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Needle-Tissue Interaction Force State Estimation for Robotic Surgical Suturing

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Abstract

Robotically Assisted Minimally Invasive Surgery (RAMIS) offers many advantages over manual surgical techniques. Most of the limitations of RAMIS stem from its non-intuitive user interface and costs. One way to mitigate some of the limitations is to automate surgical subtasks (e.g. suturing) such that they are performed faster while allowing the surgeon to plan the next step of the procedure. One component of successful suture automation is minimizing the internal tissue deformation forces generated by driving a needle through tissue. Minimizing the internal tissue forces requires segmenting the tissue deformation forces from other components of the needle tissue interaction (e.g. friction force). This paper proposes an Unscented Kalman Filter which can successfully model the force components, in particular the internal deformation force, generated by a needle as it is driven through a sample of tissue.

I. Introduction

While the improved dexterity provided by Robotically Assisted Minimally Invasive Surgery (RAMIS) over traditional Minimally Invasive Surgery (MIS) enables more procedures to be completed using MIS techniques, several factors limit the utility of RAMIS procedures. These factors include poor manual dexterity, poorly defined training programs, time, and cost [1]–[5]. Automating surgical subtasks could mitigate these factors by reducing the total procedure time (potentially resulting in cost savings), and reducing the specialized training surgeons currently require in order to effectively use RAMIS tools. Since suturing is a ubiquitous subtask of surgical procedures, automating suturing can considerably reduce the total procedure time during RAMIS.

A high quality suture needle drive closes the wound while minimizing tissue trauma. One source of tissue trauma during suturing is the internal tissue distortion force that is generated by a rigid suture needle moving through the tissue. As the needle moves through the tissue, it sweeps out an area that creates internal tissue stresses and results in an additional needle-tissue interaction force. Needle drive uncertainties (i.e. needle grasp and tissue mechanics) can generate tissue deformation forces and lead to unnecessary tissue trauma. Consequently, minimizing the deformation force can lead to higher quality suturing. There is, however, no direct way of measuring the tissue deformation force generated by the needle sweep as force

sensor data would also include needle-tissue friction and cutting forces. Measuring the deformation force online would enable the needle driving system to respond to the tissue deformation and optimize the needle drive. In this paper, an Unscented Kalman Filter (UKF) based method for estimating the different needle tissue interaction force components using force/torque measurements at the surgical tool is presented. This work shows that online parameter and force component estimation can be completed in the needle body frame using a UKF. The proposed estimation method is validated on non homogeneous *ex vivo* tissue.

The outline of this paper is as follows. Section II outlines previous work related to needle driving and force modeling. Section III formulates a lumped force model for Kalman Filtering and estimation. Section IV describes the Kalman Filter states and implementation. Section V describes the tissue sample needle driving experiment and analyses the results on *ex vivo* tissue. Finally the conclusion outlines potential future work.

II. Background

The problem of autonomously executing surgical subtasks (and suturing in particular) has been approached before [6]–[8]. One of the more common approaches has been the introduction of master-apprentice techniques where the robotic system learns to mimic the needle drive completed by expert surgeons [9], [10]. The method proposed in the present paper differs in that it is attempting to directly model the phenomena of suture needle driving instead of inferring the optimal motions plans from recording experts.

Previously, lumped force models have been used to model the forces acting on a straight rigid needle [11] and semicircular rigid needle [12] during needle insertion. Even though lumped needle-tissue interaction forces models compromise accuracy, they are computationally efficient when compared to Finite Element Modeling (FEM) techniques [13]–[15] which means that it is easier to implement lumped models for real-time execution. Tissue material properties can vary widely between both patients and tissues and can pose a real challenge in estimating tissue response during a surgical procedure. Researchers have looked into using either the Extended Kalman Filter (EKF) or the Unscented Kalman Filter (UKF) to fit model parameters to tissue force measurements [16]–[18].

Unlike previous studies, which focus on directly estimating the tissue material properties, this work focuses on estimating the components of the needle tissue interaction wrench. The wrench component estimation lays the ground work for a controller that can use a previously generated needle path plan [19] and optimize it during execution in order to minimize the tissue trauma while maintaining a high quality suture.

III. Needle Tissue Interaction Force Models

Estimating the needle-tissue interaction force during a circular needle drive requires the derivation of a suitable force model that can describe the measured forces in the needle's body frame. The needle frame is shown in Fig. 1.

As shown in [12] and [11], lumped models can be used to estimate the force acting on the suture needle as the sum of three forces: tissue sweep, friction force, and cutting force.

$$F_{needle} = F_{friction} + F_{cutting} + F_{sweep} \quad (1)$$

Here F_{needle} (F) is the sum of the forces acting on the needle, $F_{friction}$ (F_f) is the friction force acting on the needle, $F_{cutting}$ (F_c) is the cutting force acting on the needle tip, and finally F_{sweep} (F_{sw}) is the force acting on the needle due to internal tissue compression (caused by the needle sweeping out an area),

The friction force and cutting force are impossible to eliminate from the total needle-tissue interaction force but the swept force can be reduced or even eliminated if the needle moves ideally. Using the needle coordinate frame shown in Fig. 1, the ideal needle body velocity would be

$$V_{SN}^b = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & \omega \end{bmatrix}^T. \quad (2)$$

By spinning the needle about its center, the needle traces out a circle and generates no swept area inside the tissue. This ideal needle motion plan is infeasible because suturing guidelines recommend that the needle tip penetrates the tissue sample orthogonally. The orthogonal needle insertion and ideal needle drive would fully embed the needle in the tissue sample and make the needle inaccessible [19]. Despite this, motion plans which minimize the swept force would still reduce tissue trauma.

In the rest of this section, the lumped force models are derived in the needle body frame so that the UKF force model can be applied from the perspective of the needle driving system.¹

The friction wrench acting on the needle is given by

$$F_f(t) = \begin{bmatrix} -\mu_s \rho \int_{\phi_0(t)}^{\phi_1(t)} \mathbf{s}(\phi) d\phi \\ -\mu_s \rho^2 \int_{\phi_0(t)}^{\phi_1(t)} \hat{\mathbf{r}}(\phi) \mathbf{s}(\phi) d\phi \end{bmatrix}. \quad (3)$$

This wrench component is computed by assuming that the friction is acting in opposition to needle segment tangents. Here the segment of needle is located at the point $\mathbf{r}(\phi)$ where

$\mathbf{r}(\phi) = \begin{bmatrix} \cos(\phi) & \sin(\phi) & 0 \end{bmatrix}^T$ while its tangent vector is given as

$\mathbf{s}(\phi) = \begin{bmatrix} -\sin(\phi) & \cos(\phi) & 0 \end{bmatrix}^T$. The moment calculation uses the $\hat{\mathbf{r}}(\phi)$ operator to define the cross-product matrix of $\mathbf{r}(\phi)$.² The small segment length is scaled by a friction parameter, μ_s (measured in N/mm) to convert the segment length to an incremental wrench. Integrating the incremental wrench over the embedded needle gives the total friction wrench. The

¹For succinctness, only the outline of the force model derivations are presented here. Please see [20] for the complete derivation.

²In this paper, we will follow the notation used in [21].

embedded needle segment, illustrated in Fig. 2, is defined by the range $[\phi_0(t), \phi_1(t)]$. This range is evaluated at time t

The cutting force (4) acts in opposition to the needle tip and is given by

$$F_c(t) = \begin{bmatrix} -\min(\alpha, (\phi_{tip} - \phi_0(t))^2 \beta) s(\phi_{tip}) \\ -\rho \hat{r} \min(\alpha, (\phi_{tip} - \phi_0(t))^2 \beta) s(\phi_{tip}) \end{bmatrix} \quad (4)$$

The force curve is fitted quadratic equation based on insertion depth where the force is scaled by β and the limit is α .

The final force component is the internal tissue deformation force caused by the needle sweep. The deformation force is caused by the needle sweeping out an area during its motion. The area swept out by the needle is multiplied by a tissue ‘stiffness’ matrix K in order to compute the total estimated needle force. The matrix (K) relates the swept area of the needle (in the tissue frame) to the tissue compression force (also in the tissue spatial frame). Due to the rotation between the needle body frame and the tissue frame, the constant matrix K must undergo a change of basis from K to K' where

$$K'(t) = R_{SN}^T(t) K R_{SN}(t). \quad (5)$$

The variable $R_{SN}(t)$ is the rotation matrix between the needle frame and the tissue frame. Note that since the needle moves, $R_{SN}(t)$ is a function of time and consequently $K'(t)$, unlike K , is not constant. The total area sweep (and the total force) is a linear combination of the linear velocity and the rotational velocity. The total sweep force being generated is then given as.

$$f_{sw}(\phi) = \begin{bmatrix} f_{sw,\nu}(\phi) & f_{sw,\omega}(\phi) \end{bmatrix} \begin{bmatrix} \nu^b(t) \\ \omega^b(t) \end{bmatrix} \quad (6)$$

where

$$f_{sw,\nu}(\phi) = \rho K'(t) \hat{s}(\phi) \hat{s}(\phi), \quad (7)$$

$$f_{sw,\omega}(\phi) = -\rho K'(t) \hat{s}(\phi) \hat{s}(\phi) \rho \hat{r}(\phi). \quad (8)$$

The sum of $f_{sw, \nu}(\phi)$, and $f_{sw, \omega}(\phi)$ (scaled by the needle body velocity $\begin{bmatrix} \nu^b(t)^T & \omega^b(t)^T \end{bmatrix}^T$) gives the total force $f_{sw}(\phi)$ being generated at location ϕ . Note that if (2) is satisfied, then there is no sweep force being generated.

The force components $f_{sw, \nu}(\phi)$, and $f_{sw, \omega}(\phi)$ can be used to construct an incremental wrench matrix given as:

$$Q(t) = \int_{\phi_0(t)}^{\phi_1(t)} \begin{bmatrix} f_{sw, \nu}(\phi) & f_{sw, \omega}(\phi) \\ \rho \hat{r}(\phi) f_{sw, \nu}(\phi) & \rho \hat{r}(\phi) f_{sw, \omega}(\phi) \end{bmatrix} d\phi. \quad (9)$$

The product of $Q(t)$ and the vector $\begin{bmatrix} \nu^b(t)^T & \omega^b(t)^T \end{bmatrix}^T$ gives the incremental wrench being generated along the entire needle during a small instant of time. The matrix $Q(t)$ is computed in the needle body coordinates. Since the total deformation wrench measures the net tissue deformation in the tissue spatial frame, $Q(t)$ is transformed using the Adjoint matrix of the 4×4 rigid body transformation matrix, $g_{SN}(t)$ which is denoted $\text{Ad}_{g_{SN}}$. Here, $g_{SN}(t)$ is the transformation between the needle frame and the tissue frame. Once $Q(t)$ is transformed into the tissue spatial frame, it is integrated through time to obtain the total deformation force acting on the needle in the tissue frame. This force is then mapped back into the needle body frame. The total sweeping wrench equation is then given by

$$F_{sw}^b(t) = \left[\text{Ad}_{g_{SN}(t)} \right]^T \int_{t_0}^t \left[\text{Ad}_{g_{SN}^{-1}(\tau)} \right]^T Q(\tau) \begin{bmatrix} \nu^b(\tau) \\ \omega^b(\tau) \end{bmatrix} d\tau. \quad (10)$$

When the needle is grasped by a robotic gripper, the total wrench can be directly measured using an attached force/torque sensor or estimated using the robot joint torques.

UKF implementation requires the derivation of a discrete time force model. Since both the needle cutting force and the needle friction force are computed in terms of the geometric location of the needle, they can be estimated directly from the current estimated position of the needle. The force due to needle sweep is however the result of all previous needle sweeping forces and the derivative of the sweeping force will be used to compute the discrete time step evolution of the needle-tissue sweep wrench.

A. Sweep Force Derivative and Time Step

Since the sweeping force is the sum of the previous swept forces, its time evolution can be estimated as the sum of the current swept force plus the incremental change in the swept force. The sweeping force acts in the spatial tissue frame but it appears to change its point of action as the needle body frame moves.

The incremental swept force being generated is computed using the instantaneous location of the needle and its velocity. Using differentiation identities, the time derivative of the swept force is computed as a function of the instantaneous needle velocities as

$$\frac{dF_{sw,N}^b(t)}{dt} = \begin{bmatrix} \hat{\omega}^b(t) & \hat{\nu}^b(t) \\ 0 & \hat{\omega}^b(t) \end{bmatrix}^T F_{sw}^b(t) + Q(t) \begin{bmatrix} \nu^b(t) \\ \omega^b(t) \end{bmatrix}. \quad (11)$$

Notice that the incremental sweep during the needle motion corresponds to the $Q(t)$ term while the current deformation wrench moves its point of action using the needle body velocity.

The final time evolution of the swept force can be estimated using the Taylor series approximation:

$$F_{sw,N}^b(t+\Delta t) = F_{sw,N}^b(t) + \frac{dF_{sw,N}^b(t)}{dt} \Delta t. \quad (12)$$

The force model, derived in the needle body frame, can be used as the basis for a UKF where the states being estimated correspond to the needle-tissue interaction forces.

IV. Unscented Kalman Filter Outline

The purpose of the Unscented Kalman Filter is to isolate the deformation forces (F_{sw}^b) from the total needle-tissue interaction forces (F^b). The potential states, based on the lumped tissue force model, of the UKF include F_{sw}^b , K , μ_s , α , and β . Since some of the states contain similar information, including all of them could destabilize the UKF implementation. A brief discussion of the potential states follow.

Estimating the tissue swept force F_{sw}^b is the goal of this work and as such should be included as one of the states being directly estimated by the UKF. The state update equation for the tissue sweep wrench is given by (12).

The compressive wrench state is proportional to the tissue mechanical parameter K . Since both the swept force and the stiffness matrix K model similar aspects of the needle-tissue interaction forces, including K and F_{sw} is redundant and adds potential instability to the UKF. In order to stabilize the filter and avoid redundancy, the tissue stiffness K will be roughly estimated and held constant. Empirical analysis of the UKF demonstrated that fixing K does not significantly affect the Kalman filter's performance as long as the K value used in the UKF is sufficiently close (the range of K is empirically determined to be about $[0.015, 0.032]$ N/mm² for K_x , K_y , and K_z).

The friction force acts along the entire length of the embedded needle and is one of the larger force components. The entirety of the friction force is modeled using only the parameter μ_s , which will also make up a state.

The suture needle is so sharp that the cutting force can be small compared to the friction and deformation force. When estimating the tissue parameters, the cutting force component

would be so negligible that it would sometimes converge to 0. Consequently the cutting force terms are ignored as $\alpha = \beta = 0$.

While it is true that *in vivo* tissue may not be homogeneous and the lumped parameter states may in fact be a function of many factors (e.g. position, tissue health etc), attempting to precisely model the changes in the tissue mechanics would negate computational efficiency and is outside the scope of this work.

While this work does not attempt to directly model the needle grasp geometry, the forces sensed in the gripper frame ($\mathcal{M}$) are related to the needle frame ($\mathcal{N}$) through the grasping geometry and can significantly affect the sensed forces.

$$F_{t,M}^b = \text{Ad}_{g_{N,M}}^T F_{t,N}^b. \quad (13)$$

Since the needle grasp can have a major effect on the forces generated on the force sensor, tracking the needle grasp (using a model similar to [22]) is the subject of future work. For the purposes of validating the deformation estimation, the suture needle tissue geometry and needle grasp are assumed to be known and used as constants in the UKF.

V. Experimental Validation

The online UKF filter must be robust despite the variance in both tissue parameters and needle drive geometry. To verify that, a suture needle was driven through a sample of *ex vivo* tissue using a benchtop needle driving stage to show that the results of online UKF filtering are comparable to those obtained from the parameter fitting.

The experiments show that fixing the stiffness K does not significantly degrade performance and that the UKF estimator is able to track the sweeping force data for an *ex vivo* tissue sample.

A. Experimental Hardware

The needle driving stage provides three degrees of freedom for needle insertion into the tissue. The available motion includes translation in the x-direction, translation in the y-direction and rotation along the z-axis (in the needle reference frame). The three degrees of freedom are required so that the needle driving stage, shown in Fig. 3, is capable of driving the needle with full planar motion (two translations plus a rotation). The full planar needle motion available to the driving stage ensures that the needle can follow any path plan that may be generated (please see [19] for example needle drives). While it is true that the needle driving stage is unable to move the needle in the full space of $\text{SE}(3)$, moving the needle out of plane would only serve to increase the swept area and consequently degrade the needle path. The needle driving stage is equipped with a six DOF force/torque sensor (nano17 by ATI Industrial Automation, Apex, North Carolina). The force and position data was acquired at 2 kHz using motion encoders and a full 6-dof force/torque sensor and post processed

using a Savitzky Golay filter (order: 3, frame size 35). The bias wrench and needle holder weight were found and subtracted from the measured and processed force data.

During the experiment, a suture needle (CT-1 suture needle (Ethicon Corp., Raleigh, NC)) was driven through *ex vivo* tissue, namely a sample of angus beef.

For experimental validation in this work, the needle tissue geometry are calibrated so that only the states pertaining to the wrench measurements - F_{sw} , N , and μ_s are updated using the UKF.

B. Results and Discussion

The experiment results shown in Fig. 4 demonstrate that the model for calculating the wrench exerted on the suture needle, compares closely to both the measured data and the UKF filter estimate. Some of the discrepancies between the actual data and the parameter fitted model can be attributed to the non-homogeneity of the tissue phantom. As stated before, the purpose of the UKF (and parameter fitting) is not to precisely model the actual needle-tissue interaction wrench, but is instead to develop a framework for an optimal needle drive that reduces the needle-tissue interaction wrench. Currently, UKF is performed on recorded data, but a target of future work will be to implement a real-time UKF filter.

VI. Conclusions and Future Work

In this paper, the equations for the wrench experienced by the suture needle in the needle coordinate frame are derived. This lumped force model is then used to create a UKF state estimator capable of segmenting the internal tissue deformation force from the total measured force. Experimental results on *ex vivo* tissue confirms that the sweep wrench state can be estimated online via the UKF despite the inherent inhomogeneity of the tissue. The UKF filter was able to determine the sweep wrench as well as the friction force of the tissue sample. The results were comparable to fitting tissue parameters to the entire data set.

This work can be integrated with force sensing surgical tools to estimate the total tissue forces caused by internal tissue deformation. While commercial RAMIS systems do not currently contain force sensors, experimental robots with embedded force sensors are in development [23]. There are also research studies which demonstrate successful interaction force estimation from joint measurements on surgical robotic systems [24].

Future work will focus on using a computer vision based needle tracking algorithm in order to measure the geometric needle grasp states. The combination of needle grasp estimation and force segmentation can be used to further validate the performance of UKF implementation as well as design a needle drive controller. The needle drive controller will drive a suture needle using a path that minimizing tissue trauma while completing a high quality suture.

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Fig. 1.

The semi-circular needle coordinate frame is located at the geometric center (c_N) of the needle circle and aligned such that the base of the needle (b_N) is located at the point $[\rho, 0, 0]^T$ where ρ is the radius of the needle and the needle lies in the x_N, y_N plane. The tip of the needle (t_N) is located at $[-\rho, 0, 0]^T$. The needle coordinate basis is defined by x_N, y_N , and z_N while the spatial (tissue) frame is defined by x_S, y_S , and z_S . This frame will be used throughout the rest of the paper.

Fig. 2.

The angles ϕ_0 and ϕ_1 are computed using the geometry above. The vector n_N is the tissue normal vector (given in the needle coordinate frame).

Fig. 3.
The 3 dof stage is oriented to maximize the dexterity of the in plane needle motion (Planar XY motion coupled with the Z rotation).

(a) Parameter fitted (pf) forces compared to sensor data.

(b) Parameter fitted (pf) torque compared to sensor data.

(c) Component breakdown of the x_n force for both the parameter fitted (pf) and UKF models. (d) Component breakdown of the y_n force for both the parameter fitted (pf) and UKF models. (e) Component breakdown of the $z\tau$ torque for both the parameter fitted (pf) and UKF models.**Fig. 4.**

These are plots of the wrenches generated during the 3dof needle drive through the beef sample. The measured forces are compared to the force component values estimated through offline parameter fitting (a). The same is done for the torques (b). The estimated components of the x_N forces (c), the y_N forces (d), and the z_N torques (e) are compared between the UKF and parameter fitted results.