Towards Robotics-Assisted Endomicroscopy in Percutaneous Needle-based Interventions

Citation for published version:

Digital Object Identifier (DOI): 10.1109/TMRB.2023.3337869

Link: Link to publication record in Edinburgh Research Explorer

Document Version: Peer reviewed version

Published In: IEEE Transactions on Medical Robotics and Bionics

General rights
Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.

Download date: 12. May. 2024
Towards Robotics-Assisted Endomicroscopy in Percutaneous Needle-based Interventions

Balint Thamo$^{1,2}$, Vasiliki Voulgaridou$^2$, Harry Wood$^3$, James Stone$^3$, Kevin Dhaliwal$^2$, Mohsen Khadem$^{1,2}$

Abstract—Endomicroscopy uses the properties of light to obtain microscopic images of tissue in real-time and provide insights into disease processes. To date, endomicroscopy has primarily been directed against surface/near-surface inflammatory and other conditions, as there is an absence of an integrated technology for directed and automated optical fibre delivery. In this paper, we propose a robotic platform that offers controlled optical imaging in percutaneous interventions. The platform incorporates a concentric tube robot (CTR) to steer a fluorescent imaging probe with cellular and bacterial imaging capability inside soft tissue. Moreover, we develop motion planning algorithms that accept pre-operatively defined regions of interest for imaging and calculate desired insertion configuration and trajectory for reaching the target. Finally, we refine our previous control algorithm to autonomously steer the robot on the pre-planned path toward the target region for endomicroscopic imaging. The platform is tested on phantom tissue with embedded targets. Results demonstrate the feasibility of controlled imaging of target regions at tissue surfaces equal to or bigger than 3 mm and reaching targets inside tissue at a maximum depth of 50 mm. Combining emerging endomicroscopic imaging modalities with continuum robots can enable future research in on-site diagnosis and treatment of infectious diseases.

Index Terms—Surgical Robotics, Endomicroscopy, Continuum Robots, Motion Planning

I. INTRODUCTION

In the past decade, advances in fibre optics, light sources, detectors, and molecular biology have led to the development of several novel methods for in vivo endomicroscopy. A number of promising imaging techniques have emerged, including Fluorescence Imaging, Optical Coherence Tomography, Confocal Microendoscopy, and Surface-enhanced Raman Spectroscopy. These technologies have shown to be promising tools for tissue characterization compared to traditional biopsy. However, one of the challenges in endomicroscopic procedures is the lack of control to accurately scan the target regions. In order to overcome this difficulty, we detail the proof of concept for a robotic platform (Figure 1) capable of accurate and repeatable endomicroscopic imaging in needle-based interventions. The robotic platform is composed of a continuum robot, namely, a Concentric Tube Robot (CTR) and a bespoke fluorescence endomicroscopic imaging platform called Versicolour, first introduced in [1]. Versicolour is a sensitive and modular three-colour fluorescence endomicroscopic imaging platform spanning the visible to near-infrared (NIR) range. Versicolour has been clinically translated into patients with pulmonary disease to delineate healthy, cancerous, and fibrotic tissue autofluorescent structures [1]. In this work, we develop and experimentally validate a robotic platform for automated endomicroscopic imaging for imaging platforms such as the Versicolour system. during needle-based interventions. The robotic platform provides precise control and enables the imaging probe to reach targets deep inside the soft tissue.

A. Related Work

Over the last decade, endomicroscopy or optical biopsy has shown to be a promising tool for tissue characterization compared to traditional biopsy. Modalities of endomicroscopy have been combined with surgical robots to provide high-resolution images of the tissue in real time. A review of various applications is provided in [2]. However, the application of these technologies is limited to surface or near-surface imaging due to the lack of steerable technology that can (i) guide the probe inside the tissue, and (ii) provide precise control over the distal scanning motion.

In this work, we use a CTR to steer the imaging probe of the Versicolour system to obtain controlled images of predefined target regions inside soft tissue. CTR is a type of continuum robot composed of several pre-curved elastic tubes nested inside one another. The shape of a robot can be controlled by rotating or translating ($\alpha_1$, $\alpha_2$) or translating ($\beta_1$, $\beta_2$) the pre-curved tubes. (b) The medically approved Versicolour unit. Figure from [1] with permission from the authors.

Figure 1. (a) A CTR used as a steerable needle deploying a fluorescence imaging probe connected to the Versicolour fluoroscopy imaging unit. The CTR shape and length can be controlled by axially rotating ($\alpha_1$, $\alpha_2$) or translating ($\beta_1$, $\beta_2$) the pre-curved tubes. (b) The medically approved Versicolour unit. Figure from [1] with permission from the authors.
used to control the robot’s motion. In our previous work, we have developed model-based [13] and data-driven [14], [15] controllers for accurate steering of CTRs. Controlling CTRs is generally challenging due to the robot’s nonlinear dynamics. Additionally, CTR’s workspace is constrained by the tubes’ pre-curvature, range of linear translation, and path-dependent constraints on robot motion. These constraints make the tip trajectory and joint values dependent on their traversed path [16], [17]. Therefore, previous control methods, including our work in [14], [15] that only use contemporary information may lead the robot to instabilities or configurations that it cannot recover from.

Furthermore, to control the robot across the workspace and to accomplish specific tasks, the CTR requires a motion planner capable of generating a feasible trajectory between the initial configuration and the target configuration. Sampling-based motion planners are widely used for motion planning for flexible robots such as CTRs. The most common sampling-based algorithms are based on probabilistic roadmaps (PRM) [18] and rapidly exploring random trees (RRT) [19]. These methods have been employed for motion planning of CTRs. Bergeles et al. generated a stable path with RRT* by discarding the unstable configurations based on their assumptions [20]. Leibrandt et al. demonstrated a framework for stable path planning using PRM [21], while Torres et al. used rapidly exploring random graph (RRG) combining offline and online planners [22]. An RRT-Shape algorithm was also proposed by Wu et al., which uses the CTR’s shape as a constraint for the RRT [23]. In interactions where the anatomy of the patient is known, Kuntz et al. proposed a motion planner that utilizes sampling-based motion planning along with local optimization [24].

These approaches are effective for offline path planning in free-space, as tissue interaction forces are hard to model or estimate. Moreover, often Cartesian coordinates of the robot are controlled/planned, while the robot’s orientation is neglected. However, controlling the robot’s tip pose is essential for capturing good-quality endomicroscopic images. To overcome these limitations, we propose a novel motion planner capable of generating feasible trajectories for needle-based interventions while considering the constrained motion of the CTR in contact with the surrounding environment.

**B. Problem Statement and Contributions**

In needle-based interventions, a physician inserts a needle through the skin to reach different internal organs, such as the prostate, breast, lung, and liver to perform a biopsy or target cancerous lesions with needle-based ablation procedures to burn or freeze malignant cells. Percutaneous lung biopsy and prostate biopsy or ablation are two examples shown in Figure 2. Endomicroscopy has shown to be a promising tool for tissue characterization compared to traditional biopsy. Modalities of endomicroscopy have been combined with surgical robots to provide high-resolution images of the tissue in real time. However, the application of these technologies is limited to surface or near-surface imaging due to the lack of steerable technology that can (i) guide the probe inside the tissue, and (ii) provide precise control over the distal scanning motion.

To this end, we develop and experimentally validate a robotic platform composed of a CTR for automated endomicroscopic imaging during needle-based interventions. This technology can offer accurate in-vivo real-time imaging of targeted regions during needle-based interventions to (i) guide biopsy, (ii) monitor the progression of a disease and assess the effectiveness of an experimental treatment, (iii) unify diagnosis and treatment of diseases/cancerous cells by providing real-time diagnosis followed by delivery of targeted therapies/ablation.

The main contributions of this work are (i) proposing a robotic platform for automated endomicroscopic imaging, (ii) providing prices control of the robot to enable high-quality images for the imaging probe, (iii) generating motion plans for specific tasks.

**II. METHODOLOGY**

Here, we introduce the robotic endomicroscopy imaging platform. First introduce the CTR robot in Section II-A. Then, a Affordance-aware Motion Planning is introduced to estimated robot trajectories for imaging tasks. The motion planner is discussed in Sections II-B and II-C. Finally, a data-driven control method that aims to steer the robot on the planned path is detailed in Section II-D.

**A. Robotic Endomicroscopy Platform**

The robotic platform consists of a CTR with two pre-curved tubes made of Nitinol (Figure 3). The shape of the CTR can be controlled by axially rotating and translating the tubes (Figure 1(a)). In addition to this, an electromagnetic tracking system is used (Aurora, NDI) to measure robot’s position. The tracker comprises a tabletop electromagnetic field generator, and a 5-DOF electromagnetic tracker (EMT), which is attached to the CTR’s tip to provide position feedback for the controller. Of note, the EMT is being used in all experiments. According to the manufacturer’s datasheet, the electromagnetic tracker has a mean accuracy of ± 0.7 mm and a maximum error of 1.8 mm. Finally, an imaging probe is attached to the tip of the robot to provide visual feedback to the Versicolour unit. Typical images from the imaging probe are shown in Figure 4 where Figure 4(a) shows images of
the probe when in contact with normal tissue or is in free-space, while Figure 4(b) shows a typical image when the probe is in contact with fluorescent-labeled targets. Finally, a phantom tissue is used in the experiments made according to the recipe given in [25]. Accordingly, the tissue is made by mixing bovine gelatin powder with water at a temperature of 70°C. The weight ratio of the synthetic tissues in the gelatin-to-water mixture is 18%, while the tissue’s Young’s modulus of elasticity was estimated to be 59 kPa, while its elasticity is similar to what is found in animal tissue. The robot is controlled using Robot Operating System (ROS) with C++ and tested on a desktop computer with Intel(R) Core(TM) i9-12900K CPU processor and 32.0 GB of memory.

2) The generated plan should minimise the interaction forces between the robot and the tissue. These interaction forces are unknown, hard to estimate in heterogeneous tissue [26] and will cause the robot’s tip to deviate from the desired trajectory.

3) The planned trajectory should be stable and avoid singularities. CTRs exhibit elastic instabilities due to torsional elastic energy storage in the tubes [27].

Now, we employ the concept of affordance to quantify the aforementioned requirements for a motion planner. Affordance in robotics refers to the potential actions that an object or environment offers to a robot and can improve the efficiency and effectiveness of robot-object interactions [28]. To define affordance for discussed requirements, we use the concept of manipulability for continuum robots introduced in [29]. Velocity manipulability is a measure of a robot’s ability to produce changes in its velocity by altering its joint inputs and can be estimated using the robot’s kinematic model. The kinematic model of a CTR presented in [10], [30] can be summarised as

\[ x = f(q(t), g(s), u(s)), \]  

where \( x \) is the Cartesian coordinates of the robot’s end-effector, \( t \) and \( s \) denote time and robot’s arc length, \( q(t) = [\beta_1, \beta_2, \alpha_1, \alpha_2]^T \) denotes the actuation values shown in Figure 1, \( u(s) \) is the curvature of the robot backbone, and \( g(s) \in \text{SE}(3) \) is a homogeneous transformation defining the robot’s backbone location and orientation in task space and can be defined as

\[ g(s) = \begin{bmatrix} R(s) & r(s) \\ 0_{3 \times 1} & 1 \end{bmatrix} \]

where \( r(s) \) is the arc-length parameterized shape of the robot and \( R \in \text{SO}(3) \) is a rotation matrix at every arc-length \( s \). We can numerically estimate the Jacobian by solving the model in (1) iteratively. For a two-tubed CTR, the Jacobian is a \( 3 \times 4 \) matrix, and it maps the joint velocities \( \dot{q} \in \mathbb{R}^4 \) to the end-effector velocities \( \dot{x} \in \mathbb{R}^3 \) as

\[ \dot{x} = J\dot{q} \]  

Figure 3. Experimental setup. A CTR with 2 tubes is used with an electromagnetic tracking system, which consists of a tabletop electromagnetic field generator, and a 5-DOF EMT. The EMT is attached to the tip of the robot. Additionally, an imaging probe is nested at the tip of the robot to provide visual feedback to the Versicolour unit.

Figure 4. (a) Normal image of the Versicolour, when the tip of the robot is in contact with gelatin or it does not make any contact. (b) The image of the Versicolour, when the tip of the robot makes contact with the fluorescent-labeled targets. The Versicolour is set to show a completely dark image if there is no contact with the target and a bright image when the target is found.

B. Affordance-aware Motion Planning

Here, we propose a motion planning algorithm that accepts the desired target coordinates in a global coordinate frame estimated from pre-operative medical images as input and finds (i) the initial entry point, (ii) a trajectory from a given starting configuration to the entry point, and (iii) a stable and feasible trajectory from the entry point towards the target.

In order, to take endomicroscopic images of the target region inside the tissue, the generated plan should satisfy the following requirements:

1) To ensure capturing high-quality endomicroscopic images, the generated plan should guide the robot’s tip roughly perpendicular to the tissue’s surface.

2) The initial entry point, (ii) a trajectory from a given starting configuration to the entry point, and (iii) a stable and feasible trajectory from the entry point towards the target.

The weight ratio of the synthetic tissues in the gelatin-to-water mixture is 18%. Additionally, an imaging probe is nested at the tip of the robot to provide visual feedback to the Versicolour unit.
Figure 5(a). Of note, as illustrated in [29], UME’s major axis is approximately parallel to the VME’s minor axis. Therefore, the direction where the robot has the highest ability to produce changes in its velocity is the same as the direction where it retains maximum stiffness. Now, by leveraging some of the features of the VME, we propose three variables to quantify CTR affordance for endomicroscopic tasks, namely, Dexterity Affordance ($\psi$), Stability Affordance ($c$) and Constrained Motion Affordance (CMA) ($\Gamma$).

**Dexterity Affordance:** $\psi$ quantifies how well the robot can move instantaneously through soft tissue for cutting and taking endomicroscopic images. As the CTR advances through soft tissue, cutting forces are applied to its tip in the opposite direction of the tip’s local $z$ axis [26](Figure 6(a)). In a configuration, where the principal axis of the VME with the largest singular value ($v_1$) is aligned with the local $z$ axis of the robot’s tip, the CTR can manipulate its velocity along the local $z$ with less joint efforts (left image in Figure 5(a)). The UME’s major axis is approximately parallel to the VME’s minor axis. Therefore, the CTR retains high stiffness against cutting forces making it the optimal case for cutting through soft tissue (Figure 5(b)). Furthermore, the robot advances along its local $z$ axis and will reach the desired targets perpendicularly to capture high-quality endomicroscopic images of the target. To this end, we define the Dexterity Affordance $\psi$ as the angle between the tip’s local $z$ axis and the major axis of the velocity manipulability:

$$\psi = \arccos(z \cdot v_1), \quad (5)$$

where $v_1$ is the first column of $V$ in (4) and $z$ is the last column of matrix $R(s)$ at the robot’s tip, which is estimated by solving the kinematic model of the robot in (1). Note that both vectors $z$ and $v_1$ are unit vectors.

Of note, we only consider the columns of the Jacobian which correspond to translational actuators (i.e., $\beta 1$ and $\beta 2$). The reason is that (i) intuitively we know that the robot generates axial motions using its translational actuators, and (ii) rotational and translational actuators have different units. This can lead to inconsistent results when calculating the manipulability of the robot.

**Stability Affordance:** CTRs can become unstable or “snap” when the robot’s forward kinematics loses its uniqueness and can harm sensitive tissues in the proximity of the robot. In order to characterize robot’s stability, we introduce $c$ as the inverse of the robot’s Jacobian’s condition number [31]:

$$c = \frac{1}{\| J \| \| J^{-1} \|} = \frac{\sigma_{\text{max}}}{\sigma_{\text{min}}}. \quad (6)$$

where $c$ is calculated by dividing the most significant singular value of $J$ by the least significant singular value of $J$. The Jacobian matrix becomes singular as the robot’s kinematics becomes unstable. Consequently, $c$ increases towards infinity. By minimizing the proposed stability affordance, one can avoid such scenarios.

The proposed Dexterity Affordance and Stability Affordance quantify the robot’s motion for a given configuration but cannot provide information on the transient behavior of the CTR. To this end, we introduce another variable, namely, the CMA, which aims to quantify the robot’s ability in moving along its local $z$ direction from one point to another, which is desired to cut through tissue or scan the tissue for endomicroscopic imaging.

Consequently, we introduce $\Gamma = [\gamma_1, \gamma_2]$, where $\gamma_1$ is the relative angle between the tip displacement in the next time step and the tip’s local $z$ axis in a given time step. $\gamma_2$ is the angle between the robot’s local $z$ axis in the next time step and the local $z$ axis of robot’s initial configuration at $t_0$:

$$\gamma_1 = \arccos \left( \frac{(x_{tk} - x_{t_{k-1}}) \cdot (z_{tk})}{\| (x_{tk} - x_{t_{k-1}}) \cdot (z_{tk}) \|} \right) \quad (7a)$$

$$\gamma_2 = \arccos (z_{t_0} \cdot z_{tk}) \quad (7b)$$

Figure 7 demonstrates these variables, where the robot is shown in several configurations. Assuming that it has moved from point $A$ to point $B$ at time $t_k$, now we need to find the next feasible point to move to at time $t_{k+1}$. Accordingly, $\gamma_1$ characterizes the robot’s motion along a straight path, while $\gamma_2$ quantifies the tip’s orientation during the motion. Based on this the following scenarios are possible:

1) **Optimal Scenario:** Both $\gamma_1$ and $\gamma_2$ are small, the robot moves on a relatively straight line and approaches the next point perpendicularly creating optimal conditions for cutting through soft tissue (Figure 7(b)).
2) **Lateral Movement**: The robot makes a lateral movement (large $\gamma_1$) as shown in Figure 7(c), moving to point D. This will compress the surrounding tissue, resulting in large interaction forces.

3) **Tip Orientation Misalignment**: A large $\gamma_2$ indicates that the robot’s tip is not perpendicular to the target point (Figure 7(d)).

In the next section, we propose a motion planning algorithm that leverages the developed affordance variables to estimate optimal paths for robotic-assisted endomicroscopy.

### C. 3-Phase Motion Planner

Based on the defined robot affordance measures, we propose a motion planning algorithm comprised of 3 different planning phases. The motion planner accepts the desired target location acquired from pre-operative images and employs the affordance measures discussed in the previous section to (i) estimate the robot’s entry point into the tissue, (ii) find a trajectory that takes the robot to the entry point from any given starting configuration, (iii) find the optimal trajectory from the entry point to the target to perform endomicroscopic imaging.

**Phase 1**: The first motion planning phase includes an exhaustive search to find all the configurations in which the robot is stable and has maximum capability in moving along its z direction. This can be achieved by optimising the stability affordance variable $c$ and the dexterity affordance $\psi$. To this end, we generated all configurations ($q$) between the robot’s joint limits with a 1 mm resolution for translational joint inputs and a 5 degree resolution for rotational joint inputs.

Based on the stability affordance and the dexterity affordance measures, we only accepted configurations where $c \leq \epsilon_1$ and $\psi \leq \epsilon_2$, where $\epsilon_1$ and $\epsilon_2$ are hyperparameters and should be small enough to ensure the robot’s stability and dexterity. Figure 8(a) shows the results of the 1st phase of the motion planner for a CTR with parameters given in Table I, while $\epsilon_1$ and $\epsilon_2$ were selected to be 44.7 and 5°, respectively. $\epsilon_1$ was selected as the mean of the stability affordance variable $c$ for all generated configurations.

**Phase 2**: In the second phase, a modified RRT* algorithm is applied to select a configuration where the robot can perform insertion into soft tissue on a straight line and a selected area of tissue. The algorithm accepts the results of the previous phase as inputs and runs the planner for each point. Based on the desired application, the algorithm looks for the following factors (Figure 6(b)):

1) **Deep Tissue Insertion**: The goal is to find a series of points along a straight line aligned with the local z axis of the robot’s tip.

2) **Grid Scan**: The goal is to find points along a grid with an offset from the robot’s tip position in its local z direction.

To achieve these motion planning goals, a modified version of RRT* algorithm [32] is applied to generate a motion
plan containing a sequence of stable configurations \( \Pi = (q_{\text{start}}q_1, q_k, q_{\text{goal}}) \) between starting position \( x_{\text{start}} \) with the corresponding \( q_{\text{start}} \) initial configuration and goal position \( x_{\text{goal}} \) with the corresponding goal configuration \( q_{\text{goal}} \). \( q_1, q_k \) are the generated configurations between initial and goal configurations, \( x_i \in \mathbb{R}^3 \) is the corresponding tip position of \( q_i \in \mathbb{R}^4 \) configuration of the robot.

For finding a plan \( \Pi \), we first build a tree \( \Gamma = (q_1, q_k) \), where each element (node) of \( \Gamma \) is a valid configuration based on the stability affordance and CMA criteria. The proposed planner is a modified version of RRT* with the following two differences:

1. We consider configurations where the stability and CMAAs are not optimal as virtual obstacles and avoid traversing through these configurations. \( O = (O_1, O_3) \) where \( O_i \in \mathbb{R}^4 \) is the list of all configuration where \( C \leq \epsilon_1 \) and \( \gamma_2 \leq \epsilon_3 \), where \( \epsilon_1 \) are \( \epsilon_3 \) hyperparameters.
2. Due to the different joint types (translational and rotational) with different units and magnitudes, finding the distance between two configurations in C-space is challenging. Therefore, the RRT* will be biased toward using one type of actuation (rotational or translational), preventing it from exploring W-space. To this end, joint weights are applied to prevent biasing toward rotational or translational movements.

To estimate \( w \) for a given configuration \( (q_{\text{nearest}}) \), each joint \( i \) is perturbed by a small value \( (\delta\alpha_i \text{ and } \delta\beta_i) \). Next, the tip displacement for each perturbation is recorded \( (\delta x_i) \). Finally, \( w \) is calculated as

\[
w = \left[ \frac{\delta x_{\text{max}}}{\delta x_1}, \frac{\delta x_{\text{max}}}{\delta x_2}, \frac{\delta x_{\text{max}}}{\delta x_3}, \frac{\delta x_{\text{max}}}{\delta x_4} \right]^T,
\]

where \( \delta x_{\text{max}} = \max \{\delta x_i\} \), for \( i = 1, \cdots, 4 \). \( w \) aims to normalize joint displacement during contraction to ensure that a unit change in each joint results in similar tip displacement, thus avoiding bias toward one type of motion.

Figure 8(b) shows the result of the first two phases of the motion planner for two scenarios shown in Figure 6: (i) moving on a straight line (green), (ii) scanning the tissue surface (blue). For insertion on a line, the goal is to follow a 50 mm long straight line into the tissue. For achieving this the hyperparameters were selected as \( \epsilon_1 = 44.7 \) and \( \epsilon_3 = 15^\circ \). For tissue scanning, the goal was to track a mesh grid normal to the robot’s entry point with a 25 mm offset from the tip position in the local z direction. The mesh contains a 5 by 5 grid with a maximum 10 mm distance between each point. The hyperparameters for this scenario were selected as \( \epsilon_1 = 44.7 \) and \( \epsilon_3 = 60^\circ \). Thresholds for CMA were relaxed as for tissue scanning the robot needs to be roughly perpendicular to the tissue compared to the insertion on a line where the robot needs to strictly follow a straight line.

Phase 2 of the planning goes through all feasible configurations generated in Phase 1, until it finds a path to the target. The output of this phase is the generated plan, \( \Pi^G \), defined as a set of configurations that guides the robot to the target, starting from a selected entry point \( x_{\text{enter},G} \). Note, the entry point and the generated path are defined in the reference frame of the CTR, i.e., robot’s base, denoted by \( R \). However, it is assumed that the coordinates of the desired entry point and path are pre-defined from medical images in a global frame of reference as \( x_{\text{start}}^G \) and \( \Pi^G \). We can perform a rigid registration to transform the robot’s base to a new position to register the estimated entry point and the generated path to the global frame. For this purpose, we can use classic point cloud registration algorithms, such as the Iterative Closest Point algorithm [33]. The algorithm accepts \( \Pi^R \) and \( \Pi^G \) as inputs to estimate the homogeneous transformation matrix that aligns the two cloud points \( T_{CG}^G \). This process is shown in Figure 9(a).

Phase 3: The third phase of motion planning finds an optimal trajectory that brings the robot from an initial configuration to the transformed entry point. We use a similar RRT* algorithm to phase 2 but the CMA conditions are relaxed in phase 3 as the robot will move in free-space. Results of the 3rd motion planner are shown in Figure 9(b).

D. Control Architecture

Here, we refine a data-driven control architecture developed in our previous work [14] to control the CTR’s end-effector to track a time-varying desired trajectory, \( x_{d}(t) \). The controller employs data-driven differential kinematics of the robot (i.e., Jacobian), where the data-driven Jacobian is initially estimated using the mathematical model of the robot and updated on-the-fly based on the feedback of the current measurement of the robot’s tip position. This iterative update aims to compensate for errors caused by model uncertainty and external interaction forces.
Similar to the previous section, using the model we can define the Jacobian matrix, $J$, that maps the joint velocities, $\dot{q} \in \mathbb{R}^4$, to the robot end-effector velocity, $\dot{x} \in \mathbb{R}^3$ as

$$\dot{x} = J\dot{q},$$

(9)

where the Jacobian can be numerically estimated by solving the model in (1). Now, based on [14] and using the model-based Jacobian we can define the data-driven Jacobian of the robot as:

$$J^{k+1}_H = J^k_M F + \left[ J^k_H + \left( \frac{\Delta x^k - J^k_M \Delta q^k}{(\Delta q^k)^T(\Delta q^k)} \right) \chi \right] (1 - F),$$

(10)

where the subscript $M$ and $H$ denote the model-based and data-driven Jacobians, respectively. $\chi$ is the learning rate, and $F = \text{diag}(\{F_1, F_2, 0, 0\})$, where $F$ is the Normal Forgetting Function defined as:

$$F = \exp \left( -\text{rem} \left( \frac{t}{\Gamma_2} \right) \right),$$

(11)

where rem is the remainder function, and $\Gamma_1$ and $\Gamma_2$ are constant parameters defining the speed of forgetting and remembering, respectively. Figure 10 shows the normal forgetting function for various values of $\Gamma_1$ and $\Gamma_2$.

![Figure 10. Plots of normal forgetting function for various values of $\Gamma_1$ and $\Gamma_2$.](image)

Compared to our previous work in [14], we have improved the Hybrid Jacobian in two ways:

1) We use variable learning rates for translational ($\beta$) and rotational ($\alpha$) actuators. These actuators have different units and different magnitudes. Using variable learning rates allows us to tune the controller more efficiently. To this end, $\chi$ is defined as $\chi = \text{diag}(\{\chi_1, \chi_1, \chi_2, \chi_2\})$, where $\chi_1$ and $\chi_2$ are learning rates for translational and rotational actuators, respectively.

2) We introduce the normal forgetting function that will enable the controller to employ the information from the model-based Jacobian at fixed time intervals. The frequency of forgetting and resetting can be adjusted using $\Gamma_1$ and $\Gamma_2$ as shown in Figure 10. The reason for this is that the translational inputs of the CTR ($\beta_1$ and $\beta_2$) have relatively smaller values than the rotational ones. Moreover, CTRs tend to move on curvilinear trajectories, which use rotational inputs more often than translational inputs. Therefore, rotational inputs are often updated more frequently. This will cause the controller to ignore translational inputs or the Hybrid Jacobian to become ill-conditioned. To this end, we use the normal forgetting function to reset the columns of the Jacobian estimated by the controller via the data and replace them with the model-based Jacobian.

Now, we can use the following control law to track an arbitrary desired trajectory.

$$\dot{q}_d = J_d^H [\dot{x}_d + K(x_d - x)],$$

(12)

where $q_d$ is the desired actuator velocities, $J_d^H$ is the Moore–Penrose inverse of the hybrid Jacobian matrix, and the proportional gain, $K$, is a symmetric positive definite matrix.

### III. Experimental Results

The designed planner and controller rely on a nominal kinematic model of CTR. Therefore, a system identification experiment similar to [30] is performed initially to identify the model parameters of the robot. The model parameter identification is achieved in the following three steps.

1) A stereo camera pair is calibrated and registered to the robot’s base using a grid pattern as a calibration target.

2) Through manual backbone segmentation, multiple matching backbone points are manually selected on both camera images to determine the shape of the CTR. Then, an accurate 3D point cloud is created by triangulating the data.

3) Young’s and shear moduli of the tubes are identified by fitting the kinematic model described in [30] to the robot’s shape from the manual backbone segmentation. This is achieved by applying the Levenberg-Marquardt algorithm. 25 different configurations are captured across the robot’s workspace to make the model parameter identification accurate.

Based on the parameter identification the mechanical parameters of the CTR robot are given in Table I.

In addition to this, we performed a simulation study to select the controller’s sampling frequency and desired tip velocity. Accordingly, in the simulation study, we compared the tip position error of the controller at different sampling frequencies and velocities. Figure 11 shows that the error gets smaller as the velocity decreases and the sampling frequency increases. Of note, in the experiments, the EMT provides position feedback in every 25 ms, which is the slowest part of the system. Based on these, we selected the desired tip velocity as 1 mm/s and the sampling frequency as 40 Hz. In the rest of the paper, we will refer to this as real-time.

The proposed motion planner and the hybrid controller were verified through the following three cases using the robotic platform described in Section II-A:

$(S_1)$ **Robot following pre-defined trajectories in free-space:**

Three different trajectories were followed by the robot’s tip in free-space: (i) A square trajectory with a base length of 20 mm, (ii) a spiral trajectory on the global XY plane and (iii) a trajectory generated with RRT* algorithm.
Table I
MECHANICAL PARAMETERS OF THE CTR.

<table>
<thead>
<tr>
<th></th>
<th>Tube 1</th>
<th>Tube 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner Diameter[mm]</td>
<td>0.7</td>
<td>1.4</td>
</tr>
<tr>
<td>Outer Diameter[mm]</td>
<td>1.1</td>
<td>1.8</td>
</tr>
<tr>
<td>Length[mm]</td>
<td>431</td>
<td>332</td>
</tr>
<tr>
<td>Curvature[1/m]</td>
<td>21.3</td>
<td>13.1</td>
</tr>
<tr>
<td>Young’s Modulus, E[GPa]</td>
<td>64.3</td>
<td>52.5</td>
</tr>
<tr>
<td>Shear Modulus, G[GPa]</td>
<td>25</td>
<td>21.4</td>
</tr>
</tbody>
</table>

The results of the second scenario (S2) show that the CTR can be used as a steerable needle following a pre-generated straight trajectory accurately while it is in constant contact with soft tissue (Figure 14(a)). The phantom tissue in the experiments is made according to Section II-A. The entry point for the task is selected based on the first two phases of the proposed motion planner (II-C), while the trajectory was generated by the second phase of the 3-phase motion planner. Accordingly Figure 8(a) shows all the generated entry points where the robot’s movement in its local z-direction is dominant and therefore optimal for the task. Then Figure 8(b) shows the selected entry point for a given procedure and indicates the reachable points from the selected entry point.

As a final demonstration, the third scenario (S3) illustrates the proposed CTR’s capability to perform a grid scan during an endomicroscopic procedure (Figure 13(b)). In this experiment, a fibre was attached to the tip of the CTR and connected to the Versicolour unit providing feedback on the procedure. As Figure 14(b) shows, the tip of the CTR was able to follow the pre-generated grid trajectory accurately. Figure 4(a) shows a typical image of the Versicolour when the tip of the robot is in contact with gelatin, or it does not make any contact, and Figure 4(b) shows when it makes contact with one of the fluorescent targets. The mean error of the tip during the endomicroscopy procedure was 1.0 mm. Please see the multimedia attachment for a video of the experiments.

These experimental results validate the performance of the proposed motion planner combined with the hybrid control algorithm and provide evidence for the potential use of CTRs in optical endomicroscopy and for reaching a target deep inside soft tissue.

IV. CONCLUDING REMARKS

Over the last decade, endomicroscopy has shown to be a promising tool for tissue characterization compared to traditional biopsy. Instead of taking a number of biopsies and examining these with histology, an optical probe can be inserted into the patient and used to obtain high-resolution images of tissue in real-time. Despite increased application and
Figure 12. Representative experimental results for trajectory tracking in the 1st scenario \( (S_1) \): Robot’s tip follows a) a spiral trajectory, b) a square trajectory, c) a trajectory across robot’s workspace generated by the proposed RRT* algorithm.

Figure 13. Experimental setup for the second scenario \( (S_2) \) and third scenario \( (S_3) \). (a) The tip of the robot is required to follow a straight trajectory inside gelatin. (b) A fibre is attached to the tip of the robot to provide an image for the Versicolour. The robot is required to follow a grid trajectory. The goal of this experiment is to detect the fluorescent targets embedded in phantom tissue made of gelatin.

growing research interests in this area, the clinical application of endomicroscopy, however, is limited by difficulties in ergonomic control, consistent probe-tissue contact, large area surveillance, and retargeting.

This paper presents a comprehensive proof of concept for a robotic platform designed to assist endomicroscopy in percutaneous needle-based interventions. The platform integrates a fibre-based multicolour endomicroscopy system, known as Versicolour, with a concentric tube robot (CTR). To facilitate precise navigation, we developed a three-phase motion planner that determines the optimal entry point and trajectory for the robot. Building upon our previous work, we implemented a hybrid controller to achieve the level of precision required for real-world applications. Experimental results validated the effectiveness of our affordance-aware motion planner, demonstrating the platform’s capability to provide real-time in vivo molecular information based on disease signatures.

The proposed robotic endomicroscopy platform enables in-vivo real-time imaging of targeted regions during needle-based interventions. This can be used for repeated sampling of pre-defined targets to monitor the progression of a disease and assess the effectiveness of an experimental treatment. Additionally, the platform can be used to unify diagnosis and treatment of diseases/cancerous cells by providing real-time diagnosis followed by delivery of targeted therapies/ablation. Moreover, a noted limitation in endomicroscopy is the restricted field of view. The robotic platform presents an exciting avenue to address this challenge. Leveraging the precision and control of robotic imaging, there’s potential to systematically capture a broader tissue area, facilitating the development of comprehensive image mosaicking techniques. This could greatly enhance the diagnostic capabilities of endomicroscopy techniques by providing clinicians with a more expansive and contextual view of tissue structures.

We acknowledge the necessity for more realistic experiments using ex vivo tissue to further substantiate the clinical feasibility of our platform. We also intend to refine various system components, including the controller, to improve real-time operation. These enhancements are crucial steps towards the translation of the robotic platform into clinical settings for the discussed applications.