kohonen Neural Network.

In Júnior et al. (2008), the vertices of the initially mesh is moved using SOM to the point set. In Boudjemaï et al. (2005) work, they using Kohonen learning rule for the adaptation process and then the topological neigbourhood is obtained by using graph representation. While for Boudjemaï et al. (2003), the benefit of learning process of this method to generate a mesh model for the surface is used. Barhak and Fischer (2001) developed the parameterization method using Kohonen Network in creating an initial base surface.

Growing cell structure (GCS) is a neural network which gains enhancively (Ivrissimtzis et al. 2003) and is the dynamic version of Kohonen Network (Hoffmann 2005). This method do not same as Self organizing feature map. Each node will contain a winning counter and this counter will be increased by 1 if this node is the winner (Hoffmann 2005) and the competitive input will automatically determine the number of nodes and network structure as mentioned by Tsai and Wang (1999). When the counter reach certain limit, additional row or column will be added next to the nodes. Based on this, it implies that GCS contains good topology and vector quantization. The advantages for this method is the number of training is reduced and the speed is faster although some counters is added to the network (Hoffmann 2005). In Ivrissimtzis et al. (2003) work, they proved that this method is able to handle the sharps features and concavities of the recosntructed surface.

For Tsai and Wang (1999), this method is used and is joined with BNN to perform surface reconstruction as a hybrid model where BNN is used to overcome the drawback of GCS. Ivrissimtzis et al. (2003) used Neural Network to generate the mesh whereas for searching the nearest neighbors of a given signal, they use octree-based searching tree to deal with it. In Júnior et al. (2004) work, self-organizing neural network was used in positioning the vertices of triangle mesh and they moved the vertices coordinates to the data sampled from the surface by using Kohonen learning algorithm.

4.1.2 Radial basis functions (RBFs)

Radial basis function (RBF) is a three layers feed-forward network (Wu et al. 2008a, b,c; Liu et al. 2004; Ivrissimtzis et al. 2003). Same as neural network, the structure of network for this method contains input, hidden and output layer (Wu et al. 2008a, b,c). RBF neural network sometimes is referred as local perceptive field network (Liu et al. 2004). RBF is also under the category of implicit surface.

As mentioned in Dalmasso and Nerino (2004) work, there are two approaches for RBFs, local and global. For local, it can produce the results faster and contains simpler computation but at the same time, it is sensitive towards the density of the unorganized data. While global able to handle non-uniform density data, but the computation is complicated for large data sets.

Work by Wen et al. (2009) shows that this method can be joined with least square method and it overcome the over-fitting problems. As for Wu et al. 2009, they designed radial basis function neural network (RBFNN) and adopted with simulated annealing arithmetic to adjust the network weights. In work by Wu et al. (2008a, b,c), they mix this method with simulated annealing to solve the incomplete point cloud data problems. Liu et al. (2004) used it to optimise the neural network parameter for process in mapping the anteype surface correctly. As for Morales et al. (2010), RBF is applied in approximating the surface sampling resolution and for spatial mapping support. Carr et al. (2003) shows that by just substituting suitable basic function, smooth RBF representation of surface data can be obtained. Due to RBF network contains classification ability, hence it is chosen to model the specular component in Cho and Chow (2001) work. While Wu et al. (2008a, b,c) used this method to reconstruct the face until reach a certain frequency. Same goes to Wen et al. (2009), the same method to get the weight of the network is used.

4.2 Genetic algorithm

Genetic algorithm (GA) technique was introduced by John Holland in 1975 and he developed this idea in his book Adaptation in natural and artificial systems (Sivanandam and Deepa 2008). Genetic algorithm is suitable to be a tool in solving the search and optimization problems. Same as the other soft computing methods, genetic algorithm is based on the principle of genetics and also evolution.

Genetic algorithm contains several operations in performing the algorithm. First step will be initializing the population. For each population, it contains several individuals or refers as chromosomes. These chromosomes will sub divided into genes. Then this population will be graded based on the objective or fitness function. The fitness values will show how good the solution is based on the minimizing or maximizing problem.

It proceeds by the selection, crossover and mutation operation. For selection, two chromosomes (parents) will be selected based on the fitness values. While for crossover and mutation operations, it is highly based on the probability generated by the algorithm. If the generated probabilities are less than the default probabilities, hence both of the operation will not be carried out. The operations will be done if the generated probabilities are greater than the default probabilities. The operations will be continued iteratively and will stop until it already reached or fulfilled the termination or convergence criteria. Hence, new offsprings (children) will be produced after the operations were done. All the new offsprings will be graded using the objective or fitness function.

The last step will be the replacement. If the new offsprings (children) were better compared to the old generation (parents) based on the fitness values, hence it will replace the old generation and form the new generation.

Several previous researches were studied related to this method. GA is used by Gálvez et al. (2007) for the curve and surfaces fitting. They combined GA with least square fitting as hybrid method and used GA to find the parameter values, t_i for the data points. While for Bokhabrine et al. (2007), they used GA to recover Gielis surface parameters. Although it is slower compare to the previous method, but it can evades from fundamental problems of the symmetry detection and at the same time, can deal with all parameters.

GA is applied in Liu et al. (2005) work to reconstruct the shape and the dielectric constant of the object. They minimized the cost function by using GA in the inversion procedure. While in Cheng et al. (2007), GA is used because the problem is to manage with lot of data and since GA contains the characteristics such as random, iteration and evolution, hence it is suitable to apply in this case study.

As in Saeedfar and Barkeshli (2006) work, GA is applied to solve the optimizing process in the inverse problems. They applied the GA by changing the parameters in the next iterations based on some rules. GA is used to deal with the minimization problems on difference between the real and predicted measurement in Wang and Dhawan (2007) work. They coded the parameters into GA and recover them through the global optimization.

4.3 Simulated annealing

Simulated annealing (SA) was proposed by Kirkpatrick et al. (1983) and Cerny (1985) as a probabilistic method in finding the global minimum (Bertsimas and Tsitsiklis 1993). This method is based on the physical phenomenon of cooling metals where the parameter will be the initial temperature, reducing temperature, conducting the duration at a temperature and terminal criterion (Wu et al. 2007, 2008a, b, c). This algorithm will be terminated when there is no improvement in the function value or small temperature is obtained (Chandrasekaran et al. 2009). Since this method is a straightforward global optimization method, hence it is suitable to use in combinatorial questions (Wu et al. 2007, 2008a, b, c).

As they mentioned, SA has the characteristics of global optimisation and hence it can keep the network from getting local minimum. In Wu et al. (2007), (2008a, b, c). works, they coupled SA with RBF to overcome the drawback of RBF by used SA arithmetic to adjust the network weights. The result from the experiment proved that the learning speed is faster and the reconstruction surface is smoother using the combination. While in Aganj et al. (2009), they optimize the energy function by replacing greedy algorithm with photo-consistency optimization using SA on the surface of Power crust.

4.4 Particle swarm optimisation

Particle swarm optimisation (PSO) was developed by Kennedy and Eberhart in 1995. This technique is a population-based stochastic optimization technique which is based on bird flocking and fish schooling (Kennedy and Eberhart 1995). Each "particle" mentions in PSO actually is the solution which is analogous to a bird (Chandrasekaran et al. 2009). It iteratively updating the generations by firstly initialise the population of the particles and searching for the optimum result. Fitness value of each particle in the population will be evaluated by the objective function (Chandrasekaran et al. 2009).

According to Chandrasekaran et al. (2009), PSO has been reported better than GA in finding the solution. But for Rekanos (2008), the researchers compare PSO with Differential Evolution. Based on the numerical results, it shows that DE is better than PSO in terms or speed and accuracy. In Gálvez et al. (2008), they used PSO algorithm to obtain proper parameterization of the data points for Bézier surface. PSO is proposed by Forkan and Shamsuddin (2008) to explore the optimum fitting points and to inspect the ability in reconstructing the objects.

4.5 Differential evolution

Differential evolution (DE) was introduced by Storn and Price (1997) as a search heuristic method (Ardia et al. 2011). It is a population-based search strategy and a method for mathematical optimisation of multidimensional functions (Engelbrecht 2002; Weise 2009). Same as genetic algorithm (GA), it will initialise the population and then come across the operation such as mutation, crossover and selection to minimise the objective function according to Holland in 1975.

Although the operations are the same, but the way to operate and the steps are different. Donor vector, trial vector and target vector were involved in the operations in producing next generation. Mutation, crossover and selection operations continue until the stopping criterion is reached. As mentioned by Dehmollaian (2011), DE algorithm is better than other methods in optimizing problems due to its simple implementation and fast convergence characteristics.

For Studholme (2001), the method is applied by crossing the parameter from one parent with another parent where the parameter is mutated. While in Rekanos (2008), this technique is used in minimizing the discrepancy for measured and estimated data with respect to parameter for spline expansion. They concluded that DE produced better result for shape reconstruction and giving lower reconstruction error compare to PSO. In Li et al. (2003a); Lin et al. (2003b), they used DE to deal with the image reconstruction of electrical impedance tomography (EIT). DE is used in Dehmollaian (2011) for the reconstruction of the front shape of different 2D conducting targets hidden behind walls and wall parameters estimation.

5 Analysis on the review techniques

Based on the literature review that has been done, all techniques contain its own pros and cons while using it. As for overall conclusion, Neural Network seems to be the best technique to be used compare to the other techniques, either for explicit, implicit or computer vision technique. This is because Neural Network is able:

i. To deal with unorganized data and non-uniform density data. This is proved in the work of Yang et al. (2004) where they deal the unorganised scanned point data using neural network.
ii. To represent and done reconstruction at the same time. Hwang and Li (1991) shown and proved the ability of Neural network in their work.
iii. To used iteratively for the training steps by improving and obtain better results. This is shown by Hoffmann (2005) where he mentioned that by adjusting the number of iteration steps and other parameters, the quality of the approximation will be different.
iv. To merge with other techniques and represent as hybrid method as mentioned by Gálvez et al. (2007).
v. To deal with data points because of its network layer characteristics. As done by Yu (1999), he consider the vertices as the cells for neural network and coordinates as the weight vector for each cell.
vi. To further derived and represent as Kohonen Network, Growing cell structures and Radial Basis Function techniques. This can be shown in the works of Yu (1999); Júnior et al. (2008); Ivrissimtzis et al. (2003). They used neural network characteristics to deal with the case study.

Of course, if this method can be combined with other methods and hence better result can be produced.

6 Conclusion, future work and future direction

6.1 Conclusion

In this paper, we presented the general reviews on the surface reconstruction in data set and the problems arise, surface reconstruction techniques and representation which covers the explicit, implicit, computer vision and soft computing techniques. Following are the observations from the literature:

Basically, the problems and the selected techniques were based on the input data types. Some methods cannot deal with the large data set and hence the results produced might contain errors. Hence before choosing suitable method for the reconstruction process, the data type should be identified. Apart of that, maybe some pre-processing steps need to be done in clear the noise data so that the reconstruction process can be smoothed.

Most of the soft computing techniques were used as the fitting methods in obtaining the better results. Some of the techniques has been merged and presented as a hybrid method to overcome the drawbacks of the existing methods. Lot of reviews used neural network techniques in solving their research problems. This is because neural network is able to represent the network structure of the data points which can straightly shows the topology of the model. Besides that, it is a soft computing technique which is able to do the iterative steps and looping to get better results.

6.2 Future work

Future work for this paper should be focused in improving the literature review in deep for the methods mentioned in the text and also including the review on visualization and beautification of reconstructed surface. Besides that, problems related to each technique can be determined in deep and some comparison on the methods based on the same data can be included in the paper too.

In terms of methods, new methods should be proposed to deal and handle different kind of data from different fields such as geoinformatic and medical field. This is because current methods discussed in this paper are only able to deal with only one field data that is engineering field. Hybrid methods is expected to be the proposed method because based on the combination of the methods, the characteristics of each method can be combined and maybe new finding can be discovered. Enhancement towards current existing methods can be done by exploring the limitation of each existing methods and improving it by adding new ideas.

In addition, the problems related to the size of data set that is mentioned in the text can be solved. If the method is able to solve the problem but it unable to deal with large data set, it is a waste. Hence, this problem should be considered while generating new ideas for the new method.

6.3 Future direction

For the future direction of surface reconstruction, maybe the researchers can scan the face of people and construct it using the best reconstruction techniques. This is useful in scanning the mummy face for the artifact field. Researchers will be able to determine the face of mummy after the reconstruction process is done and represent it as a face statue in museum when the machining process is done.

While for medical field, current existing medical device maybe still unable to straightly figure out the illness suffered by the patient based on the data collected. Further research should be done towards the result in determining the cell structures and hence conclude the sickness of the patient. The expectation after the completion of surface reconstruction is a doctor can straightly determine what kind of disease is being suffered by the patients and best treatment can be offered. This is very useful especially for the cancer disease because it is the critical illness and the treatment should be applied as soon as possible towards the patient.

For geoinformatic field, the expectation is the researcher is able to determine the changes of the map before or after certain disasters that happened such as flood and earthquake. Based on the reconstructed results, which place should be given a precaution advice can be located in securing and protecting people from disaster.

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