LIVE MESH: AN INTERACTIVE 3D IMAGE SEGMENTATION TOOL

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Abstract—Image segmentation is the process by which objects are extracted from their surroundings in images. Segmentation in two dimensional images is a well-researched area, with both user-interactive and non-user-interactive tools to perform this function. While research has been done in three-dimensional image segmentation, few user-interactive tools exist that work directly in 3D. We present Live Mesh, an algorithm that provides a highly user-interactive environment for effective 3D image segmentation. It expands on the concepts of Live Wire, and uses a three-dimensional implementation of the powerful Dijkstra's algorithm. The Live Mesh algorithm allows the user to effectively drag mesh patches, or surfaces over a 3D object. *SimpleSeg* is an implementation of Live Mesh that shows the utility and effectiveness of the Live Mesh method.

Index Terms—Segmentation, edge and feature detection, image processing software.

1 Introduction

Three-dimensional object segmentation refers to the task of detecting and describing objects in volume data. Applications such as medical imaging, geological surveying, and computational fluid dynamics can all benefit greatly from 3D image segmentation. This paper outlines Live Mesh, a novel, interactive 3D image segmentation algorithm.

Many interactive 3D object segmentation strategies are based on 2D techniques such as Snakes [12] or Live Wire [1,2] (also known as Intelligent Scissors). After segmenting in 2D, the descriptions are combined and interpolated to produce a 3D object. While simple to use, these approaches don't allow the user to work on the data as a whole. Rather, they present the user with one slice at a time. The tools and user may make errors because of lack of context of the slice data. The Live Mesh algorithm works on the volume data, and, in addition, allows the user to interact in a 3D environment.

The Live Mesh method is a 3D extension of Live Wire, an algorithm that uses Dijkstra's shortest-cost algorithm and a user-interactive interface to find object edges. Live Wire has proven to be very powerful and is widely used because of its high degree of user-interactivity. This is because automatic segmentation is still an unsolved problem and many datasets still require expert knowledge from users. Live Mesh retains the user-interactivity of Live Wire while extending the working space to three dimensions.

Novel ideas proposed herein include a 3D extension of the Live Wire cost function, a spatial restriction for the 3D graph search and the Live Mesh algorithm. A simple implementation of the Live Mesh method, the *SimpleSeg* application, is also briefly discussed.

2 Previous Work

Live Wire stands out among the class of user-interactive image segmentation tools. The user clicks on an edge of the object with the mouse, defining a “seed point”. The user then moves the cursor to some other portion of the object’s edge. The pixel that lies under the cursor is called the “free point”. As the free point moves, a wire connecting the seed point and the free point automatically snaps to the edge. While the algorithm does do significant automatic segmentation (by snapping to the edge), the user maintains complete control in that he or she can adjust the location of the free pixel if the algorithm fails to find the correct boundary.

There are many different methods of extending Live Wire to 3D, though most of them use 2D Live Wire on successive slices. Schenk *et al*. [5] have optimized this process by only computing the cost for successive slices on regions that fall within a given distance from a reference slice’s completed boundary. A distance map, showing distances from the reference slice’s boundary, is generated using a chamfering process. This distance map is used to determine which pixels in the current slice will be used for the local cost computation. In addition to speeding cost computation, local cost feature optimization can be performed.

Schenk *et al.* also introduce an automatic segmentation step using shape-based interpolation followed by a Live Wire-driven optimization process [5,7]. The user segments selected slices, then intermediate slices are automatically interpolated.

Falcao and Udupa [6] developed a method that determines object boundary information from orthogonal slices of a volume segmented by a user. This technique allows the user to segment a minimal number of slices, reducing the total segmentation time.

König and Hesser's method [9] allows the user to select three seed points. After selection, Live Wire is used to generate an initial frame and then "spokes." After the spokes are found, a gap filling algorithm is used to close the space between spokes.

The above 3D segmentation methods have steps in which automatic segmentation is done that can't be controlled by the user in real-time. Additionally, the entire segmentation is done in disjoint steps. Live Mesh overcomes these weaknesses by providing the user with a single interface and a single technique so that the user can perform the entire segmentation using one continuous method. Live Mesh also avoids automatic segmentation, thereby keeping the user in control of the algorithm at all times, just as 2D Live Wire allows real-time user control.

3 Graph Search

Live Mesh is used much like Live Wire. A mesh of wires snaps to the object boundary as the user drags the cursor over the surface of an object. Each wire in the mesh is the shortest-cost path from the current location of the cursor (free point) back to the location where the user initiated the mesh (seed point). The dynamic nature of Live Wire and Live Mesh (i.e., the wires snapping to the boundary immediately upon movement of the cursor) is possible through use of Dijkstra's algorithm.

Graph searching in three dimensions requires a 3D version of the cost function (Section 3.1). In addition, since Live Mesh is a user-interactive tool, we have developed optimizations (Section 3.2) so that the algorithm is fast enough to keep the software responsive to the user.

3.1 Cost function

The cost function used in Dijkstra's algorithm is formulated such that the cost is lowest along edges of an object, ensuring that the lowest cost path will lie along a boundary. Three primary image features are used: Laplacian zero-crossing (f_Z), gradient magnitude (f_G) and gradient direction (f_D). Each feature is weighted with constants (ω_Z, ω_G and ω_D). The cost function (as formulated by Mortensen and Barrett [1,2]) is

$$\text{cost}(u,v) = \omega_Z * f_Z(v) + \omega_G * f_G(v) + \omega_D * f_D(u,v)\,. \tag{1}$$

The Laplacian zero-crossing feature gives an indication of whether a pixel is on an edge or not. The Laplacian operator sums the second derivatives of the image intensity in the axis directions. We consider zero or zero crossing pixels to be an inflection point in the intensity. The Laplacian image is binarized such that all pixels on zero crossings are given a pixel value of zero and all other pixels are given a value of one. $f_Z(v)$ is defined as the value of pixel v in the Laplacian image. Since this value will be zero or one, the contribution the Laplacian makes to the cost function (Equation 1) will be either zero or ω_Z.

The gradient magnitude feature of the cost function gives us an idea of how confident we are that this voxel is an edge (as opposed as "whether the voxel is an edge or not," which is given us by the Laplacian zero-crossing calculation). Voxels with a high gradient magnitude have a high likelihood of being edges. The final cost of a voxel near an edge should be low, so $f_G(v)$ is computed using the inverse of the gradient:

$$f_G(v) = \frac{\max(G) - G(v)}{\max(G)} = 1 - \frac{G(v)}{\max(G)} \tag{2}$$

where $\max(G)$ is the maximum gradient magnitude value of any voxel in the image. Therefore f_G is the inverse of the normalized gradient magnitude at voxel *v*.

The gradient direction feature is defined as follows: let *p* and *q* be two voxels in a 3D image. A normalized gradient direction vector $D(p)$ is defined by the partial derivatives I_x, I_y and I_z and by definition points up the steepest slope at that point. We first define L as the vector orthogonal to $(q-p)$ such that the difference between L and $D(p)$ is minimized:

$$L(p,q) = \frac{T(p,q) \times (q-p)}{\left\| T(p,q) \times (q-p) \right\|} \tag{3}$$

where

$$T(p,q) = D(p) \times (q-p)\,. \tag{4}$$

$T(p,q)$ is the vector orthogonal to both $D(p)$ and $(q-p)$ (Figure 1b). By taking the cross product of $T(p,q)$ and $(q-p)$ we find L, which is the vector orthogonal to

$(q-p)$ that is closest to $D(p)$ (Figure 1c). We can also think of L as being a vector orthogonal to $(q-p)$ that is in the plane containing both $(q-p)$ and $D(p)$.

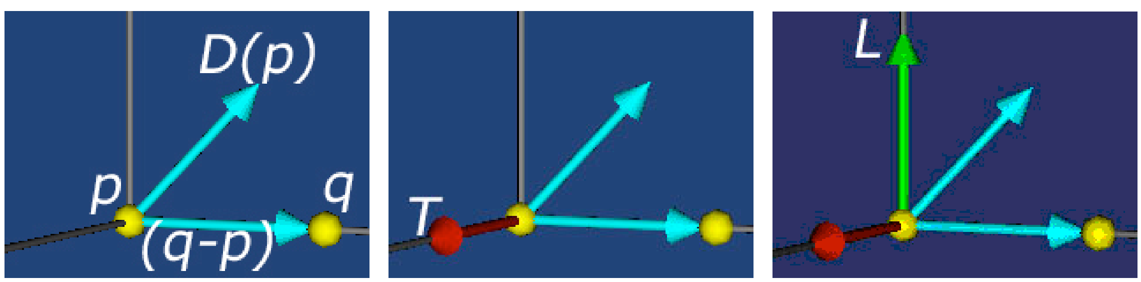
At this point we define angles $d_p(p,q)$ and $d_q(p,q)$:

$$\begin{aligned} d_p(p,q) &= \cos^{-1}\left(D(p)\cdot L(p,q)\right) \\ d_q(p,q) &= \cos^{-1}\left(L(p,q)\cdot D(q)\right) \end{aligned}. \tag{5}$$

f_D is then defined as the sum of these angles:

$$f_D(p,q) = \frac{2}{3\pi}\left(d_p(p,q) + d_q(p,q)\right) \tag{6}$$

$\frac{2}{3\pi}$ is used to normalize f_D to a value of one. L is defined such that it is no more than $\frac{\pi}{2}$ different from $D(p)$ (Equation 5), so $d_p(p,q)$ has a maximum value of $\frac{\pi}{2}$. $d_q(p,q)$ can have a maximum value of π. Thus the normalization factor is $\frac{1}{\frac{\pi}{2}+\pi} = \frac{2}{3\pi}$.



(a) (b) (c)

Figure 1 Calculation of L
(a) Starting vectors $(q-p)$ and $D(p)$. (b) $T(p,q)$ is a vector orthogonal to both $(q-p)$ and $D(p)$. (c) L is orthogonal to $(q-p)$ and $T(p,q)$.

3.2 Search optimization

One challenge in extending Live Wire to three dimensions is the actual computation time of the graph search. The computational complexity of the search is increased by an order of magnitude when adding another dimension, which renders a traditional Dijkstra search very expensive. We have developed a new method of restricting the search space.

By default, the graph search expands throughout the entire image while the user is usually interested in only a portion of the image. The time required for the graph search to find the shortest cost path from the free point to the seed point can be decreased by restricting the graph search to voxels in the neighborhood of the free and seed points (Figure 2a). We define the search space as all voxels within x voxels of the line between the seed and free points, where x is a user-specified value.

If a restriction is used, the path is optimal only within the search space. This is fine if the edge contour is relatively linear, but if the image edges are poorly defined or jagged, then the locally optimum path may in fact be very far from the globally optimum path. An additional problem is that once the free point is moved outside of the restricted search space the search must be restarted. The following two sections address these difficulties.

3.2.1.1 Expanded Search Space

Suppose a restricted search has run to completion and each point in the search space has a locally optimal path back to the seed point. If both the seed and free points are still in place, then a new, expanded search can be started to find a path that is optimal within a larger search area. A naive implementation might be to simply re-search all points in the new, larger search area. However, many of the points in the original search likely have globally optimal paths already. For example, every neighbor of the seed point is guaranteed to have a globally optimal path even in a restricted search.

Our algorithm takes advantage of the fact that we already have some globally optimal information. The original search area is re-searched from the outside-in only as far as needed. We use Dijkstra's algorithm with a few modifications, as follows:

Algorithm 1 Expanded Restricted Search

```
Description: Finds shortest cost path from every Vertex v back
to a seed Vertex s.
Structure: Vertex containing three properties:
     Vertex prev
     Number cost
     Boolean isVisited
Input: seed vertex s, graph G, SortedList q, Set restriction
Output: prev pointer for each vertex v in G, list r suitable for
expanded active list

 (1) SortedList q r
 (2) Vertex v
 (3) Number c
 (4) for every Vertex v in G
 (5)    if q is empty
 (6)       set v.cost = INFINITY
 (7)    end if
 (8)    set v.isVisited = false
 (9) end for
(10) set s.cost = 0
(11) insert s into q
(12) while q is not empty
(13)    set v = least cost Vertex in q
(14)    remove v from q
(15)    set v.isVisited = true
(16)    for each neighbor Vertex v_i near v
(17)       if not v_i.isVisited
(18)          if restriction does not contain v_i
(19)             insert v into r
(20)          else
(21)             set c = cost(v, v_i)
(22)             if v.cost + c < v_i.cost
(23)                set v_i.cost = v.cost + c
(24)                set v_i.prev = v
(25)                insert v_i into q
(26)             end if
(27)          end if
(28)       end if
(29)    end for
(30) end while
```

The active list *q* contains all voxels that have a non-infinite cost and that have not yet been visited. *q* is passed into the algorithm as input rather than being created inside the algorithm, as it is in the original Dijkstra's algorithm. Every vertex is given a value of infinity on only the first search.

In the above algorithm, any vertex in the search space that has a neighbor vertex that is outside of the search space is added to a cost-sorted list *r* (line 19). At the conclusion of the algorithm, *r* contains all vertices along the boundary of the restriction. *r* can then be used as the active list in a subsequent, expanded search (Figures 11 and 12).

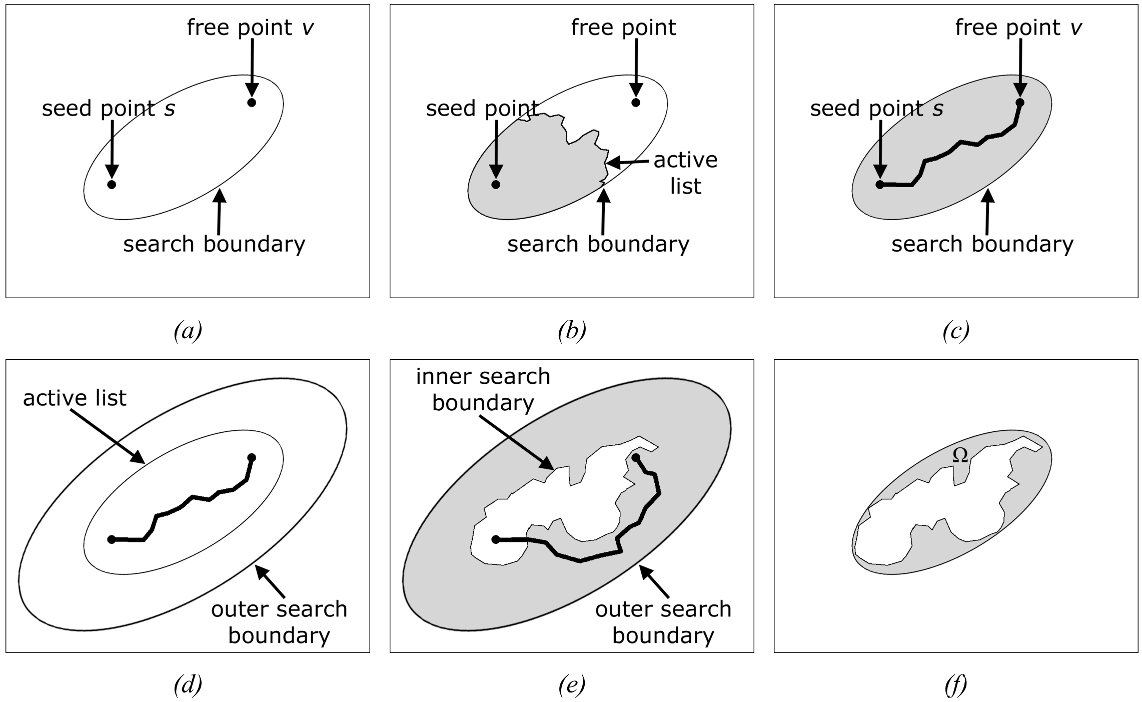


Figure 2 Expanded search
(a) Setting up the initial graph search. (b) Search in progress. Searched area is shaded. (c) Completion of initial graph search. (d) Setting up the expanded graph search. (e) Completion of expanded graph search. (f) _ is the area re-searched.

Each vertex in the graph must be reset to "not-visited" (line 8) in case vertices inside the old restriction need to be re-searched. Any vertex inside the old boundary that does not have an optimal path within the new boundary will be visited again in the new search. The area inside the previous search that is re-searched is called _, and ideally it should be very small. In some cases, however, it is large, even as large as the previous search space itself. In these cases the restricted search is extremely inefficient, as the previous search space is entirely re-searched the second time.

While improved, the new path found after an expanded search is still not globally optimal, unless the path from the *v* to *s* is shorter than the path from each point on the search boundary back to *s*.

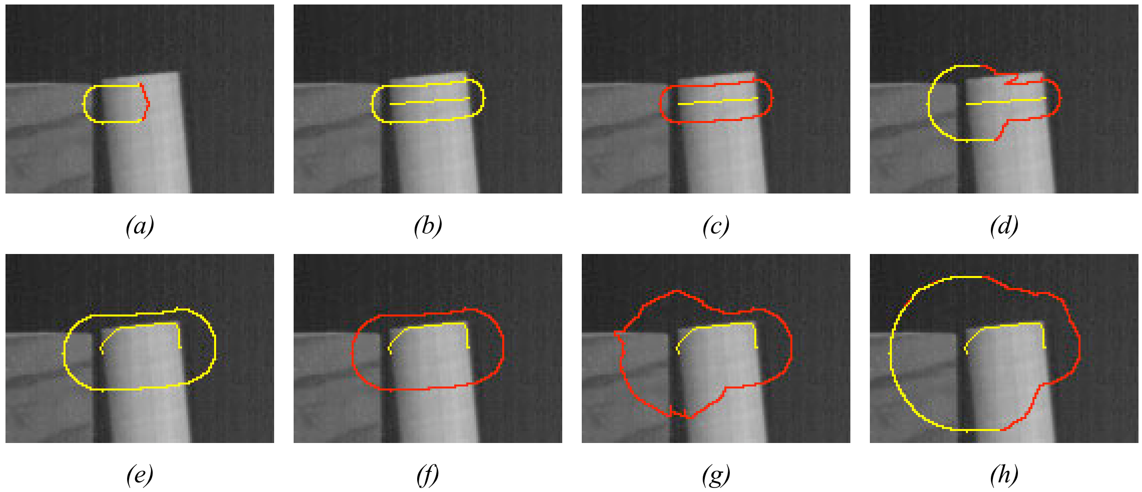


Figure 3 Expanded Search Example
The active list q is in red while the sorted list r is in yellow. (a) Beginning the initial search. (b) After the initial search has completed. (c) The new search with active list initialized to be r from the previous search. (d-h) Continuing on through the first and second expanded searches.

3.2.1.2 Changed Search Space

Suppose a restricted search is running and the free point is suddenly moved outside of the search space. A new search must be started, ideally using information obtained in the aborted search. This can be accomplished using exactly the same algorithm as the expanded search (Algorithm 1). The only difference is that, after the free point is moved and the current search is aborted, r and the active list q must be combined to form the new active list before restarting the algorithm (Figures 4 and 5).

The area _ tends to be somewhat larger for a changed search compared to an expanded search. However, in practice, users tend not to move the free point (e.g., mouse cursor) much at all until at least an initial wire appears. At that time, if the free point is moved at all, it is usually moved either closer or further from the seed point, not in a different direction from it. If it is simply moved closer, the free point usually remains within the search space and an expanded search can take place. If it is moved further away, _ tends to be small as the new search space is close to, and often is a superset of, the old search space.

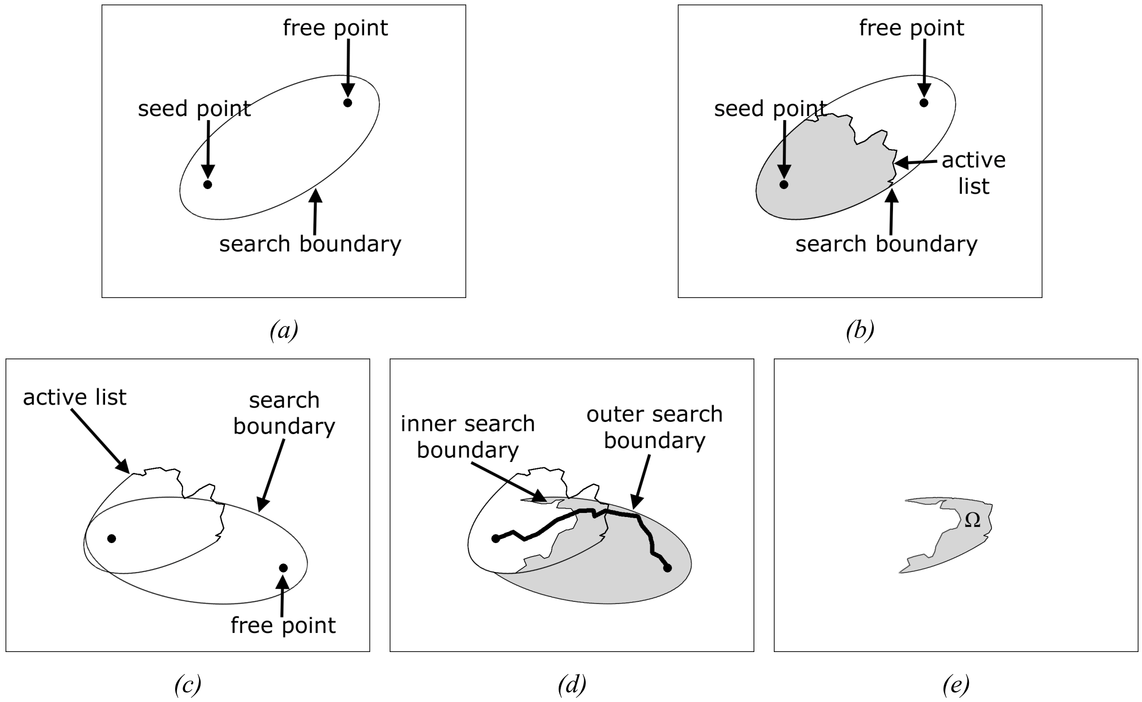


Figure 4 Changed search

(a) Setting up the initial graph search. (b) Search in progress. Searched area is shaded. (c) After the free point is moved the changed search is set up. The new active list is the union of *r* and the active list *q*. (d) Completed changed search. (e) Area _ of initial search that had to be re-searched.

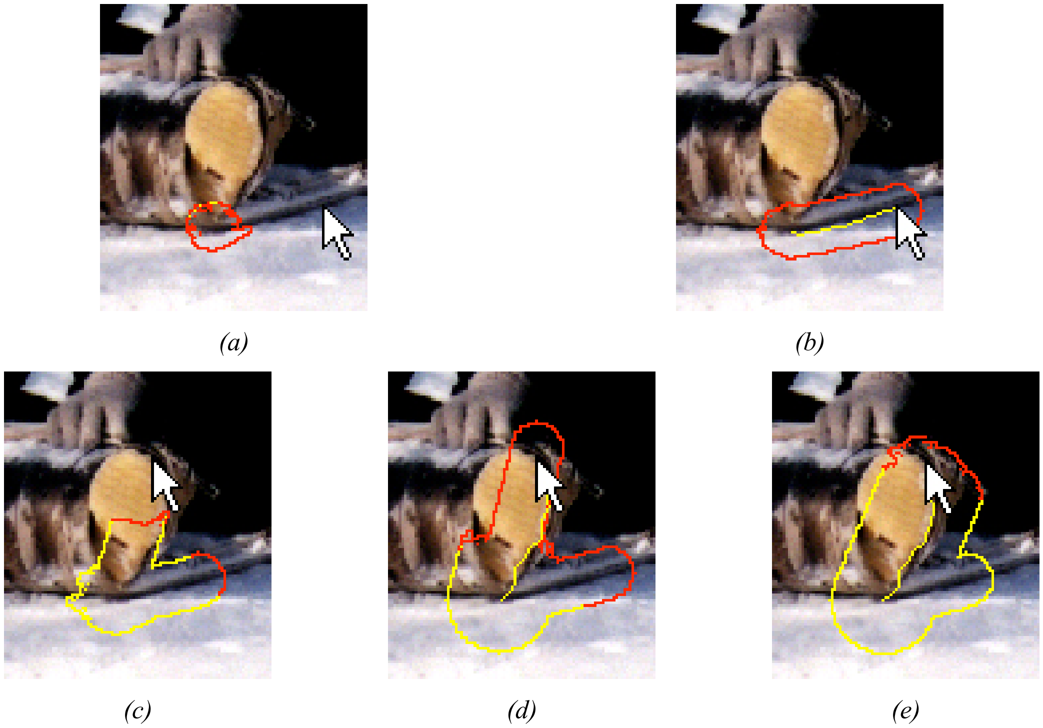


Figure 5 Changed search example
The active list q is in red while the sorted list r is in yellow. (a) At the very beginning of the initial search. (b) At the beginning of an expanded search. (c) A changed search in progress. (d) At the beginning of an expanded search after the changed search completes. (e) Expanded search in progress.

4 Live Mesh

This section presents Live Mesh, the major emphasis of this paper. Live Wire, described in the previous sections, allows users to pull out wires that snap to 2D object boundaries, thus segmenting objects out of 2D images. Live Mesh provides a way for users to stretch mesh patches (Figure 6c) over a 3D boundary. These patches fill in between three user-defined points, looking something like a rough triangulation, except that the triangular patches snap to the boundary's contour. The remainder of this section describes the manner in which Live Mesh accomplishes this.

4.1 Method

The Live Mesh method utilizes the power of Dijkstra's algorithm to form a mesh from multiple wires. First, the user picks a point s_0 in the volume and then moves the cursor with trailing live wire w_{10} until a contour of arbitrary length is defined by picking the ending point s_1 (Figure 6a). While defining this wire, the graph search is not only finding the shortest-cost path from s_1 to the seed point s_0, but also finds the shortest-cost path from every voxel within the search space (ideally defined by the entire image, but possibly bounded by a restriction). That is, after the graph search completes we are left with shortest-cost paths reaching back from each voxel in the search space to s_0.

After picking s_1, the user moves the cursor to define the next wire w_{21}. A new graph search is started with s_1 as the seed voxel and wire w_{21} is displayed in real-time (Figure 6b). As mentioned, Dijkstra's algorithm has already found shortest-cost paths from voxels surrounding the original seed point s_0, and so, with no additional path searching, we can display shortest-cost paths leading to s_0 from every voxel defining wire w_{21} (Figure 6c).

Once point s_2 has been chosen, thereby fixing the mesh s_0 s_1 s_2, the user moves the cursor and a new mesh drags out, using graph searches that have already been completed or are well in progress. If the free point s_3 is close to s_1 then the new mesh is defined as shortest-cost paths from every point in w_{32} back to s_1 (Figure 6e). If s_3 is closer to s_0 than s_1, the new mesh is made of paths from w_{32} back to s_0 (Figure 6h). s_0 and s_1 both work equally as well as seed points for a wire mesh as they both have expanded their wavefronts during the definitions of w_{10} and w_{21}, respectively. The user selects s_3 which completes the second patch using s_1 and s_2, or s_0 and s_2.

The user continues defining meshes in this way until the surface is covered. The fact that little or no extra graph searching needs to occur to define the extra wires forming the mesh makes this algorithm very powerful. Once the graph search out from s_0 has been completed, any two points s_1 and s_2 in the entire image can compute a wire w_{21}, and every point in w_{21} will immediately have a shortest-cost path back to s_0.

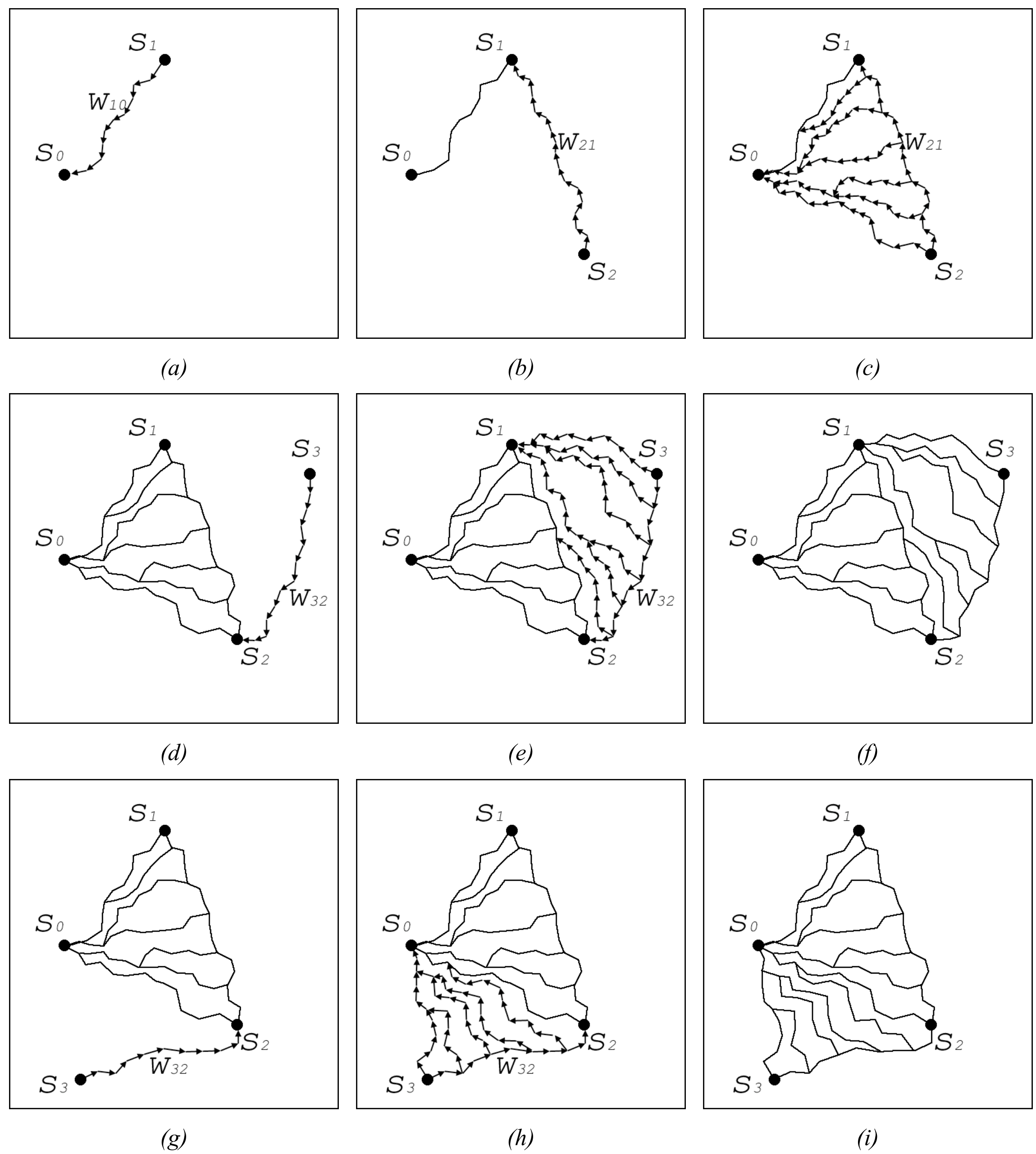


Figure 6 Live Mesh Diagram
(a) Initial Live Wire with s_o as the seed and s_1 as the free point. (b) s_2 is the new free point. (c) Shortest-cost paths to s_0 have already been computed so a mesh is formed from w_{21} to s_0 with only minimal overhead. (d-f) A new mesh from w_{32} to s_1. (g-i) Free point s_3 was moved from its previous position and new mesh goes back to s_0 rather than s_1 since the new free point is now closer to s_0.

The end result, once the user has covered the object in meshes, is a set of points that lie on the object boundary. The points are generally very dense; along the wires of the mesh they are contiguous. Exactly how an object is segmented using these points is application-specific. The application may simply use the points as a set, or it may use topological information found in the individual wires (e.g. (102,58,10) is linked to (101,58,10) which is linked to (100,57,11) ...).

5 The *SimpleSeg* Application

The previous sections discuss the Live Mesh algorithm and its powerful features. This section describes *SimpleSeg*, an application implementing the Live Mesh algorithm. We first describe the visualization and picking techniques of *SimpleSeg*. Following that discussion we provide the results of a small user study conducted using *SimpleSeg*.

5.1 Data Visualization

Since Live Mesh deals with data in three dimensions, a way for the user to interact with the data in three dimensions is needed. *SimpleSeg* provides four different views of the data (Figure 7a): a volume-rendered view and three orthogonal 2D slices of the volume. These 2D slices are present to allow the user to visualize and pick obscured data. This has no effect on the underlying Live Mesh algorithm, which still searches in 3D, regardless of which views are used to visualize the data.

5.2 Mesh Visualization

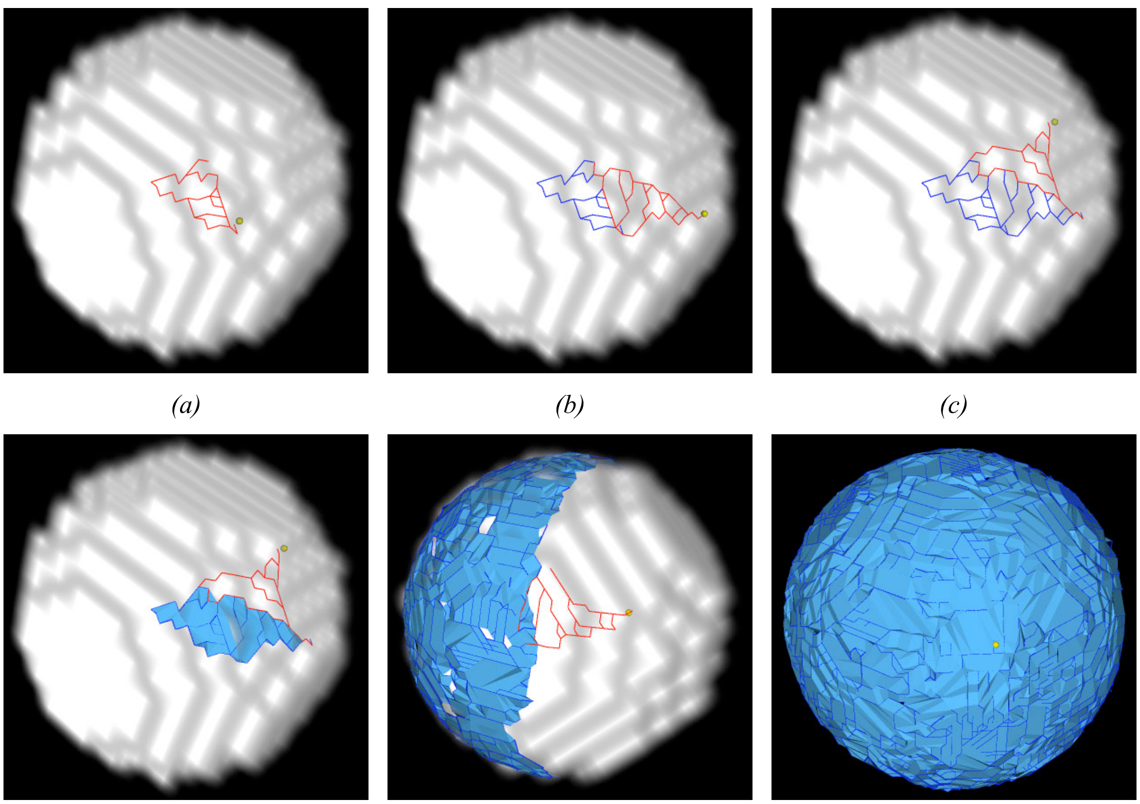
As the user creates a new mesh, each wire in the mesh is displayed in red. Once the user finishes a mesh, the wires are displayed in blue and the new, current mesh is displayed in red. This is shown in Figure 8.

A surface can be generated from finished meshes dynamically. It has been observed that turning on the surface display has been very helpful to users in visualizing the mesh.

The mesh is displayed in the volume rendered window. This way the user can observe the entire mesh being constructed while the user works. Even while the user works on the 2D slices the mesh can be seen in 3D (Figure 7). If the object is obscured, then the rendering of the volume itself can be turned off and the mesh displayed alone. This is assistive especially if the user has some *a priori* idea of what the object looks like.

(a) *(b)* *(c)*

Figure 7 Mesh visualization while working in 2D
(a) View of entire application. (b) Close-up view of the upper-left window in which the user is currently working. (c) Close-up view of the lower-left window (volume rendered) where the user observes the mesh being constructed.



(d) *(e)* *(f)*

Figure 8 Mesh Visualization
(a) Dragging out an initial mesh. (b-c) Finished meshes displayed in blue; active mesh in red. (d-f) With surface display turned on. (e) In the user's hurry he failed to notice certain holes (which were visible only from certain angles). (f) After completing the segmentation and closing holes.

5.3 Testing Results

We tried out the *SimpleSeg* application on a few users to find out how accurate, reproducible and fast the Live Mesh algorithm is in the *SimpleSeg* implementation compared to traditional Live Wire. We found that accuracy was about two orders of magnitude better with Live Mesh on a dataset containing only a sphere. We measured repeatability and segmentation time using more complex datasets, including one (the caudate nucleus of the human brain) in which the data was obscured in the 3D view, so the users had to work exclusively in the 2D view of *SimpleSeg*. Live Wire performed better than *SimpleSeg* in both repeatability and segmentation time. We observed that the users learned Live Wire more quickly than Live Mesh, largely due to the fact that they had difficulty navigating and interacting in the three-dimensional *SimpleSeg* interface. A more complete study would test using both novice and experienced *SimpleSeg* users using more complex datasets.

6 Conclusions and Future Work

Live Mesh is a powerful 3D image segmentation tool, and has great possibilities for the future. The 3D cost function extension is effective for finding object edges. The restricted search and pre-processing of the cost function make the algorithm fast enough to be responsive to the user. The Live Mesh algorithm, including the idea of pulling patchwork meshes over 3D object boundaries, is an intuitive extension to the Live Wire method.

Preliminary results from using *SimpleSeg* show that points composing the meshes tend to be on or very close to the desired object boundary for simple datasets, though the repeatability of such needs further study. The Live Mesh algorithm provides a solid foundation for highly repeatable segmentations, but to get a more meaningful repeatability measure the segmentation needs a gap-filling post-processing step, such as is presented in [9].

Live Mesh could be improved by modifications suggested for Live Wire such as using user motions to restrict the search space [3,4] and pre-processing steps to reduce the size of the search graph [9,10]. The gradient direction element of the cost function is highly sensitive to noise, and Mortensen and Barrett [8] removed it altogether, preferring a tobogganing pre-processing step. Haenselmann and Effelsberg [11] use a wavelet-based cost function to account for weaker edges and even for instances where there is no clearly recognizable edge.

References

[1] E. N. Mortensen and W. A. Barrett, "Intelligent scissors for image composition," in *SIGGRAPH 95 Conference Proceedings*, R. Cook, ed., Annual Conference Series, pp. 191-198, ACM SIGGRAPH, Addison Wesley, Aug. 1995. held in Los Angeles, California, 06-11 August 1995.

[2] E. N. Mortensen and W. A. Barrett, "Interactive Segmentation with Intelligent Scissors," *Graphical Models and Image Processing* **60**, pp. 349-384, 1998.

[3] A.X. Falcao, J.K. Udupa, S. Samarasekera, S. Sharma, B.E. Hirsch, and R.A. Lotufo, "User-steered image segmentation paradigms: live-wire and live-lane," *Graphical Models and Image Processing*. vol. 60. no. 4. pp. 233-260, Jul, 1998.

[4] A.X. Falcao, J.K. Udupa, S. Samarasekera, and F.K. Miyazawa, "An ultra-fast user-steered image segmentation paradigm: live-wire-on-the-fly," *Proceedings of SPIE on Medical Imaging*. San Diego, CA, vol. 3661, pp. 184-191, Feb, 1999.

[5] A. Schenk, G. Prause, and H.O. Peitgen, "Local Cost Computation for Efficient Segmentation of 3D Objects with Live Wire," *Proceedings of SPIE on Medical Imaging*. vol. 4322, pp. 1357-1363, 2001.

[6] A.X. Falcao, and J.K. Udupa, "Segmentation of 3D Objects using Live Wire," *Proceedings of SPIE on Medical Imaging*. vol. 3034, pp. 228-235, 1997.

[7] A. Schenk, G. Prause, H.-O. Peitgen, "Efficient Semiautomatic Segmentation of 3D Objects in Medical Images," *Medical Image Computing and Computer-Assisted Intervention, MICCAI*. pp. 186-195, Oct, 2000.

[8] E. N. Mortensen, W. A. Barrett, "Toboggan-Based Intelligent Scissors with a Four Parameter Edge Model," *IEEE: Computer Vision and Pattern Recognition*. 2, pp. 452-458, 1999.

[9] S. König, J. Hesser, "3D Live-Wires on Pre-Segmented Volume Data," *Proc. Of SPIE*. vol.5747, 2005.

[10] K. C. H. Wong, P. A. Heng, T. T. Wong, "Accelerating Intelligent Scissors Using Slimmed Graphs," *Journal of Graphic Tools*. 5(2), pp. 1-13, 2000.

[11] T. Haenselmann, W. Effelsberg, "Wavelet Based Semi-Automatic Live-Wire Segmentation," *SPIE Human Vision and Electronic Imaging VII*. vol. 4662, pp. 260-269, 2003.

[12] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *International Journal of Computer Vision* **1**(4), pp. 321-331, 1988.