Important Issues of Needle Insertion into Soft Tissue

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Abstract: Needle insertion procedures have been gaining in popularity with medical communities and patients over the recent years. Currently, their applications span a wide range of diagnostic and therapeutic procedures and there is still a growing tendency toward integrating needle insertion into other procedures and surgeries. Its less invasive nature, which is performed locally on the body, largely explains this growing trend. This results in less intraoperative tissue damage and shorter post-operative recovery time. Many procedures like biopsy, deep brain stimulation, and cancer treatments are done using needles/catheters. However, despite all the advantages of needle insertion procedures, the inherent complications resulting from them, such as tissue deformation, needle deflection, tissue inhomogeneity, patient variability, and associated uncertainty, can hardly be missed. Therefore, a needle insertion procedure requires that we address promising aspects and associated concerns. Against this backdrop, this paper provides a review of some of the main issues associated with a generic needle insertion procedure.

Key words: Needle Insertion; Steering, Control; Path Planning; Modeling and Simulations; Needle Deflection and Deformation; Needle Curvature.

1 Introduction

To date, many researchers have worked on different aspects of a needle insertion system. For example, regarding the needle, some aspects like its diameter, tip type/shape, flexibility, rigidity, and torsional compliance have been examined. Similarly, regarding tissue, some aspects like its elasticity, linearity/nonlinearity, homogeneity/heterogeneity, and isotropy/anisotropy have been studied. However, when it comes to a coupled system, their interaction is determinant. The ultimate goal in a needle insertion system is to control the needle during insertion in such a way that it follows the desired trajectory with as little tissue trauma as possible. Different inherent complications such as limited visibility, the difficulty of needle maneuverability, needle deflection and tissue deformation arise during needle insertion. It is virtually impossible for the surgeon to manually provide accurate control over the needle motion in the face of all these complications. It is little wonder, then, that the automation or semi-automation of manual insertions in the hope of raising the success rate have gained in popularity. However, it seems much more research still has to be done and the concerns have to be more adequately addressed before applying this technology into operating rooms. The primary goal of this paper is to introduce some important topics on needle insertion in soft tissue, instead of introducing a review on needle insertion into soft tissue which can be found in [1] [2], and [3]. Therefore, four main aspects of a general needle insertion system are chosen: (I) modeling and simulation, (II) steering, control, and path planning, (III) needle deflection and tissue deformation, and (IV) needle curvature.

2 Modeling and Simulation

Needle-tissue interaction modeling can be used in simulating, control, steering, and path planning of needle insertion inside soft tissue. A comprehensive model that can fully capture the detailed features of this interaction has yet to be developed. Modeling living tissue material and needle-tissue interaction forcesare extremely complicated due to the inherent physiological and biomechanical variations of soft tissue before and during needle insertion. Even for a certain organ in a certain person, there are implicit uncertainties in soft tissue modeling due to periodic motions of breathing and heart beating, variation in body temperature and blood pressure, healthy versus sick tissue, etc. Moreover, soft tissue properties vary during insertion due to tissue inhomogeneity, nonlinearity, and anisotropy. The two common methods currently used for soft tissue modeling are the finite-element model (*FEM*) and the mass-spring-damper model (*MSM*). For some perspective, *FEM* is based on continuum mechanics focusing on precision, while MSM calculates discrete deformations at a higher numerical rate. DiMaio [4] used the *FEM* to consider elastic tissue deformation caused by a relatively stiff needle during insertion. By placing markers on the tissue phantom surface, he experimentally monitored the planar nodal tissue mesh deformations. To ease the burden of numerical calculation, he assumed a quasi-static linear elastic tissue model. As a result, the tissue nodal forces were estimated by solving a set of linear equations. He used this estimated force distribution to simulate a virtual planar needle insertion. This helped surgeons and medical residents to improve their experience by virtually rehearsing various aspects of a needle insertion. Also, using the condensation technique and low-rank matrix updates, he improved computational effciency. To achieve a more realistic model, they extended their work to [5], considering a slip-stick model in the needle-tissue contact interaction. His work also accounted for needle flexion and orientation changes by considering a large strain elastic model for the needle. Moreover, varying velocity and nonconforming needle trajectories are considered. Although *FEM* for tissue material has significantly contributed to modeling and simulation, its real-time application is limited to small linear deformations. For larger deformations, the nonlinear stress component has to be considered instead, and subsequent expensive numerical analysis has to be carried out. In [6], using a 2*D* dynamic *FEM*, a thin, rigid needle insertion is simulated during manual prostate brachy therapy.

Barbé et al. in [7] proposed a method for the online robust estimation of needle interaction forces for in-vivo/in-vitro experiments based on a variant of recursive least squares algorithm. They broke down the insertion process into three phases: before puncture, needle penetration inside tthe issue, and needle retraction. The available measured data is needle tip position and velocity. Since the velocity is obtained by numerical differentiation of position data, the Kalman filter is used to address the associated perturbations caused by quantization error. They compared two distinct models for the first phase, i.e. the Kelvin Voigt model and the Hunt Crossly model. *HC* model's generality in incorporating nonlinear interaction associated with larger deformations is its competitive edge over the *KV* model. During insertion, they modeled the insertion forces as a summation of cutting, friction and persisting tissue compression, the latter of which was not considered in [8]. Since only the position of the needle tip, which is completely different from the position of the needle entry point on the surface, is available, separation of different force components during insertion without fiducials is not feasible. For practical purposes, they modeled the needle insertion force by simply generalizing the *KV* model to the time varying version in which model parameters, K and B (stiffness and damping), depend on the needle tip position and velocity. Unlike [4] and [5], which estimate the force distribution along the needle shaft nodes; Okamura [8] modeled the needle driving forces as a combination of three components: capsule stiffness, tissue cutting, and friction forces. The first component refers to the pre-puncture phase and was modeled by a nonlinear spring, while the other two refer to needle penetration inside soft tissue and were modeled by a constant parameter and a modified Karnopp friction model, respectively. The model parameters are then derived experimentally through proper curve fitting functions during ex-vivo tests.

Unlike[4-5] where steerability of the stainless steel needle is achieved through noticeable soft tissue deformations caused by manipulating the needle base, Webster et al.[9] modeled a highly flexible bevel tip needle insertion in a relatively stiff material, which carried negligible tissue deformations, consequently inflicting less damage on the surrounding tissue. They experimentally observed that the needle tip trajectory looked like the final needle shaft shape. The data is obtained via a robotic system with two degrees of freedom: insertion and rotation about the insertion axis. In bevel tip needles, steerability is mainly achieved through unbalanced force distribution at the bevel tip. Hence, needle tip motion can be controlled by the axial rotation of its base. In view of the non-holonomic nature of bevel tip kinematics in soft tissue, they developed $2D$ unicycle and bicycle models for steering the bevel tip needle inside soft tissue. Furthermore, using the Lie group theory, the $3D$ generalization of unicycle and bicycle models is represented. Fig. 1 shows the front and back wheels of the bicycle model, which are located at origins B and C. A fixed heading angle, φ, is assumed in the model, resulting in a constant curvature (κ) needle path for the bicycle model. For the unicycle model, κ equals the ratio of φ over needle insertion velocity. Because κ is considered constant, tissue deformation is not modeled. Moreover, needle-tissue friction and torsional compliance of the flexible needle are not taken into account in their model. Since needle insertion/rotation velocities are usually of low rates, studies often examines static/quasi-static analysis and control by assuming that the needle is in an equilibrium state during each time step. However, in practice, insertion velocity does matter and can be used as a control degree of freedom. In this regard, some studies have looked at needle insertion dynamics. Drawing on fracture-based mechanics, Mahvash in [10] studied the dynamics of needle insertion into soft tissue with a particular focus on transitions between different tissue layers. The fact that ruptures are developed with uncontrolled crack extension could lead to unexpected behavior of the needle tip with a negative influence on tip position accuracy. He also spotted an inverse correlation in that as the insertion velocity increases, both the rupture force and deformation decreases, and, as a result, less tissue damage and more controlled behavior is experienced during rupture. As insertion velocity cannot be raised beyond a certain point for safety and stability considerations, he obtained an optimal velocity for practical application.

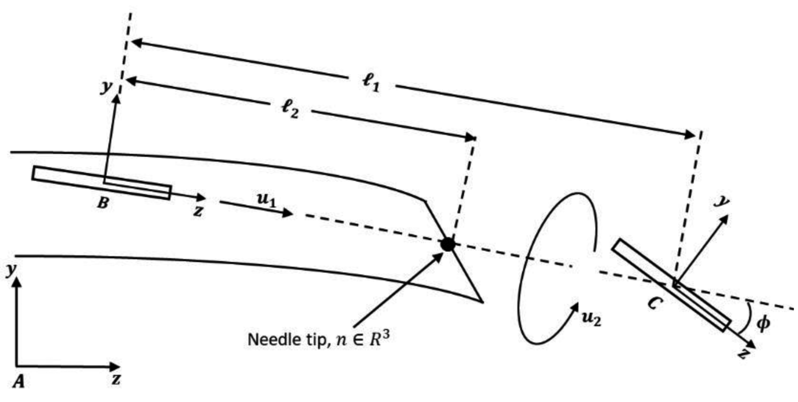

Fig. 1 Configuration of a bevel tip needle during steering showing the front and back wheels at frames B and C of a superimposed bicycle-like non-holonomic model [9].

In a similar vein, Khadem et al.[11] studied the mechanics of inhomogeneous soft tissue cutting and broke down the whole insertion process into three phases similar to [8], with negligible tissue resistance/reaction forces. Tissue cutting forces, which are considered constant in [8], is reviewed analytically as a function of needle tip geometry, tissue mechanical properties, and insertion velocity. Khadem et al. in [12] derived the detailed dynamic equations of robotically assisted needle insertion into soft tissue and predicted both the needle shape and the tip position while considering tissue resistance forces. They proposed a coupled two-body rigid/flexible model for the needle carriage/shaft. The flexible part is modeled by a compliant beam, which undergoes tissue resistance forces as the external force. Their study, like many other mechanics-based modeling works, is constrained to planar analysis.

From an experimental point of view; in view of current measurement limitations and model parameter identification challenges, researchers prefer using synthetic tissue phantoms to using living tissue. This is because phantom tissues provide a translucent, homogeneous, and more controlled environment for repeated needle insertions. Ultimately, for better assessing the feasibility and performance of any proposed approach for clinical implementation, in-vivo tests have to becarried out. Wedlick in [13] carried out a comparative study of needle insertion in artificial phantoms and ex-vivo tissues using a robotic needle insertion system. He experimentally observed that the common artificial phantoms do not closely mimic the ex-vivo behavior and exhibit different stiffness, friction, and relaxation properties. Furthermore, their study revealed that the torque measured during needle rotation is related to the needle shaft force measured during insertion. A similar trend is observed for the recorded motions. Based on their work, it is possible to obtain a needle-tissue interaction model without having to advance the needle through the skin, which leads to a less destructive model identification process.

3 Steering, Control and Planning

In many medical applications, it is desirable to control needle navigation inside the body in order to reach a target while avoiding collision with an obstacle. In current manual insertions, this is usually done by the surgeon through manipulating the tissue which requires considerable training and experience on the part of the surgeon. However, for accurate needle control and planning inside tissue, more explicit methods are needed. Based on the under-actuated characteristic of the needle motion inside soft tissue, it is not always feasible to reach this goal manually. Incorporating robots into manual insertions could help to overcome the inherent limitations of manual needle insertion. Some researchers prefer using robots in parallel with the surgeon instead of fully automating the procedure. However, due to the significant potential of robotic needle insertion systems in control and path planning, they are frequently used in current research practices. In this regard, a robotic needle insertion system with active needle steering was developed in [14]. Their experimental setup provides stereo imaging feedback as well as controlled actuation for needle linear and rotation motions. Furthermore, needle buckling was avoided using a telescopic support sheath. The goal is to improve the performance of a needle insertion system by enhancing needle steerability while moving around obstacles.

In some relatively simple applications of needle navigation, the needle steered toward the target solely based on the current needle tip deflection. Neglecting the final needle tip deflection can result in poor targeting accuracy. In this regard, Niki in [15] worked on a needle base trajectory generation for planar motions in the absence of imaging feedback. Tissue deformation was not modeled in their work. The insertion process decomposed into two consecutive intervals. During the first period, drawing Euler-Bernoulli beam theory, online estimation of the needle tip deflection is achieved. At each time step, deflection estimation is compared with a predefined threshold. Right at the time of violating the threshold, insertion is paused and the bevel direction is changed via 180° axial rotation of the needle. Thus, bevel rotations help to constrain needle motion into the plane of interest and to minimize the tip deflection at the same time. The recorded data during the first phase is used to obtain the average estimated curvature of the needle tip trajectory κ_{avg}. During the second phase, the needle motion is estimated as a uniform motion on a circular trajectory with a constant radius κ_{avg}-1 along with bevel rotations at some certain depths of threshold violation.

In more general cases the needle has to follow a complex trajectory in order not to collide with impenetrable objects and not to damage any sensitive tissue structures. Therefore, a more efficient and robust planning approach has to incorporate tissue mechanical properties, update the needle path curvature, and carry out online predictions of the rotation depth with reasonable timing.

One major categorization of planning approaches is based on the trade-off between optimality and speed. In the former case, a cost function is usually defined to numerically represent the path planning problem. It could be any combinations of different objectives such as minimum control action, minimum needle insertion length, maximum clearance with obstacles, and minimum targeting offset. In this regard, Ron et al. in [16] solved a simulation-based planning problem for a highly flexible bevel tip needle during insertion inside 2*D* soft tissue with obstacles. Ron solved the planning problem via integrating simulation and numerical optimization. Regarding simulation, the *FEM* for tissue mesh, material properties, boundary conditions, insertion velocity, needle tip cut force, and needle shaft tangential friction forces including static and dynamic components are defined. Furthermore, the needle is modeled by line segments, which are laid on the edges of the triangular tissue mesh elements. This is done through real-time mesh modifications. Regarding the planner, the insertion plan is originally defined by four variables: needle initial location, needle initial orientation, bevel flips, and insertion length; however, for simplicity, it is run with the first two variables. Generally, a feasible plan is defined as a set of variables which can direct the needle tip suffciently close to the target without the needle shaft intersecting any obstacles. Using an optimization algorithm, the planner is to pick a feasible plan that minimizes needle insertion length. However, their planner uses extensive numerical optimization to find the locally optimum path for a steerable needle inside deformable soft tissue with the presence of obstacles. Hence, in order to ensure online control and planning of the needle tip, the execution time of the planner has to be reduced significantly.

In a different work, DiMaio in [17], developed a 2*D* potential-field-based path planning approach for flexible symmetric-tip needles during insertion in deformable soft tissue in the presence of obstacles. Despite the work in [16], in which tip steering is achieved using asymmetric bevel-tip needles, in [17], he introduced a motion planning approach to symmetric tip needle via base steering. In addition, contrary to [16], which is not suitable for online applications in view of the time-consuming nature of their method, DiMaio's proposed approach is computationally efficient for online applications where fast re-planning is required. Both works rendered a locally optimum solution with no guarantee to meet the objectives. In his work *FEM*, was used in the simulation with a linear elasto-static model and a nonlinear model for the tissue and needle, respectively. For the 2*D* case, the needle was manipulated from its base by three degrees of freedom, namely two translational velocity and one in-plane angular velocity. He developed his planning approach based on the potential field concept and via introducing needle manipulation Jacobian. The Jacobian relates base velocities to needle tip velocities. Given the obstacles and target locations in the needle configuration space, a local hemi-elliptical repulsive potential field for each obstacle and a global uniform attractive potential field for the target are defined. It is known that the deeper the needle is inserted, the more constrained its trajectory is and the larger the Jacobian condition number becomes. Therefore, early corrections are preferred, which could be achieved by a hemi-elliptical choice of the repulsion field. The solution to the path planning problem is given by choosing the gradient of the resultant potential field as the desired direction for the needle tip. He tested his approach in open loop and based on physically obtained parameters for tissue properties and needle shaft forces. Although it is known that for obtaining the real value of tissue mechanical properties, online parameter estimation is required, their nominal model still shows relative robustness to model parameter uncertainties.

In [18], Duindam et al. introduced a short-distance $3D$ path planning approach for steerable needle using inverse kinematics. The fast geometric-based planner originally computes a feasible path for obstacle-free environments. However, there is some possibility of both avoiding obstacles and obtaining a better solution among certain possible candidates using the concept of null motions. They used a stop-and-turn strategy with the limitation of eight consecutive turnings and insertions. However, one major limiting factor associated with optimization-base planning problems is their time-consuming feature which increases with an increase in problem dimensionality. Consequently, this restrict their applications to open-loop planning. The scope of his work and other approaches with expensive computations is limited to open-loop planning.

On the other hand, particularly in recent years, sampling-based approaches have become far more popular in path planning problems. Without having to explicitly characterize the configuration space, the time complexity of these randomized algorithms decreases significantly. Two famous approaches are Probabilistic-RoadMaps (PRM) [19] for multi-query problems and Rapidly-Exploring-Random-Trees (RRT) [20] for single-query path planning problems. Both RRT and PRM are based on a random sampling of the free configuration space but with different specifications.

PRM mainly focuses on optimality by randomly sampling the free configuration space. Then using a local planner, it checks for collision-free connections of the already sampled states. Once the roadmap has been constructed in an off-line fashion, the globally optimal path can be computed for the given grid, using a fast graph-based search algorithm. Moreover, PRM algorithms are complete. However, both optimality and completeness are guaranteed up to the given grid resolution. It is known that there is a trade-off between the size of the grid and computation time. In other words, a high-resolution grid, where the solution is more convergent to the true optimal solution, has higher time complexity.

Conversely, the RRT method concentrates ona fast exploration of the configuration space without providing any guarantee of optimality. It is biased toward exploring the unexplored configuration space by incrementally growing a tree form the root node toward a target. The solution of an RRT path planning algorithm is either a failure or a feasible path. In other words, in limited time, it does not provide a guarantee of completeness. However, the algorithm is probabilistically complete. This means that by removing the time constraint, the RRT algorithm is able to find a solution if any.

Sachin in [21] developed an RRT planning algorithm for steerable needles in complex $3D$ environments including obstacles and narrow passages at an interactive rate. Using $3D$ real-time imaging feedback, it is possible to edit the environment in real time by adding or changing obstacles. Instead of using a classic RRT algorithm, which tries to find the best control input to expand the tree and which is quite computationally expensive, they encoded the segments of needle trajectory based on geometric quantities instead of control inputs and calculated the feasible geometric trajectory composed of piece-wise circular arcs with different curvatures. Afterwards, this geometric trajectory is mapped onto its equivalent motion plan based on a duty-cycling (DC) approach as in [22]. Using reachability-guided sampling heuristic, the planner efficiently applies the nonholonomic kinematic constraints of needle motion. Their work is based on a deterministic model of needle motion and does not explicitly consider uncertainty due to tissue inhomogeneity, tissue deformation, and model parameter uncertainty. However, the planner can be integrated into a real-time feedback controller in order to compensate for any disturbances that could occur during needle insertion by fast re-planning.

In a similar vein, Bernardes et al. in [23] and [24] introduced an adaptive 2D path planning algorithm using duty cycling. In [23], they presented an arc-based RRT planner to intraoperatively compensate for motion uncertainties and disturbances. Also in [24], they used an input-sampling version of a 2D RRT planner, rather than point-sampling to achieve even faster computation of the needle trajectory for intraoperative use. They used an adaptive motion planner to continuously update the needle path. However, the 2D scenario used in the simulations considers the target region excessively large. In [25], Sachin et al. introduced a needle steering algorithm in 3D via rapid RRT replanning. Their planner and controller are implemented in a closed-loop configuration and are capable of dealing with real-world uncertainties. Their method is similar to [21], but with a modified distance metric. Instead of choosing Euclidean distance to find the closest node in the tree, the arc length of each subtrajectory is chosen as a better candidate. They also relaxed the constant-curvature constraint using DC to perform variable-curvature trajectory planning. Furthermore, they accounted for needle buckling in their planner as well. They obtained the relationship between duty-cycle and needle curvature by fitting a polynomial function to the empirical data obtained through pre-operative images. It is known that the distribution of the vertices in the tree depends on the sampling distribution. As a result, instead of sampling the tree uniformly, biasing the sampling toward the goal is preferred to improve the planner's efficiency. In this regard, they used two types of biasing. First, they biased the growth of the tree toward the goal by sampling from the goal region with a higher probability than the rest of the free configuration space. Second, once each node has been added to the tree, the algorithm tries to connect the recently added node to a randomly sampled point in the target region. Since the planning is very fast, the planner can be run many times and finally, based on clinician-specific criteria, it selects the best candidate among the many obtained plans. Similar work has been done by Vrooijink et al. in [26]. They performed 3D RRT re-planning and steered the steerable needle in a non-static environment using the 2D ultrasound images. The configuration of the system is shown in Fig. 2. Steering is done robotically by insertion and rotation of the needle at its base. A 2D US transducer is used to track the needle tip. The tracking information is used to estimate the 3D needle tip pose required for conrolling and planning the needle motion to reach a moving traget while avoiding moving obstacles.

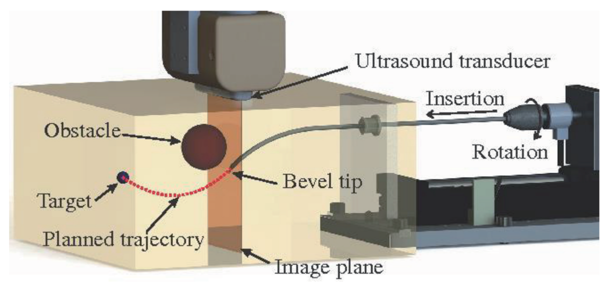

Fig. 2 A flexible bevel-tip needle is steered inside the tissue phantom by automatic insertion and rotation of the needle base. Using a 2D US transducer, the needle tip pose is estimated for 3D planning [26].

Fig. 3 shows different scenarios where the needle tip trajectory is updated intra-operatively to take into account changes in the target and the obstacle motions.

Moreover, Moreira et al. in [27] worked on the same context of adaptive 3D RRT-based planning for dynamic environments without prior knowledge of needle curvature, which is estimated online through ultrasound images.

Due to tissue inhomogeneity and needle-tissue uncertain interaction, there is always a certain degree of uncertainty in a generic needle insertion procedure. As a result, some traditional shortest-route plans may lose efficiency and may guide the needle through narrow corridors which are less robust in the face of uncertainties and, consequently, may collide with obstacles. The above-mentioned intraoperative methods attempt to regularly update the planned motion based on the most recent information obtained from the closed-loop feedback. Many of these methods do not directly model uncertainty. Instead, using deterministic models and monitoring the system response, uncertainties that are observed in the output are compensated. Alterovitz et al. in [28] introduced another sampling-based motion planning approach that explicitly considers uncertainty in needle motion in order to maximize the probability of success in terms of obstacle avoidance and target hitting. A Stochastic Motion Roadmap (SMR) is built similar to Probabilistic Roadmaps (PRM) by sampling collision-free states in a 2D configuration space. The collision-free connectivity of states is determined using distributions instead of binary values like PRM. Using SMR, the motions are locally sampled at each state for each control input and then the associated state transition probabilities are estimated. The problem is formulated as a Markov Decision Process (MDP) and is solved through Dynamic Programming (DP) to return a stochastically optimal path. A complete work of a 3D needle steering system that integrates an SMR planner with a planar controller to stabilize the needle in the desired plane with torsion compensation has been developed by Reed et al. in [29].

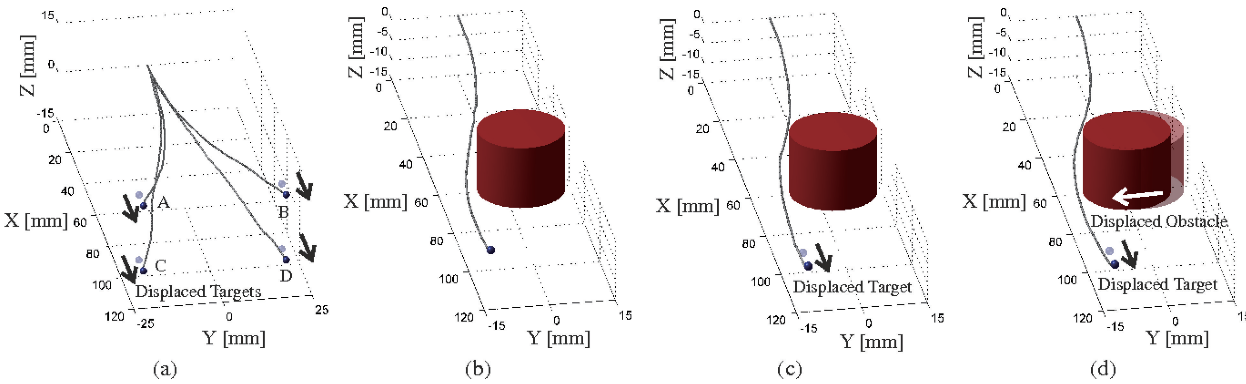

Fig. 3 The performance of the 3D planner in different scenarios. a) the moving target, b) both the static target and the obstacle, c) the moving target, and d) both the moving target and the obstacle. In all scenarios, the needle is able to reach the desired target [26].

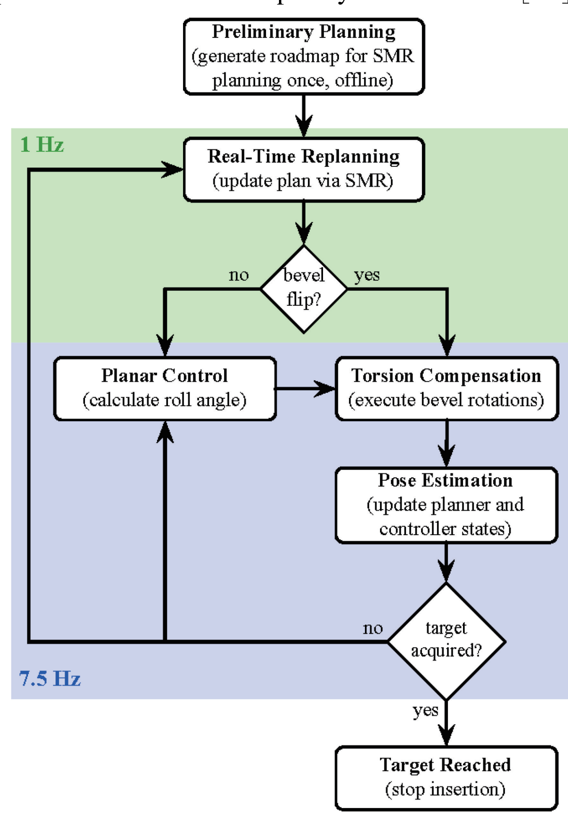

Fig. 4 Block diagram of an integrated system composed of pose estimator, planner, controller, and torsion compensator [29].

Fig. 4. best describes the overall functioning of the integrated needle system composed of different components operating at different rates. The pose estimator, planar controller, and torsion compensator are updated at 7.5 Hz. (camera imaging frequency). After capturing each image, the estimator estimates the needle tip pose and the planar controller commands a base rotation which maintains the needle tip near the desired plane. The planner operates at 1 Hz and plans the optimal bevel flip. The torsion compensator rotates the needle base to ensure that the needle tip is at the desired angle.

Other modifications of the original algorithms are available in the literature such as [30] introduced by Alterovitz et al. They developed a Rapidly-Exploring Roadmap (RRM) planning algorithm for single-query optimal path planning. It provides a user-specific balance of exploration versus refinement. These algorithms work well under kinematic differential constraints and especially for systems with high dimensional configuration spaces, consequently, making them a good candidate for steerable needle path planning problems under geometric and nonholonomic constraints.

It is worth noticing that for clinical in-vivo implementation of any of these approaches, a closed-loop control with necessary improvements has to be considered in advance. This includes high-resolution real-time imaging feedback to measure the tissue's complex $3D$ deformations as well as the in-vivo real-time measurement of tissue properties via ultrasound/MRI elastography. In this regard, different image-guided control methods have been proposed. Regarding the current practice of image-based needle control and guidance and among various imaging modalities including ultrasound, MRI, CT, and fluoroscopy, ultrasound imaging is preferred. This is because of its potential for real-time applications, compatibility with current needle material, safety in terms of no radiation exposure, and low cost. Regarding $3D$ US imaging, there is a compromise between the voxel resolution and acquisition time. Therefore, the US transducers used for real-time applications have limited resolution. To overcome this problem, Vrooijink et al. in [31] introduced a real-time $3D$ flexible needle tracking algorithm using $2D$ transverse US images. In order to consistently view the needle tip in the US images, the US probe is robotically repositioned to move in tandem with the needle tip. This is achieved by a compensator, where the needle insertion velocity is corrected by needle tip velocity to compensate for out-of-plane motions. Due to inherent noise, there is an aberration in the probe position which is compensated for using Kalman filter in a closed loop configuration. They estimated the needle tip pose with the assumption that both needle torsional stiffness and bucking along the needle shaft are neglected.

Many approaches introduced in the literature exclusively focus on the planner design, assuming that the needle motion is maintained in the imaging plane. However, neglecting the existing out-of-plane motions, especially after each bevel flip, results in a significant needle tip displacement error and divergence from the plane of interest. This issue is addressed by Kyle et al. in [32-33] through a robotic-assisted needle insertion system and by incorporating a low-level controller to a high-level planar planner. Both are based on a non-holonomic kinematic model and are able to control the 6 DOF needle tip pose. The surgeon is in the loop and is in charge of insertion. For enhanced steerability, a pre-bend bevel tip needle is used. This requires further modifications to the non-holonomic model presented in [9] to account for the needle tip position and in-plane angle discontinuities during bevel flips. This is accomplished by adding two more parameters rather than the needle path curvature, namely displacement offset and orientation angle offset. Their proposed method is composed of three main components: patient-specific planner, observer-based controller, and torsion compensator. Each component is designed independently of the other ones, thus simplifying the design procedure. The planner is responsible for steering the needle in the plane of interest to reach the target without colliding with the obstacles. It works based on a stochastic motion roadmap where inevitable model uncertainty is explicitly accounted for. Hence, it maximizes the probability of reaching a target while providing greater clearance from the obstacles. As the orientation of the thin needle tip cannot be measured directly from the images, roll, yaw, and pitch angles are estimated by the observer. The nonlinear image-based observer-controller pair [34] is responsible to stabilize the needle in the desired plane by compensating for the small out-of-plane deviations. Due to the needle's torsional compliance and friction at the needle-tissue interface, 180° rotation in the needle base does not necessarily transfer to the needle tip during each bevel flip. Accordingly, ignoring this large angular mismatch can lead to the failure or poor performance of the planner and controller. Therefore, the torsion compensator is in charge of an accurate transition of the needle axial rotation from the base to the tip during each bevel flip.

In contrast to simulation-based path planning algorithms [16-17] that account for tissue deformations, in [32-33] the needle path curvature is assumed constant without considering tissue deformations during insertion. Furthermore, needle path curvature is obtained experimentally for a specific patient and through multiple needle insertions and retractions, which is not always feasible in in-vivo applications. As a result, model-based control and planning methods that are based on nominal parameters suffer from the uncertainties associated with noisy sensors, imperfect actuators, tissue deformations as well as target motion. In in-vivo applications, tissue inhomogeneity is added as an important source of uncertainty. For example, the work in [32], which is an open-loop control and planning algorithm, addressed the uncertainties related to tissue deformations by considering the *FEM* for the tissue. Their work showed an acceptable performance for limited standard deviations from the nominal value of needle curvature. However, providing a higher degree of robustness is a more challenging task.

In an attempt to remove the dependency of a method on a specific patient, non-model-based approaches have been proposed for needle steering and control. Bita et al. in [35] proposed a simple $2D$ image-guided sliding-based control algorithm to steer a bevel tip needle toward a fixed location inside the tissue during brachy therapy. Out-of-plane deviations of the needle tip have been left out in their work. The needle tip deflection error, obtained from ultrasound imaging feedback, and its derivative are fed into the controller as inputs. Their method does not require any knowledge of needle or tissue characterizations except a rough estimate of needle tip curvature. Moreover, the algorithm is not sensitive to uncertainty in the needle curvature. During the needle's inplane motion, the bevel tip orientation is discrete, either 0° or 180°, and is characterized by the sign of curvature. Regarding the sliding-based controller, keeping the sliding surface as close as possible to zero is equivalent to maintaining zero error dynamics. A bevel flip is executed by the controller whenever the sign of the switching surface changes. This approach is in keeping with the increased number of bevel flips which can result in increased tissue trauma. To mitigate this observation, an alternative switching pattern with added hysteresis to the model is used. A higher choice of the switching threshold leads to a lower number of bevel rotations pointing to a trade-off between the targeting error and the number of bevel flips. The stability analysis and error convergence are carried out using the unicycle kinematic model for needle insertion and the Lyapunov stability method. Also, the $3D$ extension of this work has been done by the same author in [36].

A different means of needle steering is introduced in [37] based on curved concentric tubes. Regarding bevel tip needles, it is known that steering is obtained through tissue reaction forces, thus, leading to inferior steerability during needle transition inside tissues with a lower Young modulus as fluid-filled cavities. This limitation is overcome by curved concentric tubes where interaction forces are independent of tissue stiffness. As a result, this can publicize their application into various medical procedures. In [37], the details of both direct and inverse kinematics of these tubes were elaborated in quest of control and path planning.

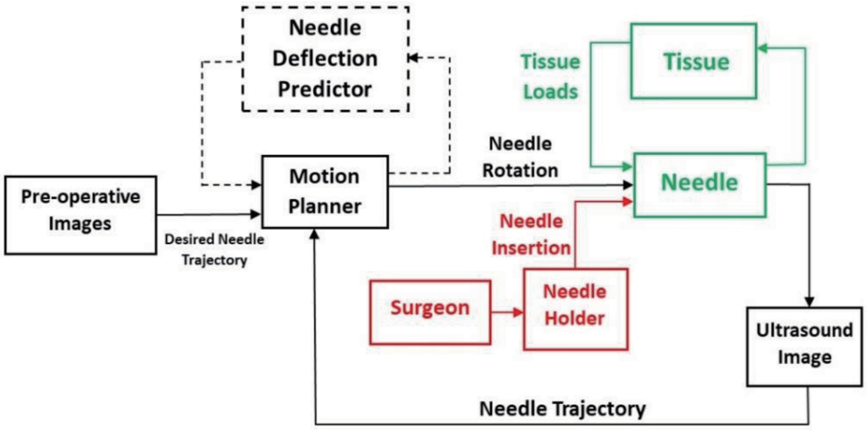

Fig. 5 Block diagram of a closed loop robotic-assisted needle steering system [38].

In many proposed methods, the needle pathcurvature is assumed constant. In fact, needle curvature is a depth-varying parameter and depends on various factors during insertion such as insertion velocity, tissue inhomogeneity, and needle-tissue frictional forces along the shaft. Khadem et al. in [38] proposed a 2*D* closed-loop control and guidance for needle insertion in soft tissue with obstacles. Their work features an online motion planner and an adaptive real-time deflection predictor, which calculate control decisions (rotation depth) and future needle tip deflection, respectively. The predictions are made based on homotopy analysis, a concept that is used to describe a continuous variation or deformation. Fig. 5 shows the block diagram of the robotic-assisted needle insertion system where needle insertions and rotations are done manually and automatically, respectively. As shown, the updated needle path curvature obtained by ultrasound imaging feedback as well as control decisions calculated by the motion planner have to be fed into the ham-based predictor. Accordingly, the planner calls up the predictor to estimate the needle tip trajectory. Given obstacle and target locations, the planner executes an optimization using a graph-based search algorithm. The needle configuration space is an n-dimensional simplex with n being the maximum number of bevel flips during insertion. Therefore, it demonstrates the different possibilities of control actions. For feasibility, the configuration space is discretized by including a 5mm distance between two consecutive bevel rotations.

Obstacles are mapped onto the configuration space through intensive offline search. Since obstacles are defined through preoperative images, they might undergo variation and motion. Against this backdrop, they made their work relatively robust by extending the nominal margins of the obstacles. Finally, starting from an initial node, the planner iteratively tries to find an optimal trajectory that minimizes both the targeting error and the number of bevel flips.

4 Needle Deflection, TissueDeformation

In many medical percutaneous procedures, the objective of reaching a target is accomplished through either regulation or tracking. Unlike regulation, which only handles the final needle tip displacement error, tracking deals with needle tip deflection at each depth of needle insertion. Needle deflection and tissue deformation are two coupled and correlated characteristics of needle-tissue interaction which depends on tissue biomechanical properties, needle mechanics and geometry, interaction forces, and the choice of the needle-tissue pair. To enhance procedure efficiency, different approaches have been proposed to reduce this coupled effect. Without having a tissue deformation model, Niki et al. in [39] experimentally investigated the effect of different types of needle motion on tissue deformation during robotic needle insertion. They classified tissue deformation before and after puncture into tissue indentation and deformation, respectively. In the former case, they performed a set of different experiments with no rotation, with continuous rotation at different speeds, with partial rotation at different angles and speeds, and with rotation with control on the force in the x and y directions to keep them as close to zero as possible. The best needle base trajectory is obtained via partial rotation with a smaller angle. Regarding the insertion phase, it is known that frictional forces attract the tissue along the needle motion direction, implying that reducing frictional forces during insertion leads to a reduction in tissue deformation. It is also observed that controlling rotational motion together with force control in the x and y directions yields the best result with less tissue damage.

Mahvash in[40] analytically studied the mechanics of deformations arising from transitions between different tissue layers during insertion into inhomogeneous tissue. This study showed that these rupture-wise transitions can deviate the needle tip from its desired path. the force-displacement characteristic of needle insertion is modeled by a modified nonlinear viscoelastic Kelvin model. Furthermore, the relation between the rupture force and insertion velocity is derived. It also revealed that for faster insertions, the force-displacement curve is steeper and tissue absorbs less energy. For instance, maximizing insertion velocity up to a certain level minimizes tissue deformation as well as tissue damage and, consequently, less needle position error is experienced.

Needle deflection is a severe complication during needle insertion. Needles with a smaller bevel angle have greater bending force at the tip and tend to deflect/bend more. Niki et al. in [15] introduced a model for needle deflection prediction based on the static Euler-Bernoulli beam theory and just by force/torque readings at the needle base. It should be noted that the tissue resistance force is not considered in their model. In contrast to their work, in [41] the needle-tissue model is fully parameterized by using partial $2D$ transverse ultrasound images. Niki et al. in [42] analytically estimated needle tip deflection based on a static model of a flexible cantilever beam, using only force/torque readings. The vertical component of the cut force P is determined through $P=F_z/tan\theta$, where F_z is the axial cut force and θ is the respective angle. However, in practice, the axial force reading is used instead and without excluding the frictional forces. Furthermore, θ is approximated by the bevel angle, which limits the application to small deflections. Both of these simplifying assumptions introduced an error in determining P.

Niki et al. in [15] extended the previous work [42] to account for the lateral tissue deformations. Tissue reaction/compression force is modeled by a triangularly distributed load, which is applied along the inserted part of the needle shaft with its maximum intensity at the entry point. It is assumed that the deflection curve has a very low slope. They locally linearized their model and needle tip deflection is calculated by summing the small-scale deflections obtained from the linearized local models. Besides, they experimentally observed that reducing needle deflection has a decreasing effect on tissue deformation. Despite the work in [15] and [42], Asadian et al. in [43] developed a planar deflection model based on the dynamic cantilever beam theory. However, for simplicity of calculations, needle tip deflection angle is limited to 25°. Moreover, the effect of friction which is ignored in [15] and [42] is considered in their model through a moving distributed external force. In this respect, the impact of insertion velocity is modeled by a linear viscoelastic friction component. Besides, tissue resistance/clamping force is modeled by virtual springs along the needle shaft. The closed-form solution of the deflection equation is obtained using Green's functions.

Another related work based on the beam theory is given in [41], where the needle-tissue model is fully parameterized using partial $2D$ transverse ultrasound images of the needle tip. Regarding needle tip imaging, to constantly maintain the needle tip in the field of view of the US probe, the probe is controlled to move in synchrony with the needle. On the other hand, the US probe moving causes further tissue deformations. To limit this deformations, the insertion process is separated into two different consecutive phases. During the first phase, needle deflection is directly calculated through US images. During the second phase, the US probe is stopped, while needle insertion continues. Therefore, future needle tip deflections are estimated based on the cantilever flexible beam model. The scope of the work is limited to a single curve trajectory. Also, it is assumed that needle rotation occurs before the US probe stops. The limitation of a single rotation is removed in [44] and deflection of the needle is predicted based on the adaptive version of the quasi-static model of the vibrating flexible cantilever beam. The model admits tissue stiffness and cut force as inputs where the tissue cut force is adaptively calculated via US images. Thanks to US images, accurate needle tracking is achieved and model parameters are updated in real time. Furthermore, lateral tissue deformations and respective tissue reaction forces are calculated in their work. The lateral deformation along the needle shaft is defined as the difference between the current position of the needle shaft and the previous path which is cut by the needle tip. By assuming tissue as a linear elastic material, lateral tissue reaction forces are simply proportional to the lateral deformations. The concept of updating deflection models via imaging feedback can be helpful, especially in updating the needle path curvature for guidance and control of the needle trajectory.

5 Needle Curvature

In view of the anatomy ofthe human body, in some applications of needle insertion procedures, it is not possible to reach a target through a straight line. Instead, a more complicated and curved trajectory is required. Therefore, for control and path planning of these problems, it is of high interest to obtain variable and/or high curvature paths. In [11], the effect of the needle diameter and the tip type on the needle path curvature as well as the insertion force magnitude is explained. It shows that bevel tip needles tend to bend more easily than the symmetric conic and triangular tip needles. Also, force magnitude increases form the triangular to the bevel tip. Nevertheless, bevel tip needles are more sensitive to tissue variations, while the other two yield a more robust behavior. More importantly, bevel tip needles deliver higher maneuverability over obstacles and sensitive tissue structures. Enhanced steerability can be extended to pre-bent and pre-curved needles with higher potential for maneuverability comparing to bevel tip needles. Thomas in [45] showed that in a pre-curved needle, the tip path curvature is inversely correlated to the arc length of the pre-curved section. Instead of its increased steerability, there are some negative implications associated with pre-curved needles. Specifically, due to the increased stress applied on tissue, lateral tissue deformation increases and the greater discrepancy between the needle tip path and the needle shaft is seen. With kinked bevel tip needles, even higher curvature can be achieved, but with increased tissue damage. This is because of the local helical path generated during the axial rotation of the needle base. This issue is addressed in [46] and solved by introducing flexure-based bevel tip needles, which offer both high steerability similar to kinked bevel tip needles and less tissue damage simultaneously. The bevel tip kinks during pure insertion in response to tissue reaction forces. Moreover, during axial rotation, the flexure tends to bend the kinked bevel tip back to its initial straight configuration. In in-vivo applications, where the needle has to penetrate inside the inhomogeneous tissue comprising different layers and structures, it is preferred to generate variable curvature during insertion. Minhas et al. in [22] introduced an active approach to generating variable curvature through the duty-cycled spinning of the needle base. Without rotation, the needle tip follows a path of maximum needle curvature, i.e. κmax. Alternatively, by incorporating constant rotation at a rate greater than the insertion velocity, straight trajectories can be achieved. By combining periods of spinning, T_{rot}, with periods of non-spinning, T_{ins}, any variable curvature less than the maximum needle curvature can be obtained. Therefore, by adjusting the duty-cycle of the needle motion, proportional control of desired needle curvature can be achieved as: $\kappa_d = \kappa_{max}(1\text{-}\alpha)$ where $\alpha = \frac{T_{rot}}{T_{rot}+T_{ins}}$.

To account for uncertain or unavailable curvature, Pedro in [47] introduced a $3D$ adaptive duty-cycle steering system based on an online estimation of needle curvature without the need for prior knowledge of the needle curvature. To increase the realism of their experiments, they considered moving obstacles and targets to simulate tissue motion caused by tissue deformation and physiological processes. Both the motion planner and the duty-cycle steering controller are updated at intervalsof 1 second. Based on the Principle Component Analysis, the $3D$ data of needle tip position are projected onto a plane, where the needle motion is performed during each interval. Consequently, the Least Squares algorithm is used to fit a circular path for the planar sub-trajectories. Noise removal and numerical robustness of the estimated curvature is achieved through Kalman filtering. At each interval based on the applied duty-cycle and the estimated curvature $\hat{\kappa}_d$, $\hat{\kappa}_{max}$ is calculated. Given $\hat{\kappa}_{max}$ and κ_d, which is determined by the motion planner, the duty-cycle steering controller sets the necessary T_{ins} and T_{rot} for needle insertion in the next interval. In a different work [37] variable curvature is achieved through the relative rotation and extension of concentric curved tubes with respect to each other.

Luca et al. in [48], inspired by nature, presented a steerable probe with a programmable bevel tip. It is composed of different interlocked segments which can slide freely in relation to each other. Hence, by adjusting the relative position of the segments the approaching angle can be controlled linearly and continuously. Investigating the bevel angle and probe diameter on the probe path reveals that both a larger bevel angle and a smaller probe diameter lead to larger curvature. However, this comes at the expense of less insertion stability. In a typical four-part prototype, two channels are considered for medical tools, while the other two are used for placing an electromagnetic tracking sensor. $3D$ steering can be reached through an independent control and actuation of each segment.

6 Current and Future Research Directions

Current research on robotic needle insertion procedures in biological tissue is still in its early stages. Most approaches presented so far work well in needle insertion simulations; however, many of other fail to keep their efficacy in practice. In this paper, some of the state-of-the-art of the current research on needle insertion has been introduced. However, there are still limitations and challenges that have to be addressed before transferring these technologies into operating rooms. In this section, we highlight some of these clinically relevant challenges and open areas for future research on needle insertion in biological tissue.

It is known that the goal of a needle insertion system is to navigate a needle to the desired location inside soft tissue while maintaining the whole procedure less invasive as much as possible. As a result, the performance of the procedure highly depends on the final needle tip placement accuracy. In some applications, acquiring sub-mm precision is required, which itself is a clinically challenging goal. The more insight is available about the complex needle-tissue interaction, the more accurate the control task is. To characterize needle insertion inside soft tissue, different models have been developed. However, developing a perfect model capable of capturing all aspects of needle-tissue interaction is highly complicated and, as such, remains under-researched and a daunting challenge for interested researchers.

Needle insertion is a complicated process consisting of such stages as tissue rupture, deformation, and cutting. An accurate modeling of each of these stages calls for extensive real-time knowledge during needle insertion inside soft tissue. On the other hand, in view of the fact that the needle insertion velocity is limited, most of the works introduced here are based on kinetic models with certain assumptions on soft tissue including tissue homogeneity, isotropy, and linearity. In addition, most of the experimental results have been carried out ex-vivo or on artificial tissues due to their controlled environment. In view of the intermixed nature of biological tissue, sometimes a certain technology or approach may not work well during the entire needle insertion. For example, passive steering of steerable bevel-tip needles may degrade in performance as tissue stiffness decreases. Since the steering is based on the tissue reaction force, these methods lose efficiency inside fluid-filled cavities. Instead, some active methods such as the use of concentric tubes [37] might prove a more potent and workable alternative. However, the associated cost is the increase in the size of the tube as compared to the that of the needle. To achieve both objectives, more research on needle material and technologies is required.

Regarding an accurate analysis of the important issue of insertion velocity, as observed in [40], one has to investigate the dynamic behavior of needle insertion procedure. It is known that biological tissue is inhomogeneous, anisotropic and nonlinear. Its mechanical properties vary with respect to location and direction. Even for a specific location and orientation inside the tissue, these properties undergo variations due to other determining factors such as body temperature, vascular pressure, and health of the organs. Other patient-specific parameters such as gender, age, and mass are extra influential factors. Biomotion of organs such as cardiac and respiratory systems can cause tissue motion. As tissue phantoms are translucent, almost homogenous, and less prone to deformations caused by US measuring probes, they cannot be a true representation of biological tissue. Instead, through in-vivo tests, there should be space for the existing uncertainty in sensing and motion which come into play, which is a necessary step in verifying the clinical effectiveness of any proposed approach.

In [33], the authors pointed out some of the complications associated with needle insertion procedures. A proof of the complex mechanical needle-tissue interaction is tissue rupture which is rather frequent, dynamic, and usually followed by uncontrolled crack extensions. They found that if the needle enters a membrane with an angle less than the perpendicular case, it is likely to significantly alter the needle tip position after puncture as compared to the no membrane case. In addition, they cited needle bucking as one of the challenges during needle insertion. For frequently used steerable bevel-tip needles with a small diameter, if the applied insertion force exceeds a certain amount, the needle is likely to buckle during insertion and, consequently, laterally slice the tissue. This observation is in contrast with the minimal invasiveness goal of the procedure. To mitigate this effect, more precise research on needle mechanics and design needs to be done. Moreover, there should be a proper measure to quantify the amount of tissue damage caused by the needle during insertion. This is an open area for research and is particularly important when reducing tissue damage can have far-reaching implications for vital organs of the body like the brain.

During insertion in real tissue, the anatomy of the intended organ and its surrounding tissue is also an important issue to be reckoned with as the needle has to pass through multiple tissue layers and membranes with different characteristics. Each of them behaves like a rupture event. For intraoperative closed-loop guidance and control of needle insertion, proper sensory modalities have to be utilized in order to detect these detailed dynamic interactions. Generally, the burden of providing feedback during insertion is mostly on medical imaging modalities. In recent years, researchers have made considerable progress in image processing technology. However, obtaining clinically high-resolution real-time 3D visual feedback from needle-tissue interaction, capable of tracking needle and tissue motions and measuring 3D tissue deformation inside the opaque biological tissue and in the presence of anatomical obstacles and air pockets, has proved a rather formidable challenge. In current practice, US imaging is preferred thanks to its safety, low cost, and ability to provide information about tissue properties such as its elasticity. Yet, it is highly corrupted with measurement noise and, consequently, expensive image processing algorithms are needed.

In the context of sensing technology, researchers have come close to integrating force sensing into robotic needle insertion systems. In this regard, obtaining the information of different force components separately is desired. However, due to the small size of the needle diameter, the current work is based on force sensing at the needle base. Since telemanipulation of needle insertion procedures is a promising application for future minimally invasive surgery (MIS), providing accurate tactile/haptic feedback to the master side is crucial and, as such, developing a proper haptic device is another challenging area.

As stated above, two main challenges are tissue deformation and needle deflection during insertion, which may introduce considerable uncertainty in terms of tissue/target movements. The finite element method (FEM) is widely used in the literature to predict tissue deformation. However, for a more realistic representation of soft tissue deformation, the FE tissue model has to be developed in order to capture the tissue complex dynamic behavior. This added complexity of needle-tissue interaction could increase the computational costs, and consequently, limit the model's applicability. Therefore, improvement in software systems is another key area for future research, which can ultimately benefit robotic needle insertion systems.

Needle natural curvature is another determining factor to be reckoned with. Although concentric tubes and DC approach of steerable bevel-tip needles are frequently used to generate variable curvature trajectories inside soft tissue, the major challenge is to obtain a smaller radius of curvature with less tissue trauma, which, as it stands now, is still an open area for future research.

7 Conclusion

The primary goal of this study was to provide some useful and essential information on the field of needle insertion. The major areas covered were steering, control, and planning, tissue deformation and needle deflection, and needle curvature. In this regard, it provided some clear points in each area. Moreover, the gap between the current and future research directions was elaborated.

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