

PAPER

Automatic Trajectory Planning from Preoperative MRI images Using the AI-Optimized RRT* Algorithm for Robotic Breast Ultrasound

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ABSTRACT

Ultrasound imaging is the most widely used technique for detecting and diagnosing breast cancer, as it provides real-time images in a non-invasive and inexpensive manner. However, performing ultrasound examinations requires experienced and well-trained operators either for probe manipulation during acquisition or during image interpretation, which makes this technique dependent. This dependency requires the employment of sonographers with extensive training and experience, which may limit access to this technique in remote areas and also expose experts to serious health issues due to repetitive movements. To overcome these difficulties, robotic ultrasound systems have emerged in recent years to enable conventional ultrasound examinations to be performed in an automated and standardized way. Our study contributes to this field through an integrated approach to automated planning of robotic breast ultrasound trajectories. This approach is based on the application of a developed version of the rapidly-exploring random tree (RRT) trajectory planning algorithm to pre-operational three-dimensional (3D) magnetic resonance imaging (MRI) images. We performed simulations with the three versions of the algorithm RRT, RRT* and RRT* with 30% reinforcement learning (RL) on two different patients. The results obtained demonstrate the potential of the RRT algorithm with 30% RL to obtain optimized trajectories with high fluidity and a short path while ensuring total and homogeneous coverage adapted to different complex breast morphologies.

KEYWORDS

Medical robotic, Rapidly-exploring random tree (RRT) algorithm, Path planning, Magnetic resonance imaging (MRI) images

1 INTRODUCTION

Ultrasound has become an essential diagnostic technique since the 1940s. Thanks to its ability to produce high-quality images in real time using a portable device that

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is easy to use and inexpensive [1], [2]. However, operators of conventional ultrasound devices are subject to considerable physical and mental stress. Since ultrasound examinations require experienced operators, this can affect image quality and yield [3]. Sonographers face significant risks of musculoskeletal disorders from repetitive motions and challenging ergonomic demands [4]. To overcome these challenges, automatic and semi-automatic systems have been developed for automated and precise guidance of probes in collaboration with remote-controlled robots. These technologies will initially reduce the workload of operators and improve access to care, while standardizing tests and minimizing direct contact, the results have already proven their usefulness during the COVID-19 pandemic, particularly in remote diagnosis [5].

In 80 medical studies, ultrasound has been shown to be effective not only in the diagnosis and screening of breast cancer, but also in the classification of benign and malignant pathologies with a high sensitivity of 97% and specificity of 98%. Ultrasound is more sensitive than mammography, and thanks to its reliability, safety and cost-effectiveness, its use in screening should be encouraged [6], [7].

Advances in robotics offer significant potential for interventional ultrasound imaging. Hennersperger et al. [8], [9] proposed a robotic system for automated 3D-US acquisition that can improve the clinical workflow by ensuring stable and reproducible ultrasound views throughout an image-guided procedure. In current practice, the operator must hold the probe manually and mentally fuse the ultrasound images with planning data (computed tomography CT or magnetic resonance imaging MRI). A robotic system would automate this task, periodically acquire 3D-US volumes, and compensate for patient movement or respiration. After each 3D-US acquisition, the CT or MRI images used for planning can be automatically co-recorded with the new ultrasound data. This fusion facilitates controlled instrument progression and helps to precisely locate the target and identify areas of risk [10]. Among the existing methods for evaluating the quality of ultrasound images include predicting image quality based on prior knowledge of the target anatomy, usually obtained from patient tomographic data such as MRI and CT [11], [12], [13].

Robotic systems appear to exceed the limitations of conventional ultrasound in terms of accuracy and reliability, and also to facilitate the large-scale implementation of medical procedures such as screening programs. This approach offers truly interesting prospects for multiple ultrasound applications. It enables automatic identification of points of interest by facilitating probe positioning, targeted acquisition of predefined anatomical structures, assistance with patient positioning in radiotherapy, and even support for learning and development in robotic ultrasound. Thanks to the integration of robotics, probe positioning and acquisition protocols become reproducible and standardized. Thus, an automated 3D ultrasound acquisition system can minimize operator variability while reducing the human and material constraints of current clinical practices [14], [15].

Trajectory planning involves defining the position and orientation of the probe for autonomous robotic acquisitions. It is performed using preoperative MRI and CT scan images to target an anatomy or region of interest. However, these predefined trajectories remain relatively rigid, as they do not take into account real-time ultrasound information. This has led to the development of approaches that incorporate real-time adjustments in some cases, semi-autonomous strategies adapted to the tissue surface [16].

In some systems, the operator manually defines the scanning trajectory during the robot's learning phase, prior to acquisition. The problem is that this predefined

trajectory does not take into account real-time tissue information, which can make acquisition less flexible. To remedy this, we incorporate online adjustment of the probe, based on ultrasound feedback, in order to improve imaging results and make the whole process more efficient [17], [18].

To measure the contact force between the tissue surface and the probe, an automated ultrasound system is proposed that consists of a depth camera and force sensors. This system acquires depth data and color images of the tissue surface, from which it can reconstruct its 3D contour. An innovative trajectory planning method was then used to guide the probe. This makes it possible to scan and reconstruct a larger number of parts of the human body while preserving the actual shape of the tissue and allowing doctors to monitor the progress of the examination [19].

A predefined scanning path does not necessarily guarantee continuous contact with the probe, because involuntary patient movements or measurement errors can always occur. As a result, several studies have incorporated acoustic coupling force control strategies, but this alone is not sufficient to ensure high-quality imaging, as shown in references [20], [21]. In addition, force-based scanning can excessively deform tissue in softer breasts, while for stiffer tissue, image quality sometimes remains insufficient. As an alternative, visual servo approaches directly link the behavior of the end effector to characteristics extracted from ultrasound images.

Our study adds to this area by combining automated robotic breast ultrasound trajectory planning using preoperative MRI data with AI-enhanced RRT* path planning. The key goal is to boost safety, precision, and speed in guiding the robotic probe, all while steering clear of sensitive anatomical zones. Essentially, we're tackling the question: how can smart trajectory planning make robotic breast ultrasounds better through optimized, collision-free paths?

What makes this work stand out includes weaving MRI-derived anatomical details right into the planning, rolling out an AI-tuned RRT* algorithm for creating paths, and building a collision-detection system for safer probe handling. Overall, it promises smoother trajectories and more dependable results than traditional methods.

2 MATERIALS AND METHODS

This paper proposes a new trajectory generation system for robot-assisted ultrasound image acquisition. A standardized procedure was designed using MRI images, drawing inspiration from clinical ultrasound practices. The algorithm was optimized at various processing and analysis stages to obtain a more accurate and faster program. This new method leverages the unique characteristics of breast ultrasound images to enable autonomous acquisition.

2.1 Workflow

This work proposes an integrated approach for the automated planning of breast ultrasound exploration trajectories using a robot. From MRI images, a 3D model of the breast is reconstructed and then used in an interactive interface developed in Python. The trajectories are generated by the RRT* algorithm, ensuring homogeneous coverage adapted to the breast morphology. Finally, virtual simulation validates the efficiency of the process and its potential for clinical application.

Figure 1 illustrates the overall workflow of our autonomous robotic ultrasound acquisition process.

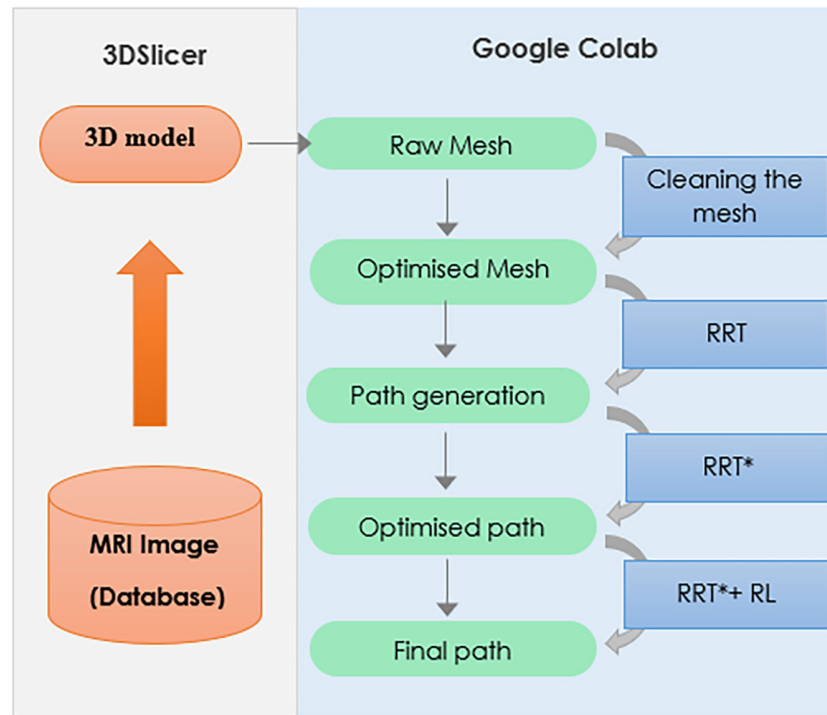


Fig. 1. Autonomous robotic ultrasound acquisition workflow

2.2 The MRI image database

This study is based on the Duke Breast Cancer MRI database, a public platform composed of annotated pre-intervention breast MRI images and clinical data from four patients from the file 1-001.dcm, used as a reference to develop and validate analysis algorithms [22].

2.3 3DSlicer software

3DSlicer is a widely used open-source software for visualizing and 3D modeling medical images (MRI, X-ray, ultrasound). In our project, it allows for the accurate reconstruction of breast morphology and the export of usable models for virtual reality simulation, thus facilitating the planning of ultrasound probe trajectories [23].

2.4 3D model construction

As illustrated in Figure 2, the construction of the 3D model constitutes the first step in our procedure. This phase converts the MRI images into a model called a mesh, ready for subsequent processing (.Obj files) to support complex applications, including robot trajectory planning with the RRT* algorithm and AI-driven systems.

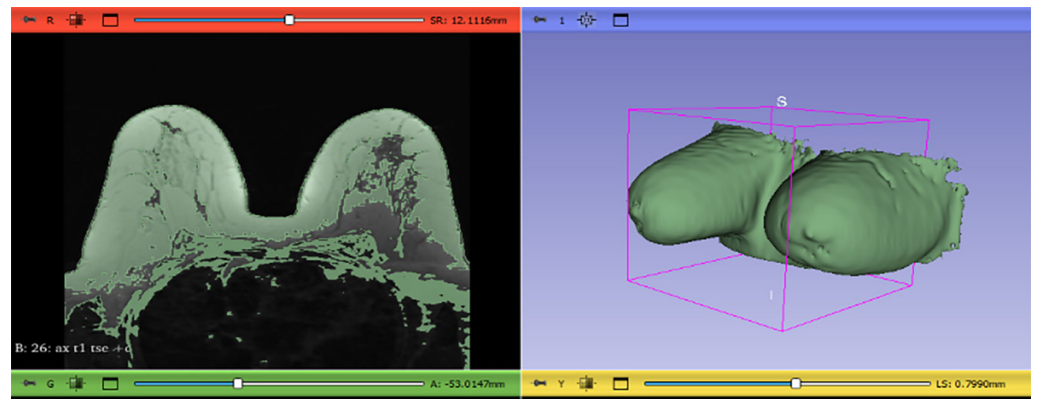


Fig. 2. Visualizing the 3D model using 3D Slicer

2.5 Google Colab

Google Collaboratory is an online platform that allows users to write and run Python code directly in a web browser without any local installation. It offers an interactive environment based on Jupyter and Notebook, and code, explanations, visualizations and results can be combined in a single document. It is widely adopted in areas such as artificial intelligence, image processing, machine learning and data science, especially for training deep learning models such as convolutional neural networks (CNNs). It also fosters collaboration among users through its integration with Google Drive [24].

2.6 Rapidly-exploring random tree, RRT* and AI-guided RRT* algorithms

The RRT, RRT*, and AI-guided RRT* algorithms have been implemented to generate optimal trajectories in an MRI-based context. In recent years, numerous variants have been proposed to improve the quality of the generated trajectories, particularly with RRT* [25], [26], and RRT* coupled with 30% RL. This paper presents an experimental comparison, based on simulations, of the performance of these three algorithms RRT, RRT*, and AI-guided RRT*, on fairly complex breast ultrasound images. The effectiveness of the three algorithms will be studied based on several performance evaluation parameters, and a discussion will be held on their limitations and potential for optimization.

The choice of RRT*. RRT* is an advanced version of the RRT algorithm designed to rapidly explore complex spaces such as the breast, and to generate the most optimal trajectory. During a breast ultrasound examination, the probe has to move over a complex three-dimensional surface while avoiding sensitive or difficult-to-access regions. RRT* is particularly well suited to this task because of its flexibility it can also adapt the scanning path in real time as obstacles are detected or new information becomes available. The adaptability of the RRT algorithm allows for the differences in patient anatomy between all patients. Instead of taking a predetermined, fixed route, RRT creates a continuously evolving path within the scan to provide safety, quality of imaging results, and comfort for the patient [27], [28].

Implemented Python-based AI algorithms. The primary contribution of our work lies in the integration of anatomical information derived from 3D MRI images into a planning strategy based on an RRT algorithm. We built this in Python

customizing it for robots that scan breasts with ultrasound. Unlike older methods, ours directly factors in the breast's shape and ultrasound limits to get better coverage and more reliable results. We even baked in a standard acquisition protocol inspired by clinical ultrasound practice to guide trajectory generation and ensure consistent probe positioning. The methodology of the RRT algorithm regarding trajectory planning from a 3D anatomical model is demonstrated in Figure 3.

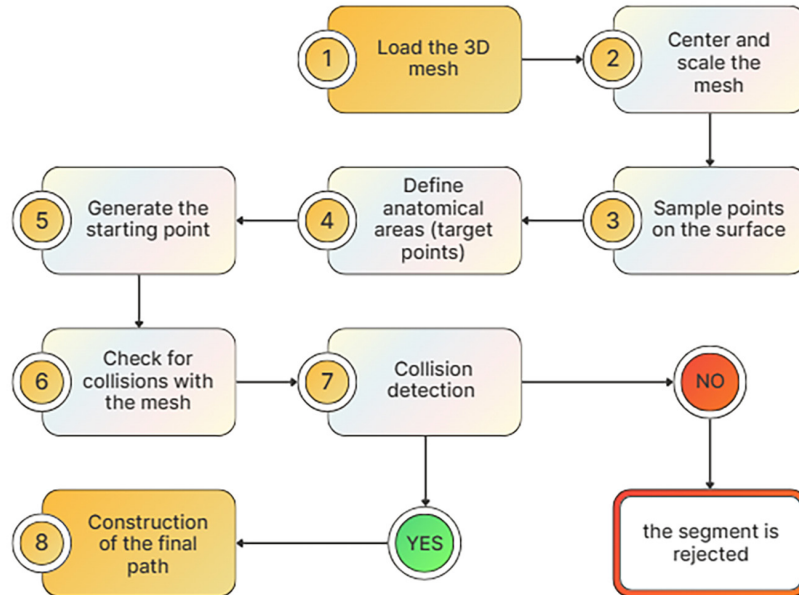


Fig. 3. Implementation of RRT-based algorithms for planning trajectories on a 3D anatomical model

The algorithm implemented is based on the concept of progressive development of a search tree: the points are selected randomly from the robot's configuration space, after which they are connected to their nearest neighbors using a step size method. In the proposed solution, the following values are set for important parameters: step size per iteration = 1.5, maximum iterations = 2,000, and threshold value = 2.5. Trajectories of the motion are checked for collisions using a corresponding detection procedure.

For improving trajectory quality, an improved RRT* algorithm that uses a cost function (with neighbor radius 3.0) has been used in this paper and as a consequence, shorter and better trajectories are obtained. Additionally, algorithm improvements have been made in sampling and validation phases to minimize the execution time without affecting accuracy.

Overall, this system is implemented using Python by making use of scientific packages such as NumPy, SciPy (KDTree), Trimesh, Matplotlib as well as general packages for flexibility and reproducibility purposes.

3 RESULTS AND DISCUSSIONS

In this section we compare the performance of three different algorithms: RRT, RRT*, and RRT*(30% RL). We will do so by using Google Colab as our simulation environment in order to run two sample patients through each method and get a reliable and appropriate result. The two sample patients chosen allowed for a better evaluation between methods since they both had different characteristics.

3.1 The paths obtained by the different RRT algorithms

First, RRT, RRT* and RRT* (30% RL) algorithms were used. They were also utilized in path planning.

To see how they build paths, we looked at the building of their trees. We also observed how this influenced the paths. The algorithms produced other smooth paths and the paths reached the target faster or had a shorter solution between the different scenarios. We also considered stable paths, paths towards the best solution, and the impact of environmental stability on paths. The paths created are depicted in Figures 4, 5, and 6.

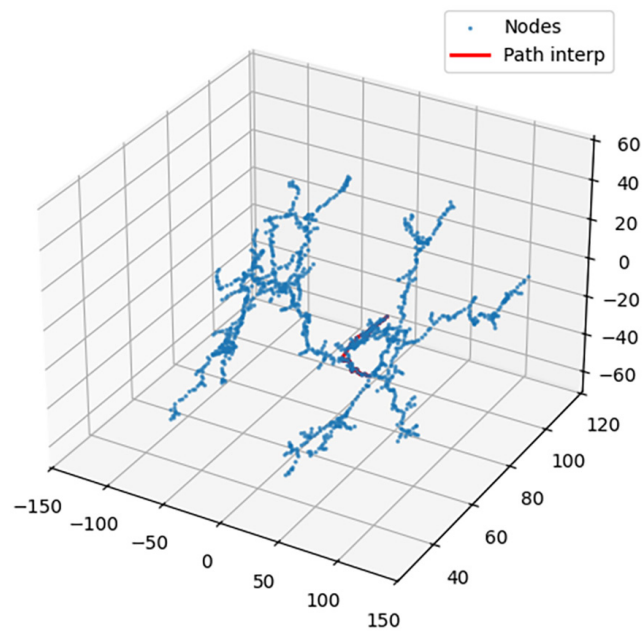


Fig. 4. Application of the RRT algorithm to the mesh

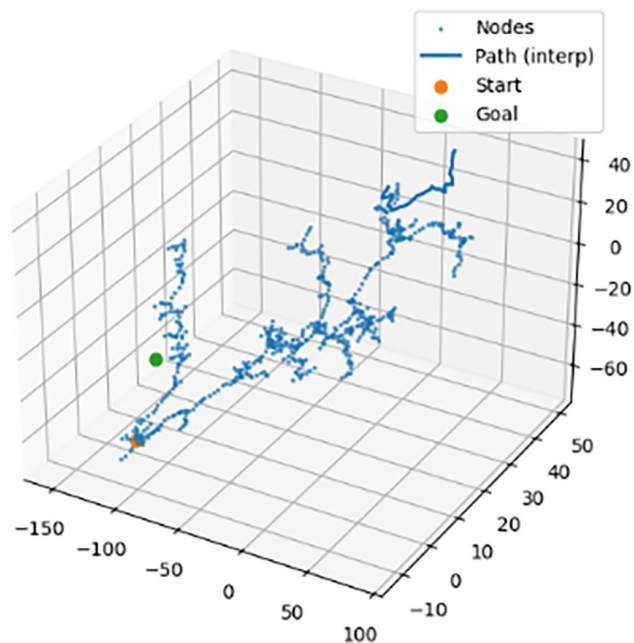


Fig. 5. Application of the RRT* algorithm to the mesh

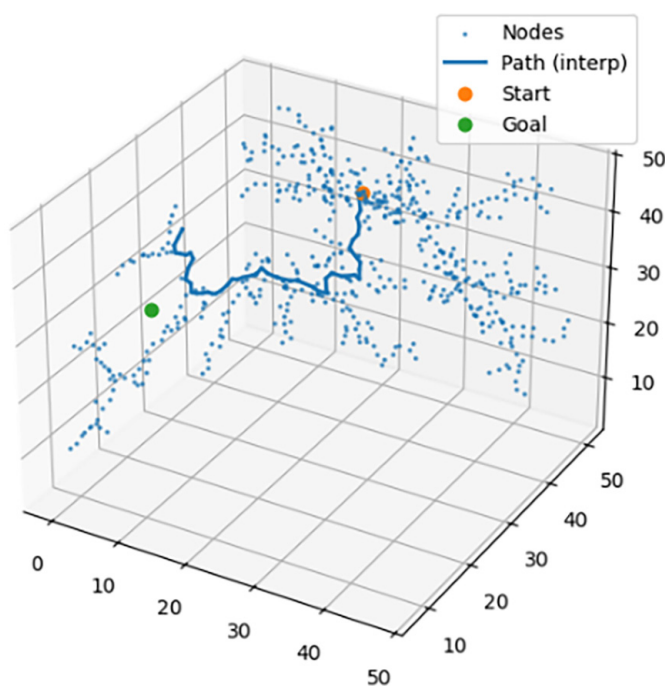


Fig. 6. Application of RL-guided RRT* at 30% to the mesh

3.2 Performance of the RRT, RRT* and RRT* algorithms with 30%RL

The evaluation relies on several criteria related to both the structure of the tree and the characteristics of the resulting path. In particular, we consider the number of nodes and edges, as well as the number of points defining the final trajectory. Path quality is further assessed using qualitative indicators such as its length, angular smoothness, conformity to the anatomical surface, and overall fluidity. The results obtained for the two patients are summarized in Tables 1 and 2, providing a detailed quantitative comparison of the three trajectory planning approaches: RRT, RRT*, and RRT*(30% RL).

Table 1. Comparison between RRT, RRT* and RRT* with 30% RL according to different metrics for patient n°1

Evaluation Criteria	RRT	RRT*	RRT*(30%RL)
Nodes in the tree	1171	580	470
Edges in the tree	1170	579	469
Points in the path	535	571	253
Path length	98.3593	101.9533	30.1005
Angular regularity (mean angle in rad)	0.9912	1.0155	0.7123
Surface adhesion	2.5722	2.8310	2.6741
Fluidity	0.3588	0.3512	5.0801

Table 1 presents the results obtained for the three compared methods, revealing significant differences in terms of tree structure and the quality of the generated path. The number of nodes and edges in the tree gradually decreases from RRT to RRT* and

then to RRT*(30%RL), dropping from 1171 and 1170 respectively (with 535 points in the path) to 580 and 579 (with 571 points), and then to 470 and 469 (with fewer points, 253), reflecting an optimization of the tree size. When examining the final trajectories, the RRT* algorithm actually results in a slightly longer route (101.95) than the classic RRT algorithm (98.36). However, the RL-guided version significantly reduces this length to only 30.10, which represents a fairly significant improvement in terms of efficiency. The RL algorithm also reduces angles more effectively, with a degree of 0.71 radians compared to 0.99 for RRT and 1.02 for RRT*, making the trajectory less jerky and more fluid. In terms of proximity to the surface, the three methods yielded similar results, with RRT* being slightly high (2.83), followed by RRT*(30% RL) (2.67), and finally RRT (2.57). The path produced by RRT* (30% RL) displayed the most fluid, smooth overall trajectory track with a total score of 5.08 points compared to 0.36 points for RRT and 0.35 points for RRT*. This indicates that RL provides adaptive capacity to the overall path's flexibility. Finally, RL and RRT* appear to produce a more fluid and greater quality path than either algorithm independently.

Table 2. Comparison between RRT, RRT* and RRT* with 30% RL according to different metrics for patient n°2

Evaluation Criteria	RRT	RRT*	RRT*(30%RL)
Nodes in the tree	897	731	552
Edges in the tree	896	730	551
Points in the path	1007	1361	289
Path length	178.0225	239.6209	34.8558
Angular regularity (mean angle in rad)	0.9258	0.9361	0.8012
Surface adhesion	2.5227	3.1159	2.3210
Fluidity	0.5738	0.4376	2.0593

As shown in Table 2, the classical RRT algorithm constructs the largest tree with 897 nodes and 896 edges, creating a long (178 units) but relatively dense path of 1 007 points. The RRT* method simplifies the tree structure (731 nodes) but results in a longer path (239.6 units). In spite of this fact, it provides the highest consistency in angular order (0.94) while having the lowest amount of surface adhesion (3.12). Adding RL will significantly reduce the size of an RRT* (552 nodes versus) and the number of points on the path (289 compared to RRT*). This version produces the shortest (34.86 units) and smoothest (2.06) path with slightly less stable angular regularity (0.80) than RRT*, but still satisfactory, and better surface adherence (2.32). Overall, RRT*(30%RL) strikes a balance between efficient structure shorter paths and much better fluidity, making it ideal for fast and reliable planning, even if the path is a little less smooth than rapidly-exploring random tree.

3.3 Effect of RRT* with (30%) RL

The addition of guided sampling in the RRT*(30%RL) version significantly alters the search behavior. As shown in Figure 7, the number of nodes and edges from 10 runs at 2,000 iterations was significantly reduced, and the exploration focused more on the significant areas of the breast. This guidance facilitates the quick

determination of shorter, more direct, and better geometrically created paths. The number of points and path length reduce quickly, simplifying the trajectory and making it easier to follow with fewer interruptions. The path length is also significantly less than that of other approaches to demonstrate that by supporting the algorithm with this guidance, the likelihood and time it takes to find a near-optimal solution improves greatly. Likewise, the RL version creates the smoothest path with the least amount of angular variation, resulting in fewer corners. The surface adhesion remains essentially the same as for other methods, and thus, there has not been a change in the basic shape constraints due to the presence of guidance. Finally, although RRT and RRT* maintain better than low fluidity, RRT*(30%RL) receives much higher fluidity scores and thus presents a more directly consistent and effective route.

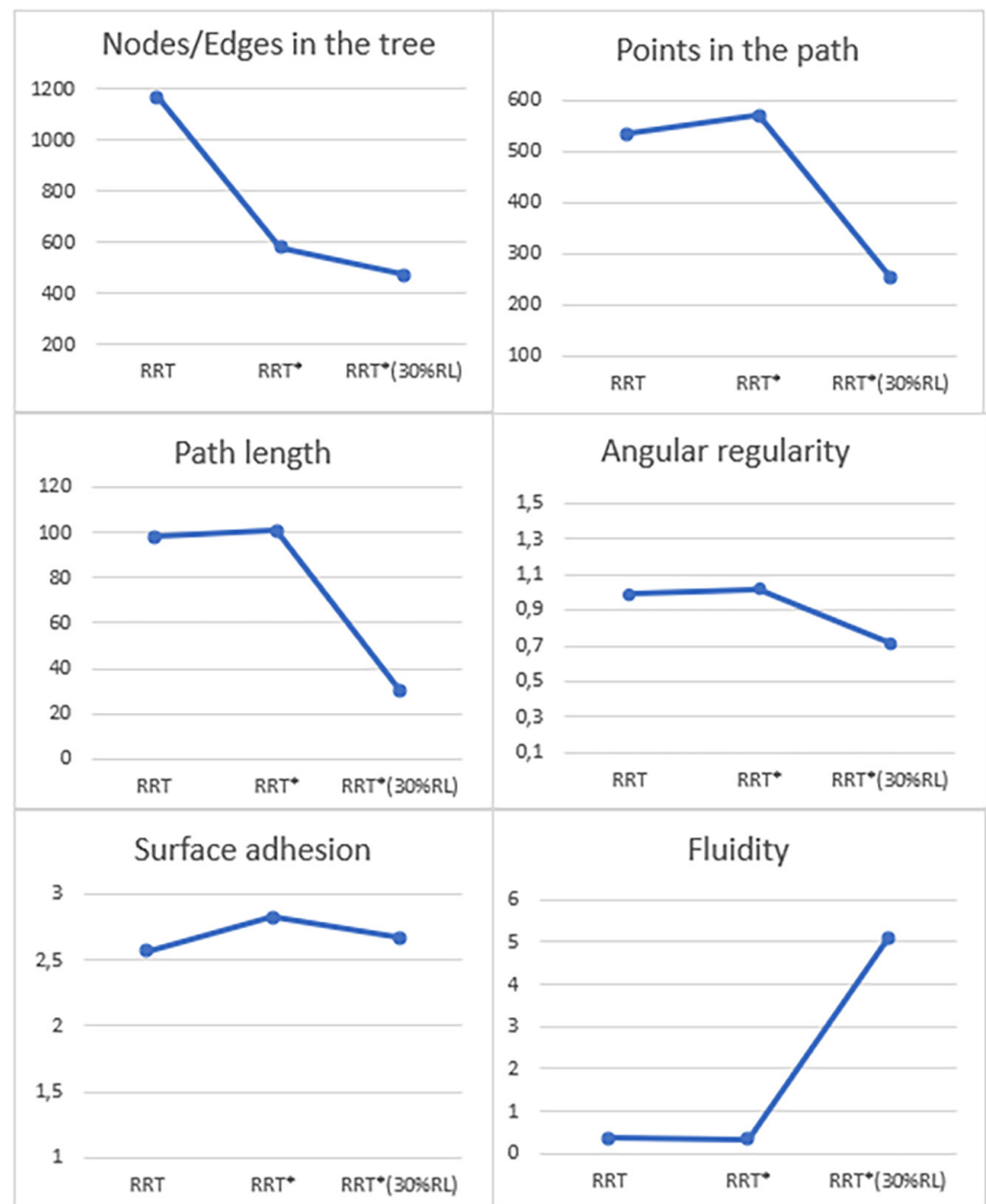


Fig. 7. The evolution of the evaluation parameters for RRT, RRT* and RRT* algorithms with (30%) RL

4 CONCLUSION

This paper discusses the methodology behind our research on automated generation of trajectories as well as a comparison of various trajectory-search methods (RTT). To develop the trajectories from a variety of scans, we first create a three-dimensional representation of each breast using 3DSlicer software and MR imaging. This critical and delicate phase of our study is crucial for understanding the complex anatomy of a breast and for correctly planning optimal acquisition trajectories. The system is also designed to adapt to individual patients, which reinforces the validity and usability of the system in a multitude of clinical situations. The consistency around patient variations allows us to achieve consistent results across individual patients. Based on our experimental results, the RRT method, which employs artificial intelligence robotics, with 30% reinforcement learning (RL), offers the best compromise when compared to other algorithms, in terms of speed of trajectory search, precision of trajectory search and simplicity of tracking (up to five times faster than any of the other algorithms), and stability during acquisition. Based on the findings from our research, these developments represent a significant advancement toward an intelligent, and automated ultrasound planning tool, which will enable greater accuracy in breast ultrasound exams, and improve access to quality breast care services for healthcare professionals.

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