Planning Nonlinear Access Paths for Temporal Bone Surgery

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Abstract

Purpose: Interventions at the otobasis operate in the narrow region of the temporal bone where several highly sensitive organs define obstacles with minimal clearance for surgical instruments. Nonlinear trajectories for potential minimally-invasive interventions can provide larger distances to risk structures and optimized orientations of surgical instruments, thus improving clinical outcomes when compared to existing linear approaches. In this paper, we present fast and accurate planning methods for such nonlinear access paths.

Methods: We define a specific motion planning problem in $SE(3) = \mathbb{R}^3 \times SO(3)$ with notable constraints in computation time and goal pose that reflect the requirements of temporal bone surgery. We then present $\kappa$-RRT-Connect: two suitable motion planners based on bidirectional Rapidly-exploring Random Trees (RRT) to solve this problem efficiently.

Results: The benefits of $\kappa$-RRT-Connect are demonstrated on real CT data of patients. Their general performance is shown on a large set of realistic synthetic anatomies. We also show that these new algorithms outperform state of the art methods based on circular arcs or Bézier-Splines when applied to this specific problem.

Conclusion: With this work we demonstrate that pre- and intra-operative planning of nonlinear access paths is possible for minimally-invasive surgeries at the otobasis.

Keywords minimally invasive · temporal bone surgery · statistical shape models · nonholonomic motion planning · curvature constraint · RRT

1 Introduction

In the last decades more and more minimally invasive procedures are introduced in the clinical work place [2]. At the otobasis, the focus of research has been the drilling of either a single [12, 20] or multiple [25] linear access paths through the temporal bone to the cochlea and initial reports on clinical studies have been presented [17, 4]. In such interventions...
several obstacles or risk structures, e.g. the facial nerve and its small branch (Fig. 1 yellow objects), severely limit the space that is available for drilling.

Unlike these linear approaches, nonlinear drilling provides several potential advantages: larger distances to risk structures, correcting misalignments while drilling, and optimization of orientation at the goal point (e.g. for the insertion of the electrode during a cochlear implantation or for instrument alignment). Yet, nonlinear planning at the otobasis is difficult to deploy due to the limited space and time constraints on intra-interventional planning. To the best of our knowledge, such an approach has never been investigated. In this paper, we consider the use of a curvature constrained drilling unit and propose two new RRT-Connect [18] algorithms to quickly (re-)compute feasible access paths for said robot: once at the beginning of the intervention and regularly in between if navigation errors occur (Fig. 1).

![Fig. 1](image)

In recent years, significant progress has been made in the development of continuum robots and instruments for minimally invasive medical applications [3]. Many of these can be categorized as "curvature constrained objects". These include, for example, steerable needles [7, 6] for interventions in soft tissue [21, 8] or flexible endoscopes [10]. If such underactuated systems are used, where instrument steering is limited to certain directions, nonholonomic motion planning based on the Rapidly-Exploring Random Tree [18, 1] or even optimal randomized motion planners [15, 11] are used to plan feasible trajectories around obstacles for the underlying instrument.

In medical applications the main focus mainly lies on steerable needles where planning is done with variants of the RRT. These methods consider, for example, special distance functions [21] or the reachable set of the nearest states [24]. Other methods speed up the convergence via potential fields [29] or utilize heavy parallelization [19].

The planning of trajectories for (unmanned) aerial vehicles such as drones or missiles also requires curvature constrained motion planning. Here, the development of an analytical solution of the 3D Dubins Problem [14] lead to an RRT*-solver [22] in the case that start and goal regions are sufficiently far away. Moreover, Yang et al. [28, 27] presented an RRT* with Bézier splines as local planning technique.

However, curvature constrained motion planning for temporal bone surgery requires fast and precise algorithms with start and goal regions in $SE(3)$ within a small and dense environment. Although we were able to show the general feasibility of such trajectories within the otobasis [9], a reliable method does not yet exist.
The main contribution in this paper is then twofold: First of all, we present two RRT-Connect algorithms which achieve fast path planning for nonlinear temporal bone surgery. Secondly we address a novel evaluation strategy in case of limited annotated data sets: The robustness of such planners is shown on synthetic anatomies based on statistical shape models from real CT patient data.

2 Objective

Minimally-invasive procedures require a planning step that computes feasible trajectories while respecting potential constraints such as clearance to organs or instrument mobility. After the computation of a set of solutions these are then optimized according to a cost function or other optimization strategies [25, 13].

In motion planning relevant parameters are usually expressed in a specific Problem Formulation [18]. In this section we describe the details for temporal bone surgery and how they are incorporated in the following Formulation:

Problem Formulation For Temporal Bone Surgery

1. Let \( O \subset SE(3) = \mathbb{R}^3 \times SO(3) \) be the obstacle region, defined by the location of several risk structures \( \mathcal{R} \subset \mathbb{R}^3, 0 \leq i \leq N \). I.e. \( O := \{ q = (x,h) \in SE(3) \mid \exists i, 0 \leq i \leq N : x \in \mathcal{R}_i \} \). Let \( C_{free} = \{ q \in SE(3) \mid q \notin O \} \) be the free space of the configuration space.

2. Let \( C_I \subset C_{free} \) be the initial region.

3. Let \( M_G \subset C_{free} \) be a set of states. The goal region \( C_G \) is then defined as

\[
C_G \equiv C_G(\epsilon_G, \phi_G) = \{ q(x,h) \in SE(3) \mid \|x - y\|_3 < \epsilon_G, \rho(h,g) < \phi_G, \text{for a } \hat{q}(y,g) \in M_G \},
\]

where \( \rho \) is defined as in Equation [1] and

(i) \( \epsilon_G \in \mathbb{R}^+ \) is the maximally allowed Euclidean distance and

(ii) \( \phi_G \in [0, \pi] \) is the maximally allowed angular difference at a specific goal state.

4. Let \( d_{max} \in \mathbb{R}^0^+ \) be the safety distance to risk structures. Let \( r_d \in \mathbb{R}^+ \) be the radius and \( \kappa_{max} \in \mathbb{R}^+ \) the maximum curvature constraint of the drilling robot.

5. Let \( T_{max} \in \mathbb{R}^+ \) be the maximum time constraint available for planning.

6. Task: Find a path \( \gamma(t) : [0, 1] \to SE(3) \) satisfying

(i) \( \gamma(0) \in C_I \)

(ii) \( \gamma(1) \in C_G \)

(iii) \( \forall t \in [0, 1] : \|\dot{\gamma}(t)\| < \kappa_{max} \)

(iv) \( \forall t \in [0, 1], o \in C : \|\gamma(t) - o\|_3 > r_d + d_{max} \)

or report that no path could be found in the available time \( T_{max} \).

**Item 1** of this Problem Formulation introduces obstacles in \( \mathbb{R}^3 \) (e.g. the facial nerve) that have to be circumnavigated, as well as the free space, which defines potential positions the drilling unit can occupy. **Item 2** corresponds to potential positions at the skull’s surface that serve as entry points of instruments, whereas **Item 3** defines a spherical volume in \( \mathbb{R}^3 \) as the intervention’s target together with a threshold \( \phi_G \) that limits the potential orientation within this target volume. The orientation between two configurations is compared in the quaternion metric (see e.g. [18])

\[
\rho(h_1, h_2) = \min \{ \rho_3(h_1, h_2), \rho_4(h_1, -h_2) \}
\]

\[
\rho_3(h_1, h_2) = \cos^{-1}(a_1a_2 + b_1b_2 + c_1c_2 + d_1d_2).
\]
In this paper, we consider the use of a prototype robot (Fig. 2) currently under development for the creation of nonlinear access paths. If we consider the z-Axis in the local coordinate frame of the model as the robot’s line of view, we want to match its pose with the ones at start and goal states: Initial states should be close to the skull’s surface normal in order to minimize deviation from the desired trajectory due to forces applied during drilling. For a cochlear implantation, for example, goal states at the round window would represent the optimal insertion angle. Here, work has been done to limit the deviation from the optimum to less than 5° [26].

The robot’s limitations are then included via Item 4: The radius of the drill bit and an additional safety distance to account for navigation errors or heat generation are combined to a distance constraint. Additionally, the maximum turning angle of the prototype results in a curvature constraint. Item 5: Potential misalignments during navigation require an intra-interventional replanning step to either provide a new corrected trajectory or stop the drilling. Therefore, an algorithm has to be fast enough to provide a smooth intervention. Item 6: A motion planning algorithm for this procedure will then try to find a feasible path in the available time which would result in a trajectory connecting both a start and a goal state (i, ii), observing a maximally allowed curvature (iii) and last, a necessary distance to risk structures (iv).

Note 1: This formulation remains valid in the case of replanning where the initial region $C_I$ of Item 2 will be set to the current pose of the robot.

Note 2: This formulation extends the problem of trajectory planning in soft tissue for bevel-tip needles, where alignment of instruments [23] and regular fast replanning [21] is needed, by introducing constraints on both start and goal orientations. We expect our planners to be useful for this kind of application as well.

3 Methods

The main difficulty of this problem is the fast and precise matching of the goal’s pose. An intuitive way to address this problem is to use an RRT-Connect algorithm [16]. This method, unlike basic RRTs, grows search trees from both the goal and the initial region in an attempt to connect these two. With this strategy more possible connections are available than just those between search tree and goal regions. Thus, successfully finding an access path is more likely. The general RRT-Connect can be described as follows (Algorithm 1):

Two trees $T_I, T_G$ are initialized with states of the initial and the goal region, respectively. Both trees are iteratively extended until either the maximally allowed time $T_{\text{max}}$ is reached
or the graphs are connected successfully. In each iteration the two search trees take turn in the following procedure: A random state is drawn from the free space $C_{free}$. Then, the nearest neighbors to the current tree are computed according to a previously defined distance function. For each of these configurations the local steering function computes an expansion towards the random state. If no collision with obstacles occurs along this path the state is added to the tree. Last, the algorithm tries to connect both trees according to the state space’s constraints (in our case the path needs to be twice times continuously differentiable). If both trees are connected within the given time threshold $T_{max}$ the resulting path is returned. Otherwise, failure is reported.

**Algorithm 1 $\kappa$-RRT-Connect**

1: $T_I$ ← initial states
2: $T_G$ ← goal states
3: while time spend() < $T_{max}$ and not connected($T_I$, $T_G$) do
4: $q_{rand}$ ← sample state($C_{free}$)
5: $T$ ← alternate($T_I$, $T_G$)
6: $\{q\}_k$ ← $k$ nearest neighbors($T$, $q_{rand}$)
7: for all $q_{near}$ in $\{q\}_k$ do
8: $q_{next}$ ← steer($q_{near}$, $q_{rand}$, $\Delta t$)
9: if collision free($q_{near}$, $q_{next}$) then
10: extend tree($T$, $q_{near}$, $q_{next}$)
11: end for
12: attempt connection($T_I$, $T_G$)
13: end while

In the following, we shortly recall two local steering methods, one based on circular arcs of varying curvature and one based on Bézier-Splines. We then present two individual solutions that extend these planners to RRT-Connect versions.

**Bevel-Tip-RRT & $\kappa$-B-RRT-Connect:** We use the local steering function developed for Bevel-Tip needles presented in [21] to create access paths of variable curvature. This method extends the search tree along circular arcs of variable radii. The RRT-Connect version uses Dubins Paths in 3D to connect the search trees as, unlike circular arcs, this is a technique to connect states in $SE(3)$.

**Spline-Based-RRT & $\kappa$-SB-RRT-Connect:** The second RRT utilizes cubic Bézier-Splines to interpolate in $SE(3)$, resulting in an approximation of states in the search tree and a two times continuously-differentiable trajectory [28]. Here, the local steering method can be used naturally to attempt a connection.

The individual steps in Algorithm 1 (lines 4,6,8,12) are then as follows:

**sample state:** Sampling in $SE(3)$ would require solving a two point boundary value problem, i.e. matching both location and orientation at the random state. This is not possible with either steering function. Instead, a state is merely sampled in $\mathbb{R}^3$ and the direction is implicitly defined according to the respective method.

**k_nearest_neighbors:** The nearest neighbor function and its underlying metric have significant impact on the time efficiency and the theoretical properties of the algorithm. For curvature constrained instruments the Euclidean metric does not represent a good approximation on the actual distance. On the other hand, the computation of a more complex metric like the reachable set of a particular state [24] can be very time consuming. As the main interest in this application lies in the fast computation of a feasible path, we return the k-nearest
neighbors in terms of the efficiently computable metric
\[ d(q_1(x, h_1), q_2(y, h_2)) : SE(3) \times SE(3) \rightarrow \mathbb{R}^3 := \|x - y\|_R^3 + \rho(h_1, h_2) \]

steer: \( \kappa\)-B-RRT-Connect propagates the search along states on circular arcs. The local planner of \( \kappa\)-SB-RRT-Connect uses a spline consisting of two Bézier-Spirals to expand the search tree. We refer to the original papers \([21]\) and \([28]\) for a detailed description.

attempt_connection: The original RRT-Connect does not address nonholonomic planning and considers the trees connected if both trees meet at the random sample. This approach would result in a discontinuous orientation at the connecting state as we sample only in \( \mathbb{R}^3 \) and do not enforce a specific orientation. Instead, a two point boundary value problem has to be solved in our approach to match both position and orientation:

First, we search for a state of the other tree in the vicinity of \( q_{next} \). Specifically, we check if a state lies within a cone that apex and direction is described by the location and orientation of \( q_{next} \). If such a state is found, we try to connect these two:

The \( \kappa\)-B-RRT-Connect algorithm connects two corresponding states by solving the 3D Dubins problem with the geometric approach presented in \([14]\). A similar method is used in \([22]\). Both papers address the computational complexity of their approach. However, our c++ implementation requires on average only 45 microseconds to solve the underlying nonlinear system of equations which makes it suitable for fast computation.

The \( \kappa\)-SB-RRT-Connect algorithm iteratively uses the local steering function to steer from \( q_{next} \) to its counterpart and vice versa. This procedure is repeated until either the interpolation criterion of the Bézier-Spline is satisfied during an iteration or the states missed each other and thus no connection was possible.

4 Scenarios for the Temporal Bone

We address three typical medical interventions for the experiments to show the general suitability for temporal bone surgery (Fig. 3): one access to the cochlea via the facial recess (Cochlea-Access) and two accesses to the internal auditory canal: through the superior semicircular canal (SSC-Access) and via the retro-labyrinthine region (RL-Access). Parameters for each Problem Formulation (see Section 2) are listed in Table 1. The curvature constraint reflects our current robot prototype. We tested with higher values of \( r_d \) and \( d_{max} \) for the RL- and SSC-Access as there is usually more space between obstacles. The time and orientation constraints were chosen according to real applications \([23, 26]\).

The risk structures, i.e. organs in the vicinity of access paths that must not be harmed, were extracted from real CT data of patients. To this purpose, our clinical partners manually
Table 1 Parameters for the Problem Formulations (see section 2) of the three access paths.

| Access Path       | κ_{max} | ε | θ_{L} (deg) | d_{max} (mm) | r_{d} (mm) | T_{max} (s) |
|-------------------|---------|---|-------------|--------------|------------|-------------|
| Cochlea-Access    | 0.05    | 1.0| 5           | 0.3          | 0.5        | 0.5         |
| SSC-Access        | 0.05    | 1.0| 5           | 0.5          | 1.0        | 0.5         |
| RL-Access         | 0.05    | 1.0| 5           | 1.0          | 1.0        | 0.5         |

segmented the internal carotid artery and jugular vein bulb, facial nerve and chorda tympani, cochlea, ossicles and labyrinth as well as the internal and external auditory canal in 40 high quality, but typical routine CT scans of the human temporal bone (Siemens Somatom, average resolution 0.18 × 0.18 × 0.4 mm³).

The manual assembly of such real scenarios is a necessary but extremely laborious and time consuming task. However, a statistical analysis of the motion planner’s performance requires a much larger number of samples than this manual procedure can provide. Consequently, we divided the experiments into two setups:

**Real Anatomies:** For the first 22 data sets we also segmented the brain and the skull’s surface. In the resulting 3D environment, entry and target positions of potential interventions were manually placed in each individual data set with the help of a custom planning tool to provide samples on real patients (Fig. 3 A).

**Synthetic Anatomies:** First, we created statistical shape models of the manually segmented risk structures of the otobasis in all 40 data sets. Then, we generated 100 synthetic anatomies based on the real ones. For each new synthetic anatomy, one of the real anatomies was chosen randomly to serve as an atlas, including its risk structures and its goal regions of the three potential interventions. A variation of the statistical shape models was then registered to the atlas to replace each original structure with an altered variant (Fig. 3 B).

5 Experiments

In the following, we describe in detail the setup of real and synthetic anatomies as well as the parameters of our motion planners.

**Real Anatomies:** In each data set and for each of the three applications (RL-, SSC-, Cochlea-Access) we placed one state within the temporal bone and one state on the skull’s surface to define the regions C_I and C_G of the Problem Formulations. Start states were positioned at the bottom of the internal auditory canal, at its top and next to the round window for the RL-, SSC- and Cochlea-Access, respectively. This resembles a potential position of an acoustic neuroma (RL-, SSC-Access) or the entry point of the electrode in a cochlear implant (Cochlea-Access). The directions at these start states were defined as a compromise between the respective organ’s normal at this position and a direction towards the skull’s surface. Last, three states were placed on the skull with orientations approximately orthogonal to its surface which serve as goal states for the individual access paths.

**Synthetic Anatomies:** For each new synthetic anatomy, random variations of the individual statistical shape models’ modes were computed by sampling the corresponding eigenvalues between ±1.0 times of their standard deviation. The resulting model was then registered with the reference atlas. For the respective goal states we used the ones in the atlas. The start states required a new strategy for positioning, as their original pose in the atlas might be invalid. Thus, new start states were placed above/below the center of mass of the internal auditory canal (SSC-/RL-Access) and below the center of mass of the cochlea (Cochlea-Access). For orientation, individual reference points P_{ref} ∈ R³ were computed: For the RL-
Access slightly inferior to the lower side of the bounding box of the facial nerve; for the SSC-Access above the center of mass of the semicircular canals and for the Cochlea-Access in the center of mass of the chorda tympani. The start states were then oriented so that the z-axis of the local coordinate frame points to the respective reference point.

**Motion Planning:** In both setups we let each of the four planners of Section 3 calculate as many paths as possible within 20 seconds for all three applications. We used the number of found paths to quantify the performance of each planner. In order to compare the quality of paths computed by each planner, we measured for each trajectory both the deviation at the goal state and the minimal distance to risk structures.

For goal biasing we chose a value of 25%. The attempt_connection method of κ-RRT-Connect was most successful with parameters $h = 5.0 \text{ mm}$ and $\alpha = 20^\circ$ for height and angle of the cone. A kd-Tree was used for collision checking between states and obstacles. All experiments were performed on a system with an Intel Core i5-6500 CPU @ 3.20 GHz and 32.0 GB RAM.

### 6 Results

We start with analyzing the motion planners’ results on real anatomies. Then, we discuss their generalization on synthetic data.

**Real Anatomies:** First, we look at the number of paths found in a specific time to ensure a planner is fast enough for intra-operative replanning [21]. Figure 4 and Table 2 show the statistical distributions: For both the Cochlea- and the SSC-Access our RRT-Connect algorithms clearly outperformed standard RRT planners. In the case of the RL-Access the Spline-Based-RRT showed similar performance but none of the three algorithms really stands out. The number of paths found per second and the low number of failures indicate that κ-RRT-Connects work very well for the first two access canals and we can expect that successful intra-operative planning can be performed in minimal time. In contrast, the search through the retro-labyrinthine region was unsuccessful for almost half of the anatomies. This is, however, not unexpected because the risk structures vary highly between patients: in case of a narrow passage between facial nerve and chorda tympani, a small semicircular canal or a high reaching bulb of the jugular vein, the creation of a feasible access path was impossible. Indeed, a careful inspection showed that in the 6 cases algorithm C failed, a high reaching jugular vein bulb made a trajectory of the requested size completely impossible. The discrepancy between the first two problem formulations and the latter is also due the nature of...
Table 2 Performance of each planner for the real anatomies. Measured in median number of paths (#), median number of paths per second (#/s) and percentage of failed scenarios (F).

| Planner Type | Cochlea-Access | SSC-Access | RL-Access |
|--------------|----------------|------------|-----------|
|              | #   | #/s | F(%) | #   | #/s | F(%) | #   | #/s | F(%) |
| Bevel-Tip (A)| 0   | 0   | 80   | 1   | 0.05 | 50   | 0   | 0   | 75   |
| Bevel-Tip-Connect (B) | 2635  | 131.75 | 5 | 760  | 38   | 0 | 4 | 0.2 | 45 |
| Spline-Based (C) | 17  | 0.85 | 5 | 14  | 0.7 | 5 | 9 | 0.45 | 25 |
| Spline-Based-Connect (D) | 2031  | 101.55 | 0 | 442  | 22.1 | 0 | 17 | 0.85 | 40 |

relevant obstacles in the respective area. In the first two cases a bottleneck had to be passed (two nerves / the SSC), whereas for the RL-Access the facial nerve and the jugular vein had to be circumnavigated.

Now we look at the matching of the goal’s pose. Naturally, RRT-Connect algorithms matched the orientation of goal states perfectly, whereas the RRTs were limited to an approximation (Fig. 5). We also note, that in all three cases both Bevel-Tip-RRT and Spline-Based-RRT tended to accomplish the maximal allowed deviation rather than a perfect match.

Next, we focus on the minimal distance an access path had to risk structures as this is usually the most relevant metric to clinicians. To this purpose, we interpolated between the states of the search tree at a resolution of 0.1 mm. For each of those interpolated states, we then sampled points on a circle with radius $r_d$ and orthogonal to the state’s direction and computed the minimal distance to the next obstacle. Figure 6 shows in small images the narrowest region that had to be passed together with three statistics for each planner across all 22 anatomies: the percentage how often it computed the best path for a specific anatomy (Best), the mean minimal distance its best path had to risk structures (Mean) and the overall best path it computed across all anatomies (Max). Clear superiority of a specific algorithm was not observable although the Spline-Based-RRT tended to find paths with the largest distance more often. Hence, our new $\kappa$-RRT-Connect did not suffer from lower quality. From the observed distances we also got an impression of the average size of the passed bottleneck. This can help in the design for the robot prototype. According to Table 2, for example, $\kappa$-RRT-Connect always found trajectories for an SSC-Acces with the specifications in Table 1 having on average still a minimal distance above 1.0 mm to the nearest obstacle.

Last we address the issue that in many scenarios the Spline-Based-RRT found paths with the highest minimal distance. A closer inspection showed that the $\kappa$-RRT-Connect just quickly found a solution as soon as the relevant obstacle had been passed. When we enlarged the allowed safety distance, the $\kappa$-RRT-Connect computed paths with similar minimal dis-
Fig. 6 Close-Up of the narrowest region of each access canal. The corresponding table shows the mean and max distance of each planner over all real anatomies together with the percentage of how often each planner found the best path according to the maximum distance.

Fig. 7 RL-Access planned by a standard RRT (pink tube) with safety distance 1.0 mm and by a $\kappa$-RRT-Connect (green, orange) with safety distances 1.0 mm and 1.5 mm, respectively.

7 Conclusion

In this paper, we address a minimally-invasive procedure with demands on fast computation and high precision of both initial and goal pose. We present two suitable RRT-Connect motion planners, one based on Bézier-Splines, the other on circular arcs and 3D Dubins Paths, which quickly compute feasible curvature constrained access paths for the proposed interventions. The efficiency of these planners is shown in real CT data of patients as well as
Fig. 8  Box-Plots about the success rates of the planners in 100 synthetic anatomies (higher=better).

Table 3  Measured in median number of paths (#), median number of paths per second (#/s) and percentage of failed scenarios (F).

|               | Cochlea-Access |               | SSC-Access |               | RL-Access |
|---------------|---------------|---------------|------------|---------------|-----------|
|               | #  | #/s | F (%) | #  | #/s | F (%) | #  | #/s | F (%) |
| Bevel-Tip (A) | 0  | 0   | 80   | 0  | 0   | 57   | 0  | 0   | 66   |
| Bevel-Tip-Connect (B) | 208 | 10.4 | 0    | 398 | 19.9 | 12   | 27 | 1.35 | 37   |
| Spline-Based (C) | 15 | 0.75 | 7    | 14  | 0.7  | 7    | 15 | 0.75 | 26   |
| Spline-Based-Connect (D) | 762 | 38.1 | 0    | 1144 | 57.2 | 0    | 273 | 13.65 | 30   |

Fig. 9 Close-Up of the narrowest region of each access canal. The corresponding table shows the mean and max distance of each planner over all synthetic anatomies together with the percentage of how often each planner found the best path according to the maximum distance.

on randomized anatomies created from variations of statistical shape models. These tailored RRT-Connect algorithms outperform state of the art one-directional planners and provide a reliable and fast method for planning access paths in temporal bone surgery.

In the future we want to improve the approach for both methods with an optimization of planned paths regarding larger distances to risk structures or more advanced metrics. We also expect that an improvement of the connection method of our RRT-Connects will result in better performances for difficult cases like passing the retro-labyrinthine region. Moreover, we would like to investigate the applicability of these general purpose planners for other medical interventions such as needle insertion in soft tissue [23] or flexible endoscopes [10]. We believe such precise nonlinear planning procedures are expected to be instrumental in improving interventions and advancing patient safety at operating rooms of the future.

Compliance with Ethical Standards

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Research involving Human Participants and/or Animals: This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent: This article is partially based on anonymized patient data.
Fig. 10  Box-Plots about the deviation at the goal for 100 random synthetic anatomies (lower=better).

References

1. Alterowitz R, Goldberg K (2008) Motion Planning in Medicine: Optimization and Simulation Algorithms for Image-Guided Procedures. Springer
2. Beasley RA (2012) Medical Robots: Current Systems and Research Directions. Journal of Robotics 2012:14
3. Burgner-Kahrs J, Rucker DC, Choset H (2015) Continuum robots for medical applications: A survey. IEEE Transactions on Robotics 31(6):1261–1280
4. Caversaccio M, Gavaghan K, Wimmer W, Williamson T, Anso J, Mantokoudis G, Gerber N, Rathgeb C, Feldmann A, Wagner F, Scheidegger O (2017) Robotic cochlear implantation: surgical procedure and first clinical experience. Acta Oto-Laryngologica 137(4):447–454
5. Cootes T, Taylor C, Cooper D, Graham J (1995) Active shape models-their training and application. Computer Vision and Image Understanding 61(1):38 – 59
6. Cowan NJ, Goldberg K, Chirikjian GS, Fichtinger G, Alterovitz R, Reed KB, Kallem V, Park W, Misra S, Okamura AM (2011) Robotic needle steering: Design, modeling, planning, and image guidance. In: Surgical Robotics: Systems App. and Vis., Springer US, Boston, MA, pp 557–582
7. Duindam V, Alterovitz R, Sastry S, Goldberg K (2008) Skrew-based motion planning for bevel-tip flexible needles in 3D environments with obstacles. In: IEEE Int. Conf. on Rob. a. Autom., pp 2483–2488
8. Engh JA, Podnar G, Khoo SY, Riviere CN (2006) Flexible needle steering system for percutaneous access to deep zones of the brain. In: Proc. of IEEE 32nd Ann. Northeast Bioeng. Conf., pp 103–104
9. Fauser J, Stenin I, Kristin J, Klenzner T, Schipper J, Sakas G (2016) A software tool for planning and evaluation of non-linear trajectories for minimally invasive lateral skull base surgery. In: Tagungsb. der 15. Jahrestag. der Dtsch. Ges. f. Comput.- und Roboterasch. Chirurgie e.V. (CURAC), pp 125–126
10. Fichera L, Dillon NP, Zhang D, Godage IS, Siebold MA, Hartley BL, Noble JH, Russell PT, Labadie RF, Webster RJ (2017) Through the eustachian tube and beyond: A new miniature robotic endoscope to see into the middle ear. IEEE Rob and Autom Letters 2(3):1488–1494
11. Gammell JD, Srinivasa SS, Barfoot TD (2014) BIT*: Batch informed trees for optimal sampling-based planning via dynamic programming on implicit random geometric graphs. CoRR abs/1405.5848, URL http://arxiv.org/abs/1405.5848
12. Gerber N, Bell B, Gavaghan K, Weisstanner C, Caversaccio M, Weber S (2014) Surgical planning tool for robotically assisted hearing aid implantation. International Journal of
13. Hamze N, Collet P, Essert C (2017) Evolutionary approaches for surgical path planning: A quantitative study on deep brain stimulation. In: 2017 IEEE Congress on Evolutionary Computation (CEC), pp 1087–1094
14. Hota S, Ghose D (2010) Optimal geometrical path in 3D with curvature constraint. In: 2010 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp 113–118
15. Karaman S, Frazzoli E (2011) Sampling-based algorithms for optimal motion planning. The International Journal of Robotics Research 30(7):846–894
16. Kuffner JJ, LaValle SM (2000) RRT-connect: An efficient approach to single-query path planning. In: Proceedings 2000 ICRA. Millennium Conference. IEEE Int. Conf. on Rob. and Autom. Symposia Proc. (Cat. No.00CH37065), vol 2, pp 995–1001 vol.2
17. Labadie RF, Balachandran R, Noble JH, Blachon GS, Mitchell JE, Reda FA, Dawant BM, Fitzpatrick JM (2014) Minimally invasive image-guided cochlear implantation surgery: First report of clinical implementation. The Laryngoscope 124(8):1915–1922
18. LaValle SM (2006) Planning Algorithms. Cambridge University Press
19. Liu F, Garriga-Casanovas A, Secoli R, y Baena FR (2016) Fast and adaptive fractal tree-based path planning for programmable bevel tip steerable needles. IEEE Robotics and Automation Letters 1(2):601–608
20. Noble JH, Majdani O, Labadie RF, Dawant B, Fitzpatrick JM (2010) Automatic determination of optimal linear drilling trajectories for cochlear access accounting for drill positioning error. Int J Med Robot 6(3):281–290
21. Patil S, Burgner J, Webster RJ, Alterovitz R (2014) Needle steering in 3-d via rapid replanning. IEEE Transactions on Robotics 30(4):853–864
22. Pharpatara P, Hérissé B, Bestouyi Y (2017) 3-D trajectory planning of aerial vehicles using RRT*. IEEE Transactions on Control Systems Technology 25(3):1116–1123
23. Schulman J, Duan Y, Ho J, Lee A, Awwal I, Bradlow H, Pan J, Patil S, Goldberg K, Abbeel P (2014) Motion planning with sequential convex optimization and convex collision checking. The Int J of Rob Res 33(9):1251–1270
24. Shkolnik A, Walter M, Tedrake R (2009) Reachability-guided sampling for planning under differential constraints. In: 2009 IEEE Int. Conf. on Rob. a. Autom., pp 2859–2865
25. Stenin I, Hansen S, Becker M, Sakas G, Fellner D, Klenzner T, Schipper J (2014) Minimally invasive multi-port surgery of the lateral skull base. In: BioMed Research International, vol 2014, p 7
26. Torres R, Kazmitcheff G, De Seta D, Ferrary E, Sterkers O, Nguyen Y (2017) Improvement of the insertion axis for cochlear implantation with a robot-based system. European Archives of Oto-Rhino-Laryngology 274(2):715–721
27. Yang K, Gan SK, Huh J, Joo S (2014) Optimal spline-based RRT path planning using probabilistic map. In: 2014 14th Int. Conf. on Control, Autom. and Systems (ICCAS 2014), pp 643–646
28. Yang K, Moon S, Yoo S, Kang J, Doh NL, Kim HB, Joo S (2014) Spline-based RRT path planner for non-holonomic robots. Journal of Intelligent & Robotic Systems 73(1):763–782
29. Yang L, Qi J, Jiang Z, Song D, Han J, Xiao J (2014) Guiding attraction based random tree path planning under uncertainty: Dedicate for UAV. In: 2014 IEEE Int. Conf. on Mech. a. Autom., pp 1182–1187