Cost-Map Generation and Heuristic Based Optimal Path Planning for Neurosurgical Tools

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***Abstract*—This paper deals with cost-map generation for a set of cloud point data, obtained individually for different sections of an affected human brain and steering a curved needle through identified noncritical structures to reach the affected hippocampus region for neurosurgical tumor ablation using A* algorithm.**

***Index Terms*—Surgical robotics: Cost-map, voxel, Path-planning, motion-planning, Medical Robotics, A* algorithm.**

I. Introduction

Initially in the field of neurology the process of tumor ablation was quite unfeasible. Back in those days open skull surgeries, also known as invasive surgeries were prominent and the only possible way of removing tumors. Later with the advancement in the technology we have come to minimally invasive methods where there is a small incision made and the surgical tool in inserted through that. In the existing methods, using the information from the MRI/CT scans, the surgeons obtain the segmented view of the brain into different structures such as brain ventricles, hippocampus(left and right), brain vessels among the others. Based on this information the surgeons are required to plan a path for the surgical tool and reach a certain region of interest in the brain. This is extremely time consuming and is difficult because surgeons have to plan trajectories that avoid the vital structures and reach targets within specific angles. This is highly critical as the surgical tool should not touch or rupture any vital part of the brain as it could lead to severe medical conditions like internal bleeding or haemorrhages, and in case the tool is inserted in a wrong position then revision surgeries are required for correction and this may not be very successful at all times either.

Thus, due to the level of complexity it involves, a senior or experienced surgeon's supervision and guidance is required throughout the procedure. A generated cost-map helps the surgeon by finding the needle/tool an optimal path from the given entry point on the skull to the required target point in the brain. In this paper, the head region of hippocampus is considered as the targeted point. The idea is to generate an optimal path based on the generated cost-map, where cost is determined based on the risk for each segmented region in the brain. For better visualization and ease of selection, the surface areas are color coded according to their risk and an optimal planning method A* is implemented.

II. Plan of Action

Neurosurgical tool insertion by conventional methods involve a detailed study of the tumor affected region by a qualified surgeon. A Magnetic Resonance Imaging scan of the brain is studied in detail and we get an understanding about the structure of an affected brain- pose of critical structures like vessels and ventricles that our surgical tool has to avoid while traversing through the brain region from base of skull towards tumor affected hippocampus head region. A surgeon selects a tool insertion point on skull base, based on his calculation of principal axis location for the tumor. The same principles has been followed and an ideal tool insertion point is chosen at the base of the skull, considering its proximity to the tumor axis and with the algorithm, the best possible orientation for needle insertion is chosen such that the heuristic cost of reaching tumor region is minimized. A modified version of A* algorithm has been followed for charting out the path.

The paper has been implemented in two phases. The first phase consists of the cost-map generation as elucidated below. In the second phase a path is generated through the noncritical structure in the brain with a given start point on the base of the skull and a chosen target point on the affected hippocampus.The first step of implementation is data preparation which is as explained below.

III. Data Preparation using MATLAB

The first step is to acquire the data set. Once the required data set is obtained and imported the side of the brain where the tumor is present is found and an appropriate entry point is selected. Based on whether it is the left or right side of the brain, the STL models and the NRRD files are obtained. The obtained data from the STL files are then converted to a MATLAB/Python compatible form. Now, the STL files are imported as triangulation (TR) objects from which the vertex normal is found with respect to end point.

The next step is to convert the NRRD files into point cloud data and save it in a MATLAB/Python compatible version. This file will now contain the final list of point cloud data as a collection of triangulation points that is segmented into

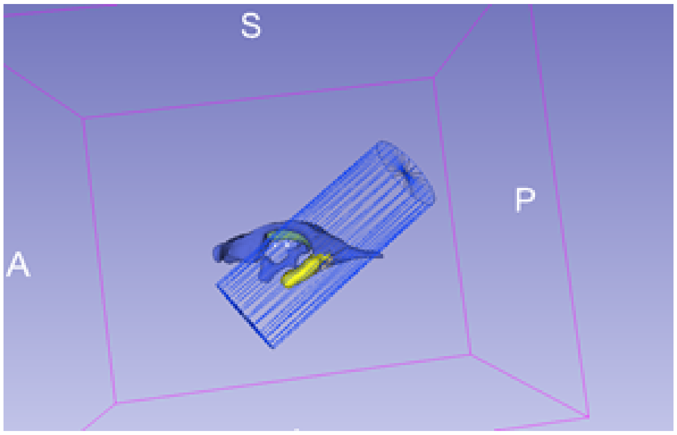

Fig. 1. ROI of brain for the algorithm [4]

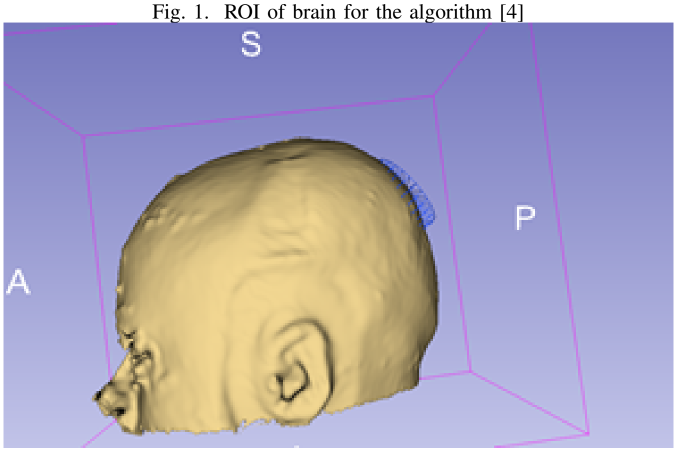

Fig. 2. STL model of human skull with the ROI [4]

the below mentioned categories for each side of the brain separately:

- Brain region of interest
- hippocampus head
- hippocampus tail
- Skull
- Ventricle region of interest
- Vessel region of interest

Once this is done the cost-map is generated based on the side of the brain the tumor is in.

IV. Phase 1 - Cost-map Generation

Now the data set is ready and the next step is to classify the various regions of the brain nodes as critical or non critical based on their proximity to vital structures. There are two different files for left and right side of the brain respectively. Based on which side the tumor is, the appropriate file is imported. So, the MRI data file is imported and from this loaded file the points are segregated as brain_ROI, vessels, ventricles and hippocampus.

The objective is to generate a voxel map for a 3D representation with the given set of triangulation points for the brain. It was found that the segmentation (vessels, ventricles, etc) in the brain data set were not mutually exclusive. Thus the data set used earlier was modified to separate segmentation, for this constraints were enforced while appending the data to the voxel map data and additional information like segmentation ID and cost associated were provided.

For segmentation purpose, the data was first sorted for uniformity. After this comes the identification of the brain regions as critical and noncritical. The noncritical region is is considered and this data is added to the voxel map data and then a segmentation value of zero is assigned to it in order to differentiate these points from the other critical structures. The motive behind cost-map generation is to calculate and obtain a cost associated with each of these points. The computation of cost is discussed later in this paper. After appending the exclusive brain points, it is added to the exclusive vessel structure list. Since these are the maximum critical points in the list, these have been associated with the maximum cost. Similarly cost is calculated for all the segmented regions. The cost associated with the tumor region is made zero so that the tool is able to approach the region. Similarly, reward map was generated consisting of the points in the hippocampus region.

The goal is to minimize the number of iterations, by considering only non critical structures in the initial iteration, and assigning high cost for inherent critical structures. Considering 200000 voxels on an average for the right section of the brain, the number of critical structures (blood vessels and ventricles combined) have an enumerated value of 9000. Therefore, the computation time was significantly reduce by ignoring these cloud points, per section.

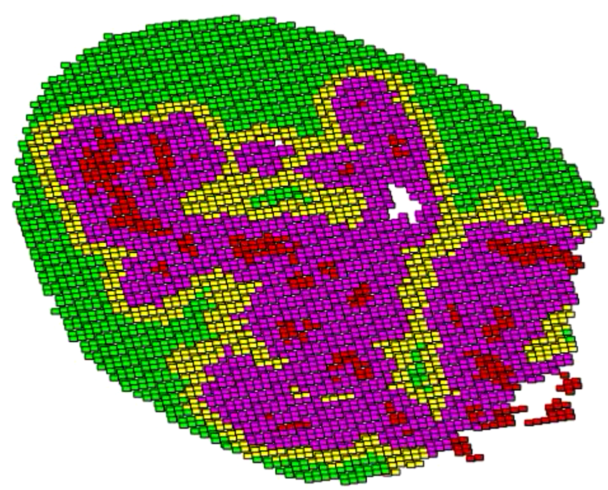

Fig. 3. 2D image of the color coded cost-map

TABLE I
COMPARING GENERATED COST-MAPS ACROSS VERSIONS

Parameters	Previous Version	Updated Version
Execution Time (secs)	231s	132s
Voxel map array length	285018	272967
Total number of iterations	285018	256002
Mutually Exclusive structures?	No	Yes

Algorithm 1: Algorithm for cost value assignment

Result: Color, cost values assigned for each voxel
initialization;
while *all exclusive brain ROI cloud points* **do**
  $p \leftarrow cloud\ point\ coordinate$;
  $CritStruc \leftarrow vessel+\ ventricle\ point\ coordinate$;
  while *blood vessels* **do**
    $vj \leftarrow CritStruc\ coordinates$;
    $D \leftarrow norm(p, vj)$;
    if $D \leq min$ **then**
      $min \leftarrow D$;
    end
  end
  if $min \leq 0.2$ **then**
    $cost \leftarrow 10^7$;
    $color \leftarrow red$;
  end
  if $min \leq 3$ **then**
    $cost \leftarrow 500$;
    $color \leftarrow purple$;
  end
  if $min \leq 5$ **then**
    $cost \leftarrow 50$;
    $color \leftarrow yellow$;
  else
    $cost \leftarrow 0$;
    $color \leftarrow green$;
  end
end

V. PHASE II - A* ALGORITHM

The A* search algorithm, is type of forward search algorithms available which constructs a search tree. At each step the child nodes are generated which could possibly be one of the valid steps to reach the final goal node and thereby resulting in an optimal path. This dynamic programming concept can help obtain the single source shortest paths in the generated tree. [3]

A. Start and End Point Selection

From the previously generated data for the region of interest, all the possible insertion points are available for the surgical tool to be inserted, now an optimal point is to be selected from the available triangulation points on the outer skull surface to safely reach the tumor with a minimum needle distance.

Using the method mentioned in neurosurgical tumor ablation with a needle by Reza et al [4], where a mean point for the tumor is calculated based on all the points in the tumor and then an eigen vector is then calculated which gives the direction for the tumor axis line. This tumor axis line is further used to calculate the distance between each point on the skull surface to the tumor axis. Based on the least distance a point can be chosen on the skull surface which is the ideally the optimal point for a tool to be inserted.

$$\parallel \hat{a} \times (\bar{p} - \bar{b}) \parallel^2 = r^2 \tag{1}$$

Where a is the direction vector of tumor axis, b is the mean point of tumor and p is any point. Similar procedure is used to find the start point for either left or right side of the brain.The end point is considered as the mean of all the tumor points as they lead to the center of the tumor.

The green region in the figure 4 is the tumor and the blue line indicates the tumor axis which is found in the previous step. The red point, on the skull surface is the start point chosen for the needle insertion, if the current point fails to generate a path to reach the tumor safely we choose the next connecting points to the current start point on the skull surface.

B. Path Exploration

From the selected start point, a subset of possible points is calculated based on a step size. These subset of points are the child steps generated in the A* algorithm, where each step is generated using the following equation.

$$\begin{bmatrix} p_{(i,1)} \\ p_{(i,2)} \\ p_{(i,3)} \end{bmatrix} = d \times stepSize \times \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix} + \begin{bmatrix} p_{(0,1)} \\ p_{(0,2)} \\ p_{(0,3)} \end{bmatrix} \tag{2}$$

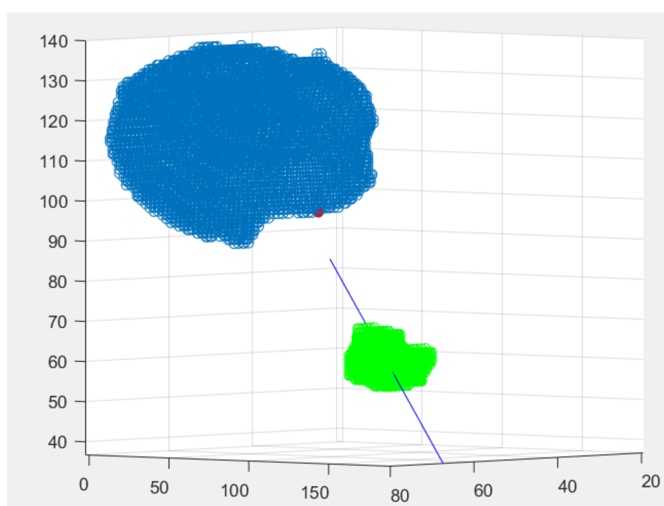

Fig. 4. Red point is the Selected start point for the Right ROI.

The matrix n is the normal vector found at any given particular point in the region of interest, which is rotated with respect to y and z axis with angles of β and α respectively. This normal vector is multiplied with a direction values 'd' which identifies the direction of the needle to reach the goal(T) or the tumor mean point.

$$\begin{bmatrix} n_{i,1} \\ n_{i,2} \\ n_{i,3} \end{bmatrix} = \frac{(p_i - T)}{\parallel (p_i - T) \parallel} \tag{3}$$

For each such points generated shown in figure 5, a heuristic value is found based on the following functions. These heuristic functions tries to reduce the total number of states explored by incorporating a heuristic estimate of the cost to get to the tumor from a given state. Let C(x) denote the cost-to-come from (x-1) to (x), where cost-to-come for each step is defined by the step size and let G(x) denote the cost-to-go from (x) to (T) or tumor. The value of C(x) can be computed incrementally by dynamic programming [3] and the value G(x) is found using the distance equation in 3-dimension. And an additional cost A(x), defined by the cost-map generated in phase 1 is used to avoid selecting the points of high critical status and thereby make the algorithm choose a safer path.

$$C(x) = C(x-1) + stepSize \tag{4}$$

$$G(x) = \sqrt{(x_{(i,1)} - T_1)^2 + (x_{(i,2)} - T_2)^2 + (x_{(i,3)} - T_3)^2} \tag{5}$$

C. Back Tracking

The exploration of the points ends as soon a point within the tumor region is reached. Each point when visited, is checked if the point lies within the region of the sphere of radius (r) around the tumor mean point or T and based on the radius defined the exploration is stopped. Now each step is backtracked using a list where the parent step index is stored, this is continued until the start point is reached. This generates the required steps in the path for the surgical tool.

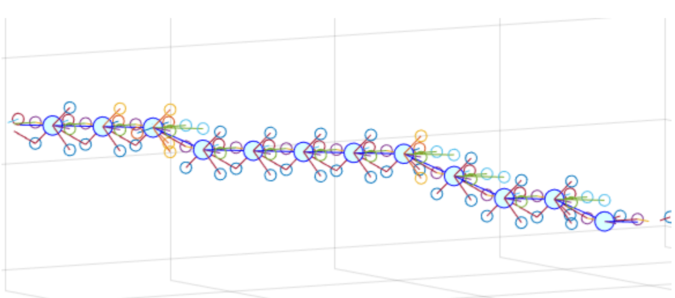

Fig. 5. Exploration of each step

Algorithm 2: Psuedo-code for Modified A* for Surgical tool

```
Result: Path for the Surgical Tool from start point on
        Skull base to end point on tumor axis
Start ← start point;
Goal ← end point;
Path=[Start];
pv ← Start;
Queue= [];
Visited= [];
Total=[]
Queue.cost ← CostMap(pv);
Queue.C ← 0;
Queue.G ← norm(Start, Goal);
while Goal not reached do
    nv ← Action set point(pv)
    if nv is Goal then
        return SUCCESS;
    end
    if nv is not Visited then
        Path.Insert(nv);
        Visited(nv) ← 1;
        C(nv) = C(pv) + StepSize;
        Queue.C ← C(nv);
        Queue.G ← norm(nv, Goal);
        Queue.cost ← CostMap(nv);
        Total(nv)
          ← Queue.C + Queue.G + Queue.cost;
        Queue.Insert(Total(nv))
    end
    if Total(nv) >
     Queue.C(pv)+StepSize+Queue.G(nv)+
     Queue.cost(nv) then
        C(nv) = C(pv) + StepSize;
        Queue.C ← C(nv);
        Queue.G ← norm(nv, Goal);
        Queue.cost ← CostMap(nv);
        Total(nv)
          ← Queue.C + Queue.G + Queue.cost;
        Queue.Insert(Total(nv));
    end
    return FAILURE;
end
```

VI. Result

Comparing the results obtained for cost-map generation time with the reference paper [4] as shown in table 1, the time taken for generation is 42% lesser. This is a direct result of reducing the number of iterations and also considering points that are mutually exclusive with critical structures, thus further reducing the number of nodes that needs to be measured against the critical structures to be assigned new cost values.

In phase 2, A* algorithm has been applied for cases of tumor on both hippocampi regions. The user is given a choice of selecting the target region, left or right hippocampus, and a cost-map is generated for the corresponding brain region of interest, including critical and non critical structures. After the cost and reward map for tumor region is generated, the user is given flexibility to choose step size and angular resolution for neurosurgical tool. Based on user inputs, the algorithm performs the search for the points in the region of interest and plans a safe trajectory path for reaching tumor mean point or the goal is found as shown in figures 6 & 7. Presented are the results obtained for specific values of angular resolution, maximum angle and step size, considering left hippocampus to be the affected region. Figure 8 shows a 2 dimensional representation of the surgical tool (shown as black dot) at a safe distance from the critical regions.

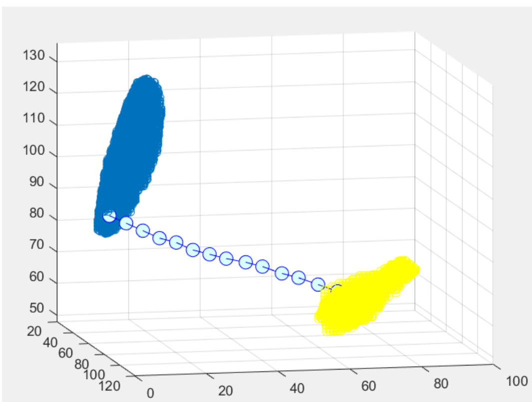

Fig. 6. Path generated for step size 5 and angular resolution 1

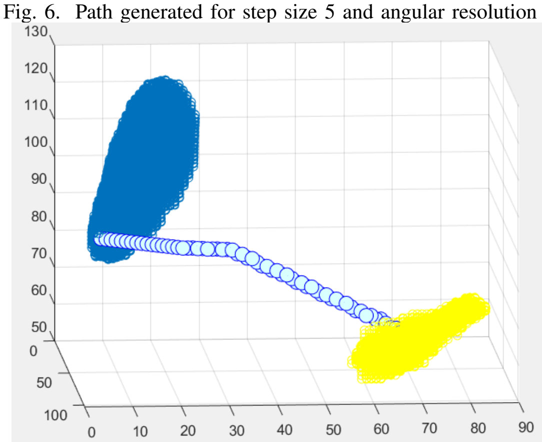

Fig. 7. Path generated for step size 1 and angular resolution 1

TABLE II
RESULTS FOR ANGULAR RESOLUTION 1 DEG AND MAX ANGLE 5°

Parameters	Step size = 1	Step size = 5
Execution Time (secs)	134s	135s
Alpha Angle	-3°	-2°
Beta Angle	2°	-5°
No. of Backtrack points	61	14
No. of Visited points	63	26
Space explored	1.29%	0.533%

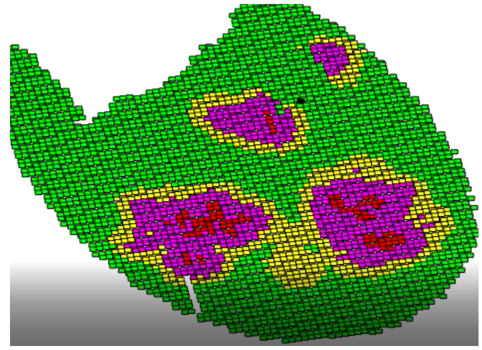

Fig. 8. A cross sectional view of the cost-map with the surgical tool (shown as black dot)

TABLE III
RESULTS FOR ANGULAR RESOLUTION 10 DEG AND MAX ANGLE 30°

Parameters	Step Size = 1	Step Size = 5
Execution Time (secs)	134s	135s
Start Alpha Angle	-30°	10°
Start Beta Angle	20°	0°
No. of Backtrack points	61	14
No. of Explored points	68	16
Space explored	1.395%	0.328%

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