Performance Analysis on Three Dimensional Surface Reconstruction of Head Magnetic Resonance Images

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Abstract— In MRI images, the boundary of an encephalic tissue is highly curved and irregular. Three dimensional reconstruction of such encephalic tissue is complicated. The surface reconstruction is the sub-field of Medical imaging which provides an effective way to investigate and determine brain related diseases in an efficient and effective manner. The basic purpose of 3-D surface reconstruction is to analyze the brain images precisely in order to effectively diagnose and examine the diseases for surgical planning and tumor localization. Reconstruction of tumor images is the goal in dealing with these images. In this paper, a brief overview is given on the advantages and disadvantages of existing surface reconstruction methods in clinical applications. The traditional cube based algorithms extracts the surface by forming imaginary cube and then determines the polygons needed to represent the part of the isosurface that passes through this cube. But, it requires post processing and needs more Computational time for reconstruction. Also they cannot provide the proof of correctness. The vector machine based algorithms like Immune Sphere Shaped Support Vector Machine (ISSSVM) transforms the highly irregular object into the high dimensional feature space and construct the hypersphere as compact as possible which encloses almost all the target object. This paper concludes that ISSSVM can outperform the cube based algorithm by reconstructing the irregular boundaries of the encephalic tissue efficiently without post processing. It can also provide its proof of correctness with greater accuracy.

Keywords—Encephalic tissue, Support vector machine (SVM), Three dimensional surface reconstruction, Magnetic Resonance Image (MRI).

I. INTRODUCTION

Three-Dimensional reconstruction of an encephalic tissue is a complicated issue, but much more important for surgical planning & localization of tumour. The 3-D surface reconstruction can be broadly classified into two categories. They are cube based methods and vector machine based methods. The cube based methods extracts isosurfaces, which are the main computational component and are heavily used in practice. They are ubiquitous in visualization which requires the ability to render an isosurface, and this can be done by converting this implicit surface into a triangle mesh [1]. Other applications, however, operate on the resulting mesh, such as finite-element method simulations, tetrahedral mesh generation, and inverse problems. These applications require meshes of good quality, which are often dictated by the quality of its worst triangle, regardless of any other triangle in the mesh [2]. Isosurface polygonization methods are efficient tools for extraction and visualization of isosurfaces since the pioneering works in the early 1980s [3], [4], [5]. Methods based on surface tracking place seed sampling points on the isosurface and perform an iterative refinement search for optimal positions or generation of new seeds. Examples include pseudo-physical algorithms [6], [7] and advancing front (afront) algorithms [8]. Spatial decomposition methods, described first by Herman and Udupa [5], rely on the assumption that inside a smaller cell of a grid it could be assumed that the underlying scalar function is locally linear [9], and thus, the isosurface can be represented by a plane. Using this simple assumption, Lorensen and Cline proposed marching cube algorithm, which extracts the surface from the three dimensional voxels. It takes eight neighbor locations at a time & forms an imaginary cube, then determines the polygons needed to represent the part of the isosurface that passes through this cube. The individual polygons are then fused into the desired surface. Even though this method is simple, the quality of the resulting mesh is poorly shaped and also it requires post processing like smoothing. The computational time is high. It also produces holes in the surface rendered [10],[11]. To overcome this drawback marching tetrahedron came into existence. This method produced improved surface, but the computational time is high [12]. Although robust and simple to implement, these generate surfaces that require additional Processing steps to improve triangle quality and mesh size. All of these algorithms are cell based. They work by iteratively examining each cell of the grid on which the scalar function f is defined and by producing a triangulation for each cell separately. These triangulations are created in such a way that when they are connected together, they produce a watertight manifold mesh [13]. The simplicity of these methods allows robust and efficient algorithms, which have been expanded and extended in significant ways [14], [15], [16], [17], [18]. Among these techniques are optimization strategies that are orders of magnitude faster than the original algorithm and can work on data of arbitrarily large sizes. However, they still produce low-
quality triangles. The Dual contouring algorithm is also an extension of marching cube algorithm [19]. It modifies the sampling grid and produces better meshes than marching cubes. But still the computational time is high and complex. Dividing cube algorithm is similar to marching cube, but divides a single cube into smaller blocks. This method achieved highest data compression [20]. But it cannot overcome computational complexity & speed. To improve the quality of the triangle mesh, generated by Marching Cube (MC) algorithm, MC using edge transformation (Macet) was introduced. In this method the sampling grid is modified in a very simple and intuitive way. Macet generates a mesh with identical connectivity to the MC mesh, and it is very close to the MC mesh as measured by Hausdorff distance. Most importantly, it consistently generates meshes whose worst triangles are well above the current state-of-the-art techniques [21]. The Second category is based on vector machine based methods. The basic support vector machine (SVM) takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non- probabilistic binary linear classifier. Firstly, conventional one class SVM was proposed [27]. This method assumes each feature of a sample has the same importance degree for the classification result. It does not take feature weights into account. It has the ability to learn the non-linear distribution of real data without using prior knowledge. But the parameters selected for one class SVM and kernel function directly affects the result. Later, one class immune feature weighted SVM was proposed [28]. This method performed better than the previous, as it is the combination of one class SVM, immune algorithm and the feature weights. Recently Immune sphere shaped support vector machine (ISSSVM) was proposed [22]. It transforms an original 3-D object space into a high dimensional feature space by the kernel function and constructs a compact hyper sphere which encloses the target object in the feature space. It needs no pre or post processing steps but its accuracy depends on the accuracy of the training data set processing and the similarity between the training data and testing data.

II. CUBE BASED ALGORITHMS

A. Marching Cube Algorithm

Lorensen and Cline proposed marching cube algorithm, which extracts the surface from the three dimensional voxels [10]. It works on the assumption that inside a smaller cell of a grid, the underlying scalar function is locally linear [9], and thus, the isosurface can be represented by a plane. It is more important isosurface polygonization algorithm due to its simplicity, efficiency, and robustness. However, MC is also known for the poor quality of the resulting triangle mesh. Several strategies for measuring triangle quality are discussed in [23]. The metric most commonly used for measuring a single triangle quality is the radii ratio: the ratio between the triangle’s incircle and Circumcircle. The radii ratio is a fair metric: every degenerate triangle has a radii ratio of zero. It penalizes both small and large angles, which makes it suitable as a “first order” metric: although some

B. Marching tetrahedron Algorithm

The Marching Cubes algorithm is a standard approach to this problem. But, the only change is that, it performs decomposition of each 8-cell associated with a voxel into five tetrahedron’s [12]. It guarantees the resulting surface representation to be closed and oriented, defined by a valid triangulation of the surface of the body, which in turn is presented as a collection of tetrahedrons. The entire surface is “wrapped” by a collection of triangles, which forms a graph structure, and where each triangle is contained within a single tetrahedron. Even though it can avoid cracks in the surface rendered, it cannot give its proof of correctness.

C. Dividing Cube

The dividing cube algorithm subdivides the voxels into smaller cubes that lie on the surface of the object and projects the intensity calculated for each cube onto the viewing plane, forming a gradient shaded representation of the three-dimensional object [20]. In medical images, surface elements and the triangles created by the polygonal algorithm may occupy only a small area. As the number of facet increases, the size of each triangle decreases and approaches the pixel size. For complex medical images, it is more efficient in memory and time. (ie) Similar to marching cubes, but utilizes the fact that the cubes are divided into smaller blocks. Smaller blocks are analyzed separately and the results are combined. This method achieves highest data compression (16:1) by quantization. Also it provides straight forward proof of correctness. This method is accurate when compared with Marching cube algorithm.

D. Advancing Front Algorithm

It works by creating an initial speed point on the isosurface and iteratively growing the triangulation over entire isosurface [21]. This method produces very high quality adaptive triangle meshes. Even though this method is efficient, it is highly complex & the computational cost is high.

E. Dual Contouring Algorithm

It is a feature-preserving isosurfacing method that extracts crack-free surfaces from both uniform and adaptive octree grids. It presents an extension of DC that further guarantees that the mesh generated is a manifold even under adaptive simplification [19]. The contoured surface generated by this method contains only manifold vertices and edges, preserves sharp features, and possesses much better adaptivity than those generated by other isosurfacing
methods under topologically safe simplification. The disadvantage is that, they may still contain intersecting polygons.

III. VECTOR MACHINE BASED METHODS

The basic SVM takes a set of input data and predicts for each given input, which of two possible classes forms the output, making it a non-probabilistic binary classifier.

A. Linear SVM

A support vector machine constructs a hyperplane or set of hyperplanes in an infinite dimensional space, which can be used for classification, regression or other tasks. As a result good separation is achieved by the hyper plane that has the largest distance to the nearest training data points of any class. Since, in general larger the margin, lower the generalization error of the classifier.

![Figure 1. A sample Binary classifier that classifies, data points](image)

Given some training data D, a set of n points of the form

\[ D = \{(x_i, y_i) | x_i \in \mathbb{R}^p, y_i \in \{-1, 1\}\} \]

were the \( y_i \) is either 1 or -1, indicating the class to which the point \( x_i \) belongs. Each \( x_i \) is a \( p \)-dimensional real vector. The task is to find the maximum-margin hyper plane that divides the points having \( y_i=1 \) from those having \( y_i=-1 \). Any hyper plane can be written as the set of points \( X \) satisfying \( w \cdot x - b = 0 \), Where . denotes the dot product and \( W \) the normal vector to the hyper plane. The parameter \( b/|W| \) determines the offset of the hyper plane from the origin along the normal vector \( w \). There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum margin hyperplane.

B. Immune sphere shaped SVM

In head MRI image sequences, the boundary of each encephalic tissue is highly complicated and irregular. It is a real challenge to traditional 3D modeling algorithms.

Support Vector Machine (SVM) based on statistical learning theory has solid theoretical foundation. Sphere-Shaped SVM (SS SVM) was originally developed for solving some special classification problems. This concept is extended to image 3D modeling which tries to find the smallest hypersphere enclosing target data in high dimensional space by kernel function [22]. However, selecting parameter is a complicated problem which directly affects modeling accuracy. Immune algorithm gives the solution to this problem.

i) Immune Algorithm

The Immune Algorithm (IA) [22, 28] is mainly applied for optimization, and it is used for searching optimal parameter for SS SVM. So, Immune SS SVM (ISS SVM) is proposed to construct the 3D models for encephalic tissues. As the experiment demonstrates, the models are constructed, and it reaches satisfactory modeling accuracies. Theory and experiment indicates ISS SVM exhibits its great potential in image 3D modeling. Appropriate parameters can make the model more flexible and it can help to obtain more accurate data description. Immune algorithms (IA) have the abilities of memorizing and self-adaptively adjusting. Combining SS SVM with IA, Immune SS SVM (ISS SVM) is used in 3-D reconstruction of the encephalic tissue in MR images.

ii) Immune Sphere Shaped SVM

The kernel function can make the method more flexible and more accurate when compared with the very rigid spherical shape in the original space. Different kernel functions result in different types of feature spaces and differently shaped domain descriptions. If a polynomial kernel is used, the distances between data points are enlarged with the increase of the degree of the polynomial. It results in a very large and sparse data description. In order to suppress the growing distances for a large feature space, the radial basis function (RBF) kernel function is more appropriate for the sphere method [22].

\[ K(x,y) = \exp(-\frac{\|x-y\|^2}{2\sigma^2}) \]

Where, \( \sigma \) is the width of the kernel.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>Time (S)</th>
</tr>
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<tbody>
<tr>
<td>Lobster</td>
<td>MC</td>
<td>3130.5</td>
</tr>
<tr>
<td></td>
<td>Macet</td>
<td>767.9</td>
</tr>
<tr>
<td>Grey matter</td>
<td>MC</td>
<td>11.5612</td>
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<tr>
<td></td>
<td>MT</td>
<td>2.5676</td>
</tr>
<tr>
<td>White matter</td>
<td>MC</td>
<td>1.982</td>
</tr>
<tr>
<td></td>
<td>MT</td>
<td>3.026</td>
</tr>
<tr>
<td>Encephalic tissues</td>
<td>ISS SVM</td>
<td>527</td>
</tr>
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TABLE I. PERFORMANCE COMPARISON OF TRADITIONAL ALGORITHMS WITH ISS SVM
The brain MR images include seven contrasted objects including the Background (BG) and six kinds of encephalic tissues, i.e., Scalp (SC), Osseous Compact Substance (OCS), Osseous Spongy Substance (OSS), Cerebral Spinal Fluid (CSF), Cerebral Gray Matter (CGM) and Cerebral White Matter (CWM).

Table I indicates that the Marching cube (MC) method takes 3130.5 for reconstructing a surface. When Comparing Marching cube with Mact (Marching cube with edge transformation), the latter takes lesser time to reconstruct. (ie) Macet is 4.07 times faster than MC. But ISSSVVM reconstructs all the encephalic tissues in 527s.

<table>
<thead>
<tr>
<th>Dataset</th>
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<th>Radii ratio</th>
<th>Min</th>
<th>Avg</th>
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<td>MC</td>
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<td>LS</td>
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<td>DC</td>
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<tr>
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<td>Afront</td>
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<tr>
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<td>LS</td>
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<td>DC</td>
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<tr>
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<td>Macet</td>
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<td>Macet</td>
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</tbody>
</table>

### iii) Accuracy

The traditional algorithms cannot give the proof of accuracy. This was the biggest drawback of them. But ISSSVVM [22] gives its correctness using MATS (%) & MAWS (%)

1) MATS: Modeling Accuracy on Test set
   Using the ISSSVVM, the optimal $e^*$ and $\sigma^*$ which correspond to the best Modeling Accuracy on the Test Set in the training process was obtained.

2) MAWS: Modeling Accuracy on the whole set
   After the training process, the whole 3-D coordinate set of the target object was fed into ISSSVVM with the optimal parameters to compute MA on the whole set.

### iv) Performance of ISSSVVM

The ISSSVVM can reconstruct six kinds of encephalic tissues, i.e., Scalp (SC), Osseous Compact Substance (OCS), Osseous Spongy Substance (OSS), Cerebral Spinal Fluid (CSF), Cerebral Gray Matter (CGM) and Cerebral White Matter (CWM) tissues including the Background (BG) in 38-527s. It provides the modeling accuracy both for test set and whole set. The modeling accuracy is taken for Linear Immune sphere shaped support vector Machine (LISSSVVM) and Immune sphere shaped support vector machine(ISSSSVVM). The LISSSVVM reconstructs the surface using only one parameter (ie) without kernel function. So the resulting image lacks in flexibility. This makes ISSSVVM to use, kernel function which is responsible for selecting parameters. So the resulting image is flexible & visually impressive.

![Figure 2](image-url) Comparison of MAWS % using LISSSVVM & ISSSVVM

![Figure 3](image-url) Comparison of MATS % using LISSSVVM & ISSSVVM
The MATSs of ISSSVM are higher than the MATSs of LISSSVM. To demonstrate the ability of solving the nonlinear problem of the ISSSVM, linear ISSSVM (LISSSVM) without kernel function was also implemented. In LISSSVM, only $\lambda$ was optimized. On seeing Fig. 2 & 3 it can be concluded that, the more irregular the object is, the higher the MAs of ISSSVM than the MAs of LISSSVM.

**IV. ANALYSIS USING ISSSVM**

It is also shown that the visual effects of ISSSVM are better than those of LISSSVM. Lots of target points were lost by using LISSSVM. ISSSVM, however, can obtain satisfied results of 3-D reconstruction no matter how irregular an object is. The main reason is that ISSSVM with an optimal kernel function can transform the highly irregular object into the high dimensional feature space and construct the hyper-sphere as compact as possible which encloses almost all the target object. In this way, an irregular object can be well described.

![Figures 4 & 5 showing 3D reconstruction results using ISSSVM and LISSSVM](image)

**Figure 4.** Results of 3D reconstruction of encephalic tissues using ISSSVM (a) Scalp (b) Osseous Compact Substance (c) Osseous Spongy Substance (d) Cerebral Spinal Fluid (e) Cerebral Grey Matter (f) Cerebral White Matter (g) BackGrond [22]

**Figure 5.** Results of 3D reconstruction of encephalic tissues using LISSSVM (a) Scalp (b) Osseous Compact Substance (c) Osseous Spongy Substance (d) Cerebral Spinal Fluid (e) Cerebral Grey Matter (f) Cerebral White Matter (g) BackGrond [22]
V. CONCLUSIONS

In brain MRI images, reconstructing the highly irregular encephalic tissues is a complicated issue for the traditional algorithms, but ISSSVM overcomes this. Due to its advantage in solving nonlinear problems, ISSSVM can be applied in the 3-D image reconstruction. MC, Macet, MT cannot give its accurate proof of correctness. Comparing this ISSSVM can give its accuracy in the form of modeling accuracy for the test set & Modeling Accuracy for the Whole Set. ISSSVM can also provide better visual effects, than the previous algorithms. This concludes that ISSSVM shows better result than the previous algorithms. In future ISSSVM can be applied for 3-D reconstruction of the tumor in the brain MR images.

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