

Article

Decoupling Tissue and Abdominal Forces in Laparoscopic Robotic Surgery via Viscoelastic Modeling

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Abstract

Laparoscopic surgery provides minimally invasive access to the abdominal cavity but poses control challenges for robotic systems due to the fulcrum constraint at the abdominal wall and the simultaneous interaction of the instrument with both the abdominal wall and internal soft tissue. While current clinical platforms (e.g., da Vinci) primarily rely on visual feedback and do not possess force sensors at the instrument tip, the transition to autonomous robotic surgery requires precise force feedback to ensure safety and effective tissue manipulation. Therefore, developing methods to decouple interaction forces using a single force sensor configuration is a critical enabling technology for future instrumented surgical robots. This paper presents a force-decoupling method that estimates, using only one force sensor, the individual forces applied to the abdominal wall and to internal soft tissue through a viscoelastic modeling approach based on Maxwell elements. Two configurations were evaluated, showing that a single-element Maxwell model provides the best trade-off between accuracy and computational complexity, achieving estimation errors of 9% and 13% for abdominal wall forces, with a root mean square error (RMSE) below 0.36 N. The method was implemented and experimentally validated in a force-controlled robotic system, demonstrating its effectiveness in improving force regulation and interaction safety without requiring additional sensors.

Keywords: laparoscopy surgery; viscoelastic models; RCM; robot; control; least-squares

1. Introduction

Laparoscopic surgery involves introducing surgical instruments and a camera through small incisions in the patient's abdominal wall. These incisions act as pivot points, referred to as fulcrum points, at which the instrument shaft is constrained by the trocar and surrounding tissue, forcing all instrument motions to occur as rotations and translations about this fixed point. This configuration enables minimally invasive access, reducing mortality, hospital stay times, and overall intervention costs [1]. However, it also imposes strong kinematic and mechanical constraints on instrument motion, creating unique challenges for robotic control.

The complexity of these control algorithms arises from the fact that the surgical instrument interacts simultaneously with two anatomical structures: the abdominal wall at the fulcrum point and the internal soft tissue at the surgical site (Figure 1). Figure 1 shows how the manipulator robot carries just one force sensor, in red, in its end-effector, although forces are exerted in both the abdomen and the tissue when the instrument is in contact with the tissue inside the abdomen. As a result, any motion or force applied by



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the robot produces reaction forces both at the trocar and at the tool tip inside the patient. Since these forces are mechanically coupled through the rigid instrument shaft and only a single force sensor is available at the robot end-effector, the measured force is a mixture of both contributions, making it difficult to independently regulate trocar loading and tissue interaction.

Integrating measurements of both the fulcrum and tool–tissue interaction forces can significantly enhance the control performance of autonomous surgical robots. Monitoring the fulcrum forces allows the controller to minimize excessive contact or undesired motion of the trocar, improving safety and positional stability [2]. Simultaneously, sensing the tool–tissue interaction forces provides essential feedback for regulating contact pressure and adapting motion to tissue properties, resulting in smoother and more precise maneuvers [3]. In the current literature, limited work has focused on decoupling these two forces, creating an opportunity to develop methods that enable more precise control of the tool inside the patient.

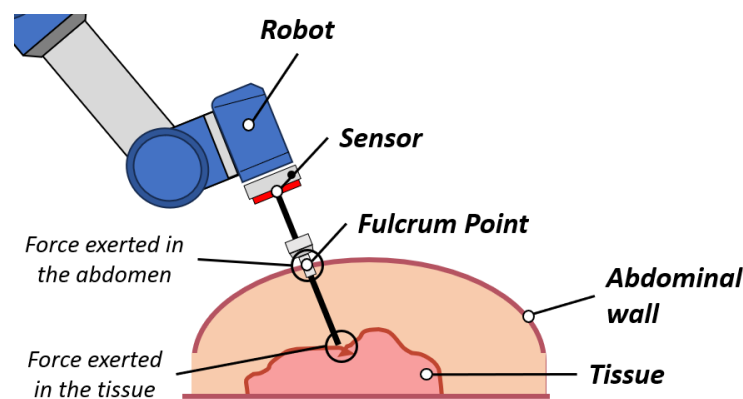


Figure 1. Graphical representation of a robotic-assisted laparoscopic surgery. A single force sensor must measure two different interaction forces along the instrument.

Robotic platforms must ensure accurate instrument positioning through the fulcrum point while regulating interaction forces. In conventional (non-robotic) laparoscopic surgery, the surgeon relies on experience to distinguish forces applied to the abdominal wall from those on internal tissue. In contrast, robotic platforms used in Laparoscopic surgery, such as the Da Vinci system, do not measure forces at the instrument tip. Instead, they maintain safe interaction with a fixed remote center of motion (RCM) aligned with the fulcrum point [4].

However, this mechanical decoupling is not directly applicable to autonomous or semi-autonomous systems, which often employ non-fixed or soft RCMs like in [5] or even continuum or articulated instruments to achieve greater dexterity inside the patient. Some autonomous systems like [6–8] use a virtual remote center of motion, since they do not have the mechanical restrictions of the Da Vinci system. In [9], the RCM constraint is embedded directly into the dual quaternion space and an uncertainty and disturbance estimator is used to compensate for model uncertainties and external forces, achieving stable and accurate tracking. However, none of these approaches include force sensors to distinguish contact at the abdominal wall from forces applied to internal tissue. An error in the RCM estimation with respect to the real fulcrum position can result in undesired interaction forces in the abdominal wall. This lack of direct force perception at the fulcrum and the correct estimation of the RCM remain major challenges in current surgical research.

Although robotic platforms have been increasingly adopted in laparoscopic surgery, these sensing limitations persist and become even more critical as the field moves toward greater autonomy. In recent years, surgical robots have evolved from purely teleoperated

systems to platforms with increasing levels of autonomy. This progression has been characterized in the autonomy classification framework presented in [10,11], which defines six levels of autonomy: level 0 is a traditional surgery with no relation to autonomy; in level 1, the robot provides passive or active assistance for the surgeon, like the teleoperated robots; in level 2, as in level 1, the robot follows orders from the surgeon, but in this level, the robot can execute and monitor these orders independently of the human; in level 3, the system has the ability to generate strategies for the surgeon to choose from, the robot executes and monitors the actions; At Level 4, the system extends the capabilities of Level 3 by autonomously selecting and executing the surgical strategy, requiring only supervisory oversight from the surgeon rather than active decision-making; finally, level 5 is full autonomy, which has not been reached yet.

According to [12], different technologies are needed to reach these levels, each presenting distinct challenges. Ref. [13] argues that advances in the autonomy of medical robotic systems rely on the development of two fundamental requirements:

1. Clear and unambiguous orders, which can come from the surgeon through teleoperation at lower levels like the platform present in [14] or the Da Vinci itself [4], such as level 1, or logical reasoning at higher levels like in [15,16].
2. The safe and reliable execution of the specified task. To achieve this, the robot must possess adequate dexterity, precision, sensing capabilities, strength, and appropriate dimensions to perform the repetitive motions [17] or the specific and more complex actions like making knots in suture, like in [18], or the ablation of a portion of tissue by means of an electric cauterizer [19]. Furthermore, the robot controller must be capable of effectively coordinating and utilizing these capabilities to accomplish the assigned task.

Therefore, this work addresses the second requirement by enabling accurate force perception without increasing hardware complexity, making it easy to implement in future force-sensing laparoscopic robots. Thus, the objective of this work is to estimate, using only a single force sensor located at the end-effector of a robotic manipulator, the individual forces exerted on the patient's abdominal wall and on the internal soft tissue. This is a significant advantage in the control tasks of surgical robotic manipulators.

The paper is structured as follows: Section 2 reviews related works. Section 3 introduces the materials and methods used in this paper. Section 4 presents the experimental results and analysis. Finally, Section 5 provides the conclusions and future prospects.

2. Related Work

The separation between the forces exerted in the abdomen and those exerted in the tissue requires the estimation of those forces at these two locations. Force estimation in minimally invasive robotic surgery has been widely studied. Two main approaches can be distinguished: direct force sensorization of the instrumentation and indirect estimation based on physical models or machine learning techniques.

For the first scenario, the sensorization of the instrumentation, according to [20], states that traditional tactile sensorization approaches can be broadly classified into four categories: piezoresistive tactile sensing, piezoelectric tactile sensing, capacitive tactile sensing, and optical tactile sensing. Early attempts at instrument sensorization primarily relied on these principles, incorporating miniaturized multi-axis sensors [21,22] as well as capacitance- and optical fiber-based technologies [23–25]. Likewise, methods employing deformable elements with visual patterns have been proposed to infer forces through computer vision techniques like in [26]. Here, according to the deformation of the colored element of the tool the vision system can estimate the forces. However, their accuracy

strongly depends on lighting conditions, camera calibration, and unobstructed visibility, which limits their robustness in realistic surgical environments.

Although functional, these approaches present significant limitations: they complicate manufacturing, reduce the instruments' lifespan, and restrict critical tasks such as palpation. In addition to traditional methods, Ref. [20] also identifies emerging tactile sensing technologies, including microfluidic tactile sensing and imaging-based tactile sensing. Microfluidic sensors offer high sensitivity and compliance but often suffer from complex fabrication processes, fluid leakage risks, and limited long-term reliability. Imaging-based tactile sensing approaches, while capable of capturing rich contact information, typically require bulky optical setups and significant computational resources, which hinder their integration into compact surgical instruments.

Due to these technical limitations, an alternative line of research focuses on simulating forces in soft tissues. In [27], mass-spring models and the finite element method are used to describe tissue-instrument interactions, while [28] employs a force propagation model also based on a mass-spring system. In [28], by controlling the extent of force propagation, the model balances physical realism and real-time computational performance without relying on complex matrix formulations. Comparatively, Ref. [29] concludes that linear viscoelastic models, such as Kelvin-Voigt or Maxwell, are preferable to nonlinear ones, as they involve lower mathematical complexity and have not shown significant drops in accuracy. Refs. [30,31] include examples of the application of viscoelastic models to accurately estimate the forces exerted on the spinal column by a drill.

In recent years, machine learning techniques have gained prominence. For example, Ref. [32] proposes an LSTM-based recurrent neural network model, enhanced with dimensionality reduction and a cyclical learning rate, for online estimation of haptic interaction forces generated in both real-time and visuo-haptic environments; Ref. [33] estimates tool-tip forces during suturing by combining Inception-ResNet-V2 for spatial feature extraction and LSTM for temporal modeling, the network infers suture tension; Ref. [34] employs a physics-guided deep learning approach for real-time prediction of displacement fields in viscoelastic soft tissues combining convolutional neural networks (CNNs) and LSTM layers to capture spatiotemporal behavior and incorporates a physics-guided loss function based on mass conservation to ensure physically consistent results; while [35,36] use vision-based algorithms and neural networks to infer forces from visible tissue deformations. Although these methods have demonstrated promising performance, they heavily depend on the availability and quality of training data and rarely consider the forces exerted on the abdomen explicitly. These methods are used in the teleoperation environment to assist the surgeon during the operation and provide them with a pseudo-haptic force, but while vision-based or indirect force estimation may be sufficient for teleoperated assistance, where the surgeon remains in the loop and compensates for uncertainties using visual feedback, high-level autonomy requires greater reliability. In autonomous tasks, relying only on indirect estimates becomes a limiting factor for safety, making it necessary to detect precise physical interaction to ensure accurate control.

More specifically, several studies have focused on analyzing the forces associated with the trocar and the abdomen. In [37], trocar insertion is characterized using dynamic measurements (force and torque) including a force sensor directly in the trocar. Moreover, Ref. [38] addresses the modeling of friction during the passage of instruments through the port in the trocar. However, both approaches neglect the interaction with internal tissue. Alternatively, works such as [39,40] employ neural networks to estimate trocar torque based on joint measurements from the Da Vinci system and convert it into Cartesian forces using the transposed Jacobian. Nonetheless, such models are strongly dependent on the specific robotic platform used, which limits their generalization. It is essential to note that these

studies typically model trocar friction or RCM constraints in isolation, assuming that there is no simultaneous contact with internal organs. Treating the force (whether measured or estimated) as a net quantity fails to provide the controller with the specific information needed to ensure safety at both locations independently. Yet, in realistic autonomous procedures, the instrument interacts simultaneously with the abdominal wall and internal tissue. Therefore, it is essential to have a method for decoupling these contributions in order to move from teleoperation, as in these methods, to autonomous execution.

In summary, while current clinical platforms tend to be sensorless relying on the surgeon's visual feedback during teleoperation, and research platforms often utilize complex multi-sensor arrays that are hard to sterilize, this work proposes a balanced approach for future autonomous systems. By utilizing a single physical force sensor and a viscoelastic decoupling strategy, we aim to provide the precise force feedback required for autonomous control without the hardware complexity of multi-sensor integration. Unlike other approaches, the proposed method is capable of separating the force exerted on the soft tissue from that transmitted to the abdominal wall, thereby reducing dependence on specific robotic configurations and providing a more realistic clinical scenario. To this end, an experimental set-up with a robotic platform has been designed to measure the forces at three locations: the robot, the patient's abdominal wall, and the soft tissue. Subsequently, different elastic models are tested and their results compared.

3. Materials and Methods

Following the force acquisition platform presented in [41], which incorporates independent force sensors to measure both the abdominal wall and soft-tissue interaction forces, a similar experimental platform was developed in this work, as shown in Figure 2a. The purpose of this platform is not to replicate a clinical robotic system but to provide a controlled experimental environment in which the different force components acting on the surgical instrument can be measured independently.

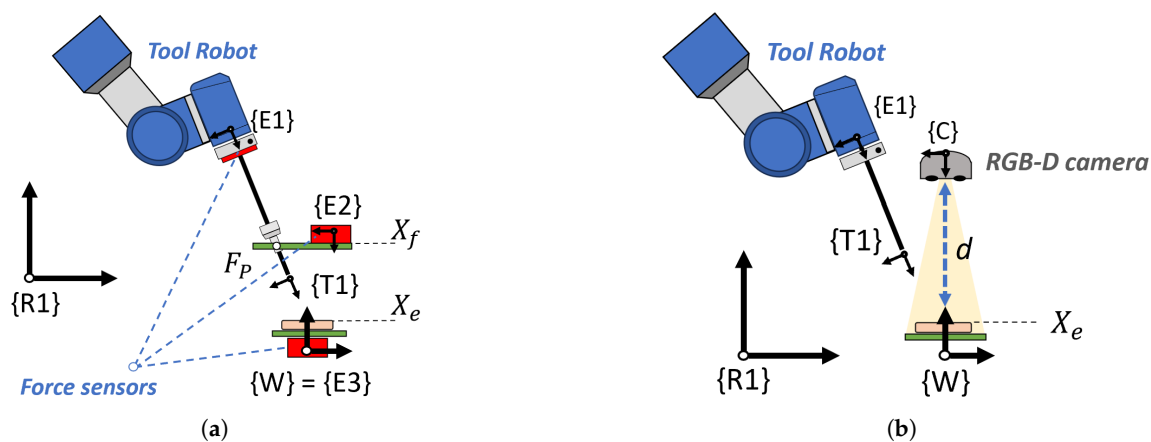


Figure 2. Robotic scenario for data collection: (a) Force data collection. (b) Distance from the tissue data collection.

Specifically, the platform enables simultaneous acquisition of the following force sensor data: the total interaction force measured at the robot end-effector, which corresponds to the only force signal available in a real laparoscopic robot; the individual force acting on the abdominal wall; and the individual force acting on the internal soft tissue. Each of these force components is acquired by using a dedicated force sensor, as shown in Figure 2a. These independently measured forces serve as ground truth data for identifying the viscoelastic tissue model and for validating the proposed force-decoupling method.

By having access to all force components during experimentation, the platform makes it possible to train and quantitatively evaluate the estimation of abdominal and tissue forces using only the single end-effector sensor, which is the scenario targeted for real surgical applications.

The platform shown in Figure 2a includes the manipulator robot reference frame of the base $\{R1\}$, the manipulator carries the surgical instrument and performs operations inside the patient. This robot has a force sensor (shown in red) on its end-effector reference frame $\{E1\}$ and a tool mounted along the Z-axis of the effector, whose tip reference frame $\{T1\}$ makes contact with the tissues in the position X_e . To measure the forces acting on the abdomen, an abdominal wall simulation phantom is used, consisting of a plate with an orifice through which a trocar is introduced, with the associated reference frame F_p (*fulcrum point*). This phantom is in a position X_f with respect to the world reference frame $\{W\}$. The phantom has been equipped with a force sensor at $\{E2\}$ capable of measuring the forces exerted only on the abdominal phantom. Additionally, to measure the forces applied to the soft tissue, a third force sensor was placed beneath the soft tissue at $\{E3\}$. The world coordinate frame $\{W\}$ was aligned with the position of the soft tissue $\{E3\}$.

In order to determine the position of the tissue in X_e , an RGB-D camera is used, whose reference system is $\{C\}$ and whose position is known. The camera measures the distance to the tissue ' d ' as shown in Figure 2b. Given this distance and the relationship between the system $\{C\}$ and the world reference system $\{W\}$, X_e is estimated with respect to the world reference system.

In this scenario, the navigation system can move according to the fulcrum point and, if the RCM is miscalculated, it can measure the forces exerted on both the abdominal wall and the soft tissue. Using this scenario and the possibility of reading the different components that compose the total interaction force simultaneously, the aim is to address the problem of force decoupling when only the force sensor at the robot's end effector is available. To do this, the approach used is to estimate the forces in the soft tissue, which are those that would be measured in $\{E3\}$. With that, and with the forces from the sensor in $\{E1\}$, it is possible to estimate the force on the abdominal wall (so that the RCM can be re-calculated?).

To achieve this goal, it is proposed the use of a viscoelastic model as the basis for estimating the forces acting on the patient's soft tissue. The estimated tissue forces are then used to derive the forces transmitted to the abdominal wall. The problem is simplified by assuming that, in laparoscopic operations, the instrument exerts force only along the Z-axis of the tissue.

First, in the following subsections, the surgical platform used for data collection and the general architecture where the viscoelastic model and force separation are estimated and used for control are presented. Next, two candidate models are analysed and, based on the presented requirements, an experimental protocol is defined to store and process data for viscoelastic model estimation. Finally, the resulting model is evaluated.

3.1. Scenario and Architecture Used

The setup shown in Figure 3 has been implemented following the one in Figure 2 to perform the data acquisition for the *Training* and *Validation*. This scenario includes a Universal Robot[®] ur3 manipulator robot with an OnRobot[®] sensor mounted on its end effector $\{E1\}$. On the other hand, the tissue has been simulated with a tissue pad on another OnRobot[®] sensor to measure the forces on the tissue. Finally, the abdominal tissue phantom has been placed on the end effector of a Universal Robot[®] ur3e robot, to monitor and control the position of the abdomen. Furthermore, the ur3e is equipped with a built-in force sensor.

In the course of the experiments, the ur3e robot remains motionless, while the tool robot (the ur3) performs different pivoting movements. The platform stores the positions,

velocities and forces of each robot and sensor at 125 Hz relative to the reference frames of each one, but also relative to the reference frame of the world $\{W\}$ which coincides with $\{E3\}$.

To perform the experiments, this setup requires a calibration process. This process includes: (i) system calibration to obtain the transformation matrices between each robot and the global reference frame $\{W\}$, ensuring that all measurements are expressed relative to this frame; (ii) trocar calibration, where translational (± 5 mm) and rotational ($\pm 5^\circ$) sweeps are performed in the absence of contact with the organ to refine the estimation of the fulcrum point and avoid spurious force generation; and (iii) the initial approach of the tool tip $\{T1\}$ toward the tissue surface to determine the initial contact position with the tissue.

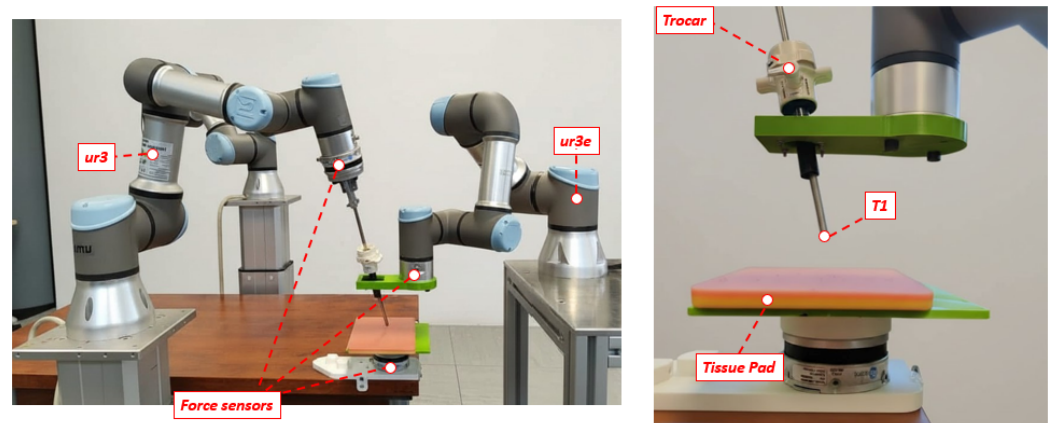


Figure 3. Training setup for model training and validation.

Figure 4 illustrates the proposed force/position control architecture and its integration with the decoupling method. It is important to note that the kinematic control architecture for the RCM constraint is beyond the scope of this article, as it was previously presented by our laboratory in [42]. However, this work introduces the specific dual-loop force feedback architecture and the force decoupler, which are the central focus of this contribution.

The proposed scheme combines a hybrid control strategy for the abdominal wall with a parallel force/position controller for the instrument tip interaction:

1. **Abdomen Control:** The lateral motion of the instruments is governed by an admittance controller with gain $K_{abdomen}$ to ensure the desired force in the abdominal wall. This loop minimizes stress on the abdominal wall by correcting the desired Cartesian positions $[X_d, Y_d]$ based on the estimated abdominal force error. The output is a compensated velocity vector $[\dot{X}_d, \dot{Y}_d]$ that effectively shifts the fulcrum point (P_f) to yield to external pressure. The selection term $(I - D(\sigma))$ directs these corrections specifically to the lateral axes.
2. **Tissue Control:** Interactions along the instrument's penetration axis (Z) are regulated by a parallel force/position controller. This structure computes two velocity components:
 - $\dot{Z}_d$: The velocity compensation generated by the tissue admittance controller (K_{tissue}) based on the force error ($F_{d,tissue} - \hat{F}_{tissue}$).
 - $\dot{Z}_d$: The velocity component generated by the position controller to track the surgical trajectory.

The selection matrix $D(\sigma)$ fuses these components, ensuring that force feedback modifies the insertion velocity when tissue contact is detected.

3. **RCM Control:** Finally, the resultant Cartesian linear velocity vector is processed to generate the full robot command. Using the current fulcrum position (P_f) provided

by the estimation block, the algorithm computes the necessary angular velocities (orientation) to enforce the Remote Center of Motion (RCM) constraint. This kinematic mapping ensures that the robot executes the force-compensated linear translations (X, Y, Z) while strictly pivoting around the incision point, following the formulation detailed in our previous work [42].

The control gains ($K_{abdomen}$ and K_{tissue}) were determined through an empirical tuning procedure to ensure stable interaction without oscillations in [42]. The adjustment process followed a safety-first approach, given that the primary objective is patient safety. The abdomen control gain ($K_{abdomen}$) was adjusted to ensure an over-damped response, avoiding over-impulses that could damage the incision port; and tissue interaction: similarly, the tissue control gain (K_{tissue}) was adjusted to achieve accurate force tracking while maintaining stability during contact transition. The parameters were kept constant throughout the experiments, as the robustness of the admittance loop was found to be sufficient for the stiffness range of the phantom tissues used.

Moreover, the *Force decoupler* on the right represents the estimation layer which is the central theme of this article. In order to separate the forces, the viscoelastic model of the tissue $G(z)$ is used, which is loaded with the parameters from the model database (the parameters are estimated offline before the operation and loaded into the online process). $G(z)$ for Δe input, where Δe is the deformation of the skin between the position of the tool tip X and the position of the tissue X_e , returns the estimated force on the tissue. In a real scenario, the forces coupled due to adhesions or connective tissue continuity must be added to the force of the tissue.

Then, it is assume that the forces read by the sensor at $E1$ is equal to:

$$F_{E1} = F_{abdomen} + F_{tissue} + F_{coupled} + F_{frictional} \quad (1)$$

therefore, the force control feedback variables are:

$$\hat{F}_{tissue} = F_{tissue} + F_{coupled} \quad (2)$$

$$\hat{F}_{abdomen} = F_{E1} - F_{tissue} - F_{coupled} - F_{frictional} \quad (3)$$

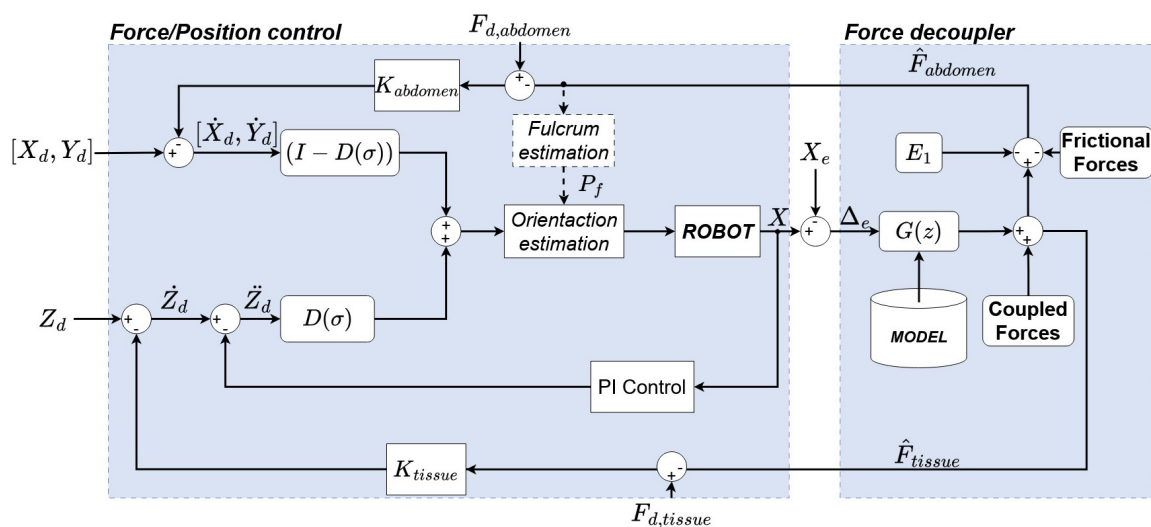


Figure 4. General architecture required for control in a Laparoscopic surgery.

Figure 5 shows the *Off-line parameter estimation*. For the parameter estimation this work uses least squares estimation methods whose inputs are the force measured in the

tissue by sensor at $E3$ and the tissue deformation Δe . The parameters μ are stored in the database to be used on-line in the scheme of Figure 4.

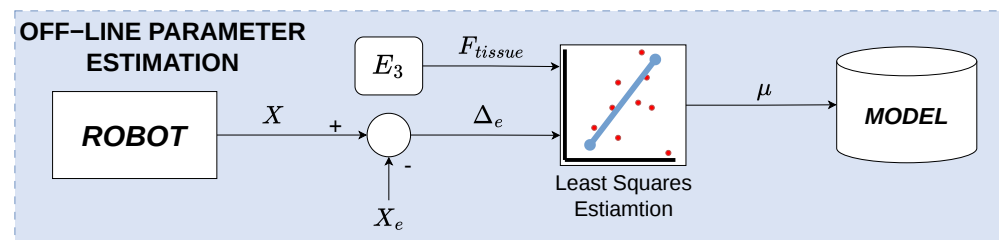


Figure 5. Off-line parameter estimation by least squares estimation methods scheme.

Design Considerations

Several considerations have been made in carrying out this work. The first relates to the frictional force. Regarding the modeling of dissipative forces at the fulcrum, prior literature characterizes trocar friction dynamics as relatively low in magnitude. Functional surgical forces analyzed by [37] during abdominal procedures are significantly higher; consequently, frictional components represent approximately 5–10% of the total force spectrum. To test this assumption in this paper, the instrumentation was introduced into the trocar and movements such as those shown in Figure 6a at different speeds were performed, concluding that the friction force with our platform can be modelled as noise and discarded.

In addition, this work addresses the separation of forces in in vitro processes, which mechanically isolates soft tissue from other forces that may couple and add to the force measured in the tissue. The project is limited to in vitro experimentation, as it cannot be performed in vivo. To measure and model the coupling forces, the following experiment was carried out: forces were exerted on the tissue with the instrument, measuring the forces exerted, while at the same time disturbances, additional forces, were exerted on the tissue to check whether the forces couple in the tissue used in this article, as shown in Figure 6b. The conclusion reached is that the coupled forces can be considered noise in our scenario and discarded.

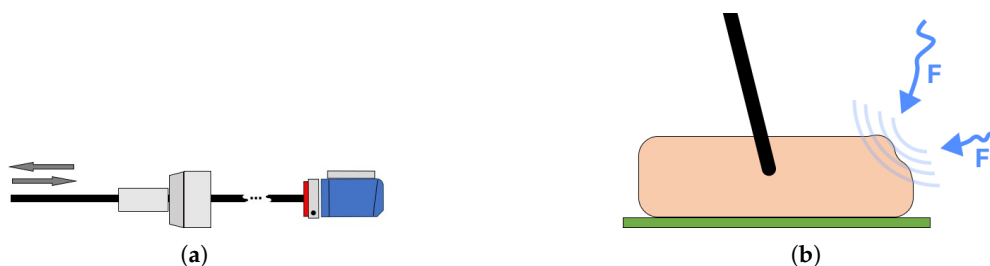


Figure 6. Scenarios for testing the design considerations of this work: (a) Scenario to test the frictional forces. (b) Scenario to test the coupled forces.

Therefore, in Figure 4, the blocks *Frictional Forces* and *Coupled Forces* can be removed, leaving the force measured by sensor $E1$ equal to

$$F_{E1} = F_{abdomen} + \hat{F}_{tissue} \quad (4)$$

where $\hat{F}_{tissue}$ is the force estimates by model $G(z)$, and the force at the abdomen is:

$$\hat{F}_{abdomen} = F_{E1} - \hat{F}_{tissue} \quad (5)$$

3.2. Parameter Estimation for Viscoelastic Models

As previously stated, viscoelastic models are chosen for their ease of implementation and their ability to estimate forces independently of the robot configuration. This viscoelastic model is the system $G(z)$ in Figure 4, and this article deals with data collection in a real-world scenario in order to obtain the parameters that best fit the model. Two formulations are considered, as illustrated in Figure 7. As this figure shows, when the instrument presses on soft tissue, the deformation caused by the tissue deformation Δe returns a force F . This force will be more accurately adjusted to reality depending on the model used.

The Kelvin–Voigt model (Figure 7a) consists of a purely elastic spring (whose parameter is K) and a purely viscous damper (η) connected in parallel. In contrast, the Maxwell model (Figure 7b) combines a spring (k_∞) in parallel with one Maxwell element. The Maxwell element consists of a spring (k_1) and a damper (η_1) arranged in series.

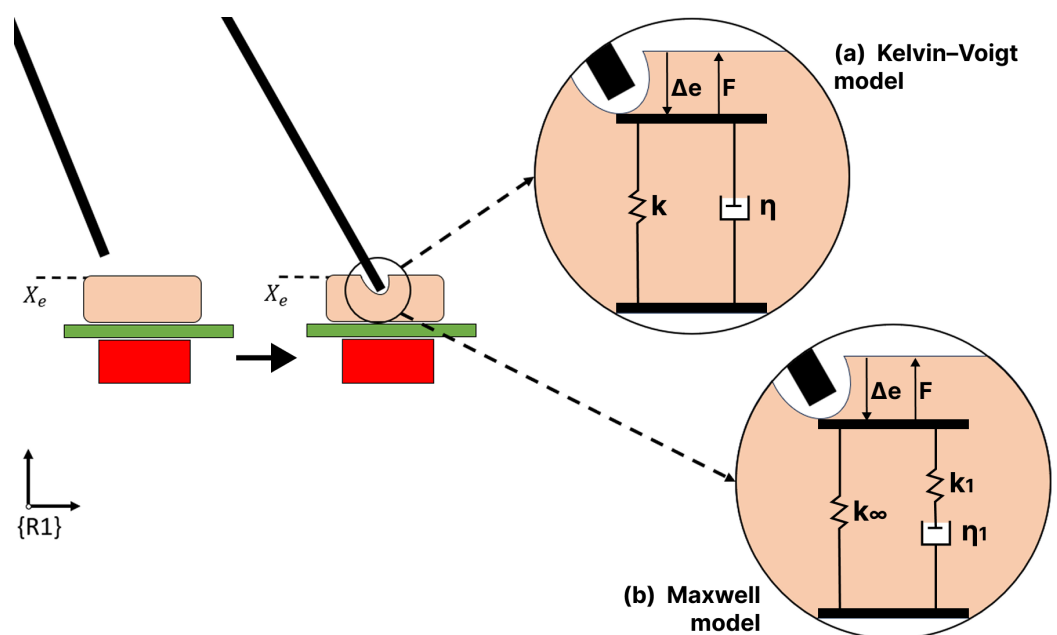


Figure 7. Viscoelastic models tested in the paper: (a) Kelvin–Voigt model. (b) Maxwell–Wiechert model.

The formalization of both viscoelastic models—the Kelvin–Voigt and the Maxwell model—into discrete-time transfer functions is presented below. Each model is discretized to allow the estimation of its physical parameters (k , η , k_1 , k_∞ , η_1) by means of least-squares identification techniques applied to experimental data. To use both models, tissue deformation (Δe) is required, which is the error between the position of the medical instrument tip (${}^W P_{T1}$) and the position of the tissue (X_e), but when the tool is not touching the tissue, it is zero:

$$\Delta e = \begin{cases} {}^W P_{T1} - X_e, & \text{if } {}^W P_{T1} < X_e, \\ 0, & \text{if } {}^W P_{T1} > X_e. \end{cases} \quad (6)$$

In addition, the deformation velocity ${}^W V_{T1}$ is required in the models, but for the following formula, as the deformation velocity is dependent on Δe , it will be named $\dot{\Delta e}$.

The discrete-time transfer function is the relationship between the input of the model (Δe) and its output (F). For the Kelvin–Voigt model the function is given by:

$$\frac{F(z)}{\Delta e(z)} = G_{d,KV}(z) = \frac{(k + \frac{\eta}{T})z - \frac{\eta}{T}}{z} \quad (7)$$

We discretize it using *Backward Euler* discretization method so that the transfer function is strictly causal and the output force does not depend on future values, which allows us to use least squares. From (7), the corresponding difference equation can be written as follows, where ‘n’ is the sample at time ‘n’, and ‘n – 1’ is the sample at the previous time step.

$$F_{KV}[n] = b_0 \Delta e[n] + b_1 \Delta e[n-1], \quad \begin{aligned} b_0 &= k + \frac{\eta}{T}, \\ b_1 &= -\frac{\eta}{T}. \end{aligned} \quad (8)$$

Similarly, the discrete transfer function of the Maxwell model, obtained from its continuous-time formulation, is expressed as:

$$\frac{F(z)}{\Delta e(z)} = G_{d,M}(z) = \frac{(k_\infty + k_1) - (k_1 + k_\infty e^{-\frac{k_1 T}{\eta_1}}) z^{-1}}{1 - e^{-\frac{k_1 T}{\eta_1}} z^{-1}}. \quad (9)$$

Equation (9) can be rearranged into the canonical discrete form required for least-squares identification:

$$G_{d,M}(z) = \frac{b_0 + b_1 z^{-1}}{1 - \alpha z^{-1}}, \quad \begin{aligned} \alpha &= e^{-\frac{k_1 T}{\eta_1}}, & \text{(discrete pole)} \\ b_0 &= k_\infty + k_1, \\ b_1 &= -(k_1 + k_\infty \alpha). \end{aligned} \quad (10)$$

From (10), the corresponding difference equation is shown below. Unlike in (8), in this function the current force at time ‘n’ depends on the previous force value.

$$F_M[n] = \alpha F[n-1] + b_0 \Delta e[n] + b_1 \Delta e[n-1]. \quad (11)$$

Following the standard least-squares formulation, Equations (8) and (11) can be expressed in matrix form as:

$$F[n] = \phi(n) \theta, \quad (12)$$

This representation follows the fundamental structure of least-squares regression, where we seek to approximate an observed output (force) as a linear combination of input features.

The regressor vector ($\phi(n)$) contains the measured data from our experimental dataset at time step n . These elements represent relevant measurements such as deformation increments, velocities, forces, or other physical quantities derived from the force–deformation experiments. Each element of ($\phi(n)$) serves as an independent variable (feature) that contributes to predicting the force response. To evaluate the Kelvin–Voith model, the deformation parameters (Δe) collected in ϕ_{KV} are used, both those of the present moment and those of the previous moment. For the Maxwell model the parameters used are the same as for ϕ_{KV} but with the inclusion of the force in the previous moment, as show ϕ_M .

$$\phi_{KV} = \begin{bmatrix} \Delta e[n] \\ \Delta e[n-1] \end{bmatrix} \quad \phi_M = \begin{bmatrix} F[n-1] \\ \Delta e[n] \\ \Delta e[n-1] \end{bmatrix} \quad (13)$$

The parameter vector θ contains the unknown model coefficients that we seek to estimate. These parameters quantify the relationship between the input features and the output force, essentially capturing the physical properties of the system being modeled. Each element of (θ) weights the corresponding element in ($\phi(n)$), determining how strongly

each measured quantity influences the predicted force. From (8) and (11) we can express θ_{KV} and θ_M for each model respectively.

$$\theta_{KV} = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} \quad \theta_M = \begin{bmatrix} \alpha \\ b_0 \\ b_1 \end{bmatrix} \quad (14)$$

The identification process aims to determine the optimal estimates of (θ) by minimizing the sum of squared errors between the measured forces ($F[n]$) from the dataset and the forces predicted by the model ($\phi(n, \theta)$). This least-squares criterion ensures that the identified parameters provide the best linear fit to the observed data in the sense of minimizing the total squared deviation across all time steps.

Experiments were conducted in the scenario shown in Figure 3 to obtain the data for $\phi(n)$. The model is simplified by applying contact forces to the tissue only along the Z axis. The experiments are done with controlled displacements along the three axes and using various angles of incidence to touch the tissue. During this experiment, as shown in Figure 8, the fulcrum position $\{P_f\}$ coincides with the remote centre of motion. Here, the tip of the instrument $\{T1\}$ moves according to a vector $\vec{v}$ from P_A to P_B , deforming the tissue surface by a value Δe . When the fulcrum point is correctly estimated, the force exerted on the abdominal wall is zero, so the robot's sensor only measures the forces of contact with the tissue.

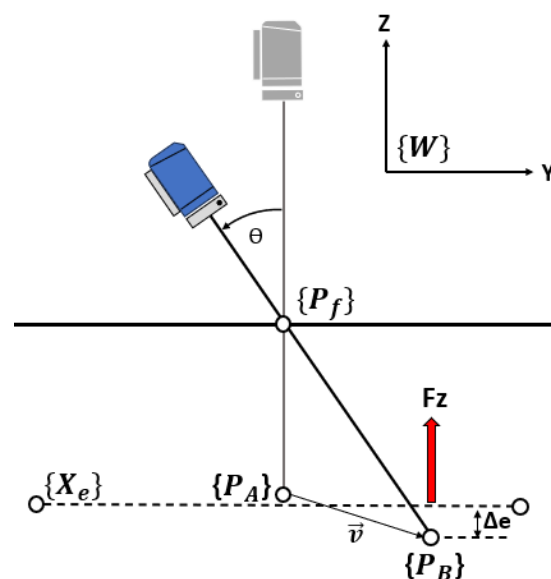


Figure 8. The position of the RCM coincides with the fulcrum in the abdomen and only forces in $\{E3\}$ are measured.

All temporal, kinematic, and force-related signals are stored in a unified dataset. Specifically, the dataset includes the forces measured by the sensors located at $\{E1\}$, $\{E2\}$, and $\{E3\}$; the positions of the reference frames $\{T1\}$ and $\{E1\}$; the Cartesian positions X_e and X_f ; and the corresponding velocities in $\{T1\}$ and $\{E1\}$ frames. In addition, the relative deformation Δe between $\{T1\}$ and X_e , as well as a timestamp for each sample, are stored. To quantify fulcrum misalignment, both the true fulcrum position at the abdominal wall P_f and the intentionally erroneous estimate $\hat{P}_f$ are also recorded. All variables are expressed in both the robot base frame and the world frame W . Table 1 contains all the variables and their definitions used in this article.

Table 1. Description of the set of variables.

Symbol	Description
F_{E1}, F_{E2}, F_{E3}	Forces measured by sensors at frames {E1}, {E2} and {E3}
P_{T1}, P_{E1}	Positions of the reference frames {T1} and {E1}
X_e	Cartesian position of the tissue
Δe	Relative deformation between {T1} and X_e
X_f	Cartesian position of the abdominal wall
P_f	True fulcrum position at the abdominal wall
$\hat{P}_f$	Intentionally erroneous estimate of the fulcrum position

To estimate the model parameters and validate the force decoupling, we first define the sets of kinematic and force-related variables involved. Let us denote the set of variables required for the estimation phase as:

$$\mathcal{V}_E = \{F_{E1}, F_{E3}, P_{T1}, \Delta e\}, \quad (15)$$

The set of variables $\mathcal{V}_E$ is used to fit the model parameters and test the results in the estimation of forces in soft tissue. Similarly, for the validation phase, it requires ground-truth interaction data. Together with the previous variables, the forces at the abdominal wall, the position of the abdominal wall, the correct position of the fulcrum, and the incorrect position of the fulcrum have been considered.

$$\mathcal{V}_V = \mathcal{V}_E \cup \{F_{E2}, X_f, P_f, \hat{P}_f\} \quad (16)$$

Consequently, the estimation dataset and the validation dataset are defined as the temporal sequences of these variable sets recorded over discrete time samples:

$$\mathcal{D}_E = \{\mathcal{V}_E(k)\}, k = 1 \dots N \quad (17)$$

$$\mathcal{D}_V = \{\mathcal{V}_V(k)\}, k = 1 \dots N \quad (18)$$

where the superscript (k) denotes the discrete time step, and N the number of samples.

4. Results and Discussion

This section presents the results of the validation of force estimation using the viscoelastic model. After determining which of the two models presents better results, the separation of forces in the abdomen is validated by comparing the estimated value with the value read using the $E2$ sensor. Finally, the use of a force decoupler in a surgical scenario is tested using different control strategies compared to the one presented in Figure 4.

4.1. Validation of the Estimation of Forces in Tissue Using Viscoelastic Models

The *estimation error*, also known as *fit error*, is used as metric for the validation. This metric can be computed as:

$$\text{Estimation Error (\%)} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (F_{\text{true}}(\Delta e_i) - F_{\text{model}}(\Delta e_i))^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n F_{\text{true}}^2(\Delta e_i)}} \times 100 \quad (19)$$

where $F_{\text{true}}(\Delta e_i)$ represents the measured force for deformation Δe_i at {E1}, and $F_{\text{model}}(\Delta e_i)$ is the force predicted by the viscoelastic model in (8) and (11) applying the parameters estimated by least squares. This metric corresponds to the normalized root mean square error (NRMSE) between the measured and predicted force signals. The numerator rep-

resents the root mean square of the prediction error, providing a measure of the average discrepancy between the experimental data and the model response over the validation set. The normalization by the root mean square value of the measured force allows the error to be expressed as a percentage, making it independent of the absolute force magnitude. As a result, the estimation error quantifies the relative accuracy of the viscoelastic model in reproducing the measured force–deformation relationship, with lower values indicating a better agreement between the model and the experimental data.

For the validation in the estimation of the force in the soft tissue, Table 2 shows the value of the parameters and the estimation error of each model. These values indicate that the material exhibits a relatively high stiffness and strong viscous damping. From this analysis in Table 2, it can be observed that the Maxwell model provides a better fit than the Kelvin–Voigt model, with 9.0% estimation error compared to the 13.6%.

Table 2. Model parameters for different viscoelastic models. Stiffness (K) in [N/m] and viscosity (η) in [N·s/m], and their estimation error according to (19).

Model	Parameters	Estimation Error
Kelvin–Voigt	$K = 958.24$ $\eta = 64$	13.6%
Maxwell	$K_{\infty} = 1171.25$ $K_1 = 210.51$ $\eta_1 = 5374.95$	9.0%

The underlying assumption for force decoupling is that the force measured by the sensor at $\{E1\}$ is equal to the sum of the force on the tissue $\{E3\}$ and the force on the abdominal wall $\{E2\}$ as illustrated Figure 4. Therefore, the estimated force on the abdominal wall, $\hat{F}_{z,abdomen}$, can be expressed as the force measured by the sensor, $F_{z,E1}$, minus the force estimated using the single-element generalized Maxwell model for the tissue, $\hat{F}_{z,tissue}$:

$$\hat{F}_{z,abdomen} = F_{z,E1} - \hat{F}_{z,tissue} \quad (20)$$

To test the proposed hypothesis, a set of experiments was conducted in which a known but intentionally incorrect fulcrum position $\{\hat{F}_P\}$ was introduced to induce interaction forces at the abdominal wall, as shown in Figure 9. While previous work has shown that an RCM misalignment of 0.02 m can generate harmful forces [43], a larger offset of 0.04 m was selected in this study to ensure that the resulting force measurements were clearly distinguishable from sensor noise.

Two configurations were evaluated, with $\{\hat{F}_P\}$ placed above and below the abdominal wall (Figure 9a,b). In both cases, the instrument contacts the abdominal wall at point $\{I\}$ while simultaneously deforming the internal tissue. Due to the RCM misalignment, tool motion generates undesired forces at the abdominal wall, which act opposite to the direction of motion along the Y axis and with a direction along the Z axis that depends on the relative position of $\{\hat{F}_P\}$. When $\{\hat{F}_P\}$ is located above the true fulcrum, the resulting Z -axis forces act in the opposite direction of the positive Z axis, whereas placing $\{\hat{F}_P\}$ below the fulcrum produces forces aligned with the positive Z direction. The total force measured at the end-effector $E1$ is the superposition of abdominal and tissue interaction forces. The experimental setup in Figure 3 was used to collect data for $\mathcal{D}_V$.

It should be noted that the sensors used, manufactured by OnRobot®, have a resolution of 0.8 N. For this reason, it was necessary to work with forces of greater magnitude than those typically found in such operations, thereby ensuring objective results and preventing the measurements from being confused with the sensor's resolution error. Although an

error of this magnitude would not occur in a real scenario, it is used in this study to obtain a higher force resolution. All the collected data forms the vector $\phi(n)$ that is used in the least-squares method to obtain the parameter of the models. The next section presents the evaluation of both viscoelastic models.

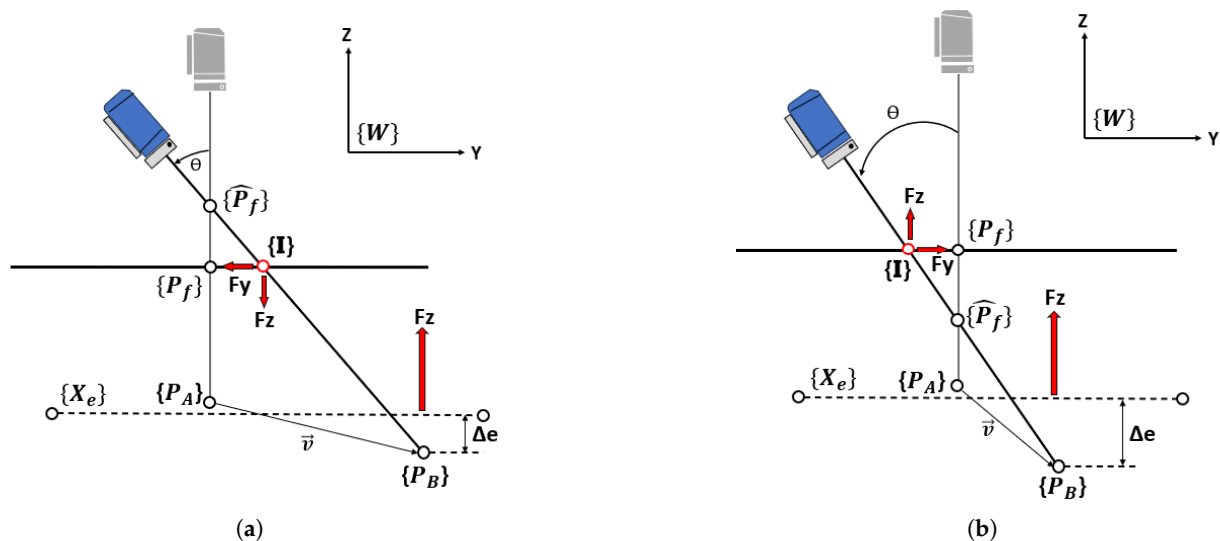


Figure 9. Laparoscopic situation in which the RCM is in an incorrect position, causing forces in the abdomen: (a) The RCM is below the correct position (b) The RCM is above the correct position.

Figure 10 presents the results obtained during the validation phase by comparing the estimated forces with those stored in the V . The upper plot shows the three Cartesian components of the force measured by the end-effector sensor $E1$ along the X , Y , and Z axes. These signals correspond to the total interaction force resulting from both abdominal wall contact at the fulcrum point and tool–tissue interaction at the surgical site.

The evolution of the three force components reveals several distinct interaction events during the experiment. In particular, three prominent peaks can be observed in the Z-axis force, reaching values close to -8 N, which correspond to significant normal loading of the tool against the tissue or the abdominal wall. At the same time, noticeable peaks of approximately 4 N appear in both the X and Y directions, indicating lateral interaction forces produced during tool motion and pivoting about the fulcrum point. These force transients represent the most demanding conditions for the force-decoupling algorithm, as they involve simultaneous multi-axis interactions and strong mechanical coupling between the abdominal wall and the soft tissue.

The middle plot of Figure 10 compares the estimated soft-tissue interaction force, $\hat{F}_{tissue}$, obtained using the proposed Maxwell viscoelastic model, with the corresponding reference force F_{E3} from $\mathcal{D}_V$. The two curves exhibit a strong agreement throughout the experiment, including during the high-force interaction events identified in the upper plot. In this case, a force of -4 N is measured in the tissue. This close correspondence demonstrates the ability of the viscoelastic model to accurately capture both the magnitude and the dynamic behavior of the tissue response. Quantitatively, the estimation error is 9.0%, as reported in Table 2, confirming that the proposed method provides a reliable real-time estimate of the soft-tissue forces using only deformation measurements and a single end-effector force sensor.

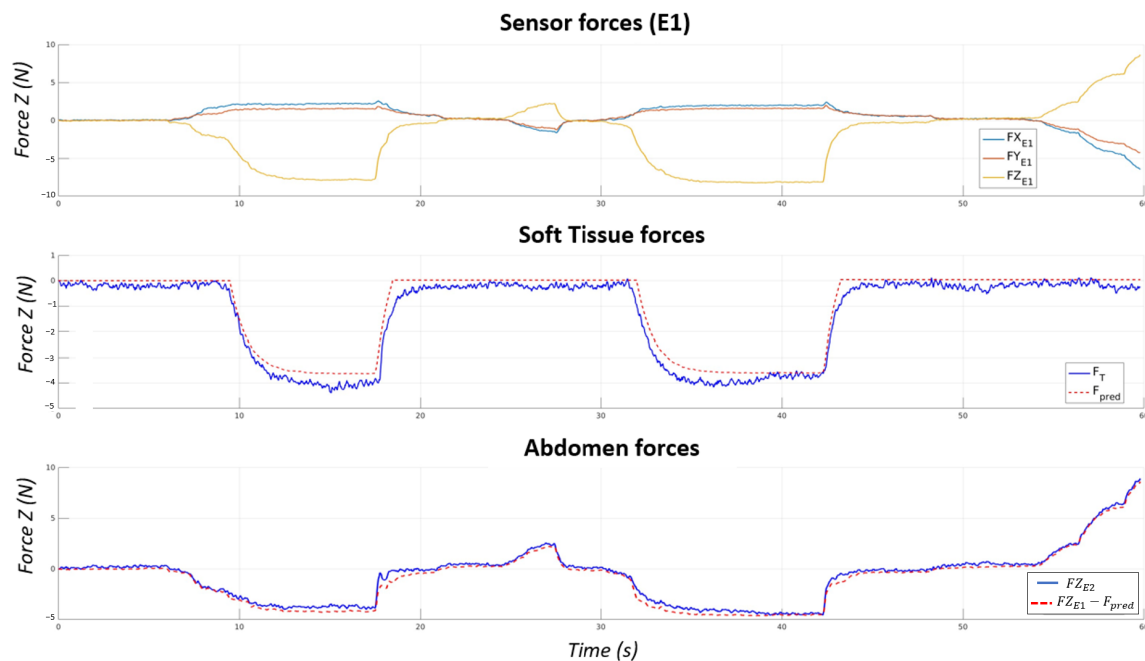


Figure 10. Representation of the forces measured in the sensor of the R1 robotic manipulator, the force measured in the tissue versus the estimated force, and the force measured in the abdomen versus the estimated force by separation of forces.

At the bottom of Figure 10, the Z-axis force at the abdominal wall measured by sensor E2, denoted F_{E2} (blue curve), is compared with the abdominal force estimated using the proposed decoupling method in Equation (20). The corresponding performance metrics are summarized in Table 3. The estimation error using Equation (19) is 13%, where F_{model} is obtain by Equation (20). The coefficient of determination of $R^2 = 0.9817$, indicating that it reproduces the temporal variations of the true abdominal force with high fidelity. The Root Mean Squared Error (RMSE) of 0.3509 N is low relative to the magnitude of the measured forces, while the Mean Error (ME) of -0.295 N reveals a slight underestimation bias, which could be compensated through calibration or a constant offset. The maximum absolute error of 1.44 N remains small compared to the overall force levels.

Table 3. Performance metrics for the abdominal force estimation.

Estimation Error	R^2	RMSE	ME	Max Error
13%	0.9817	0.3509 N	-0.2954 N	1.4377 N

The consistency across the three plots further validates the physical correctness of the decoupling. When the total force measured at the end-effector (top plot) reaches approximately -8 N along the Z axis and the estimated tissue force (middle plot) is about -4 N, the estimated abdominal force (bottom plot) also converges to approximately -4 N, satisfying the expected force balance between the total interaction force and its two components. This agreement demonstrates that the proposed method successfully separates the abdominal wall and tissue interaction forces in a physically meaningful and quantitatively accurate manner.

It is important to note that, for experimental validation, high forces were deliberately induced at the fulcrum. This was necessary due to the resolution of the sensors used (± 0.8 N), which required working with magnitudes of up to 5–10 N along the Z-axis. However, under actual surgical conditions, fulcrum errors greater than 0.01 m are not expected, which would correspond to abdominal forces on the order of 1–2 N. In this scenario, the esti-

mated 13% error translates to absolute deviations of approximately 0.13–0.26 N, a clinically acceptable value for the application, and below the 0.8 N resolution of the sensor.

4.2. Use Cases of Force Decoupling in a Surgical Scenario

In order to validate the force-decoupling approach in a laparoscopic surgery scenario, the control architecture presented in Figure 4 is implemented in the experimental setup shown in Figure 3. The experiment is designed to evaluate the performance of different control strategies when the robot navigates through a simulated surgical environment where the instrument must pass through the abdominal wall (fulcrum point) and subsequently interact with internal tissue.

To replicate realistic surgical conditions and assess the proposed approach, the fulcrum position is intentionally mislocated 0.04 m below the abdominal wall. This deliberate error simulates uncertainties that commonly arise in surgical practice due to tissue deformation, patient movement, or imperfect calibration. The robotic instrument executes a series of predefined movements along the YZ plane, as illustrated in Figure 9b. These trajectories are designed to mimic typical surgical maneuvers, including insertion through the trocar, navigation toward the operative site, and interaction with target tissue.

Three distinct control strategies are evaluated to demonstrate the advantages of force decoupling:

1. Position control without force control: The robot follows the desired trajectory using only position feedback, with no force regulation at either the fulcrum or the tissue. This represents the simplest approach, where the controller is unaware of contact forces and cannot actively manage them. This strategy aims to quantify the improvements achieved by force-based control.
2. Tissue force control without force decoupling: A force controller regulates the interaction with the internal tissue, attempting to maintain the desired contact force. However, without force decoupling, the controller cannot distinguish between forces at the fulcrum and forces at the tissue. As a result, the measured force, which is the sum of both contributions, is used directly for feedback, potentially leading to inaccurate force regulation and unintended contact at the abdominal wall.
3. Dual force control with decoupling (proposed approach): Both the abdominal wall and tissue forces are independently regulated using the decoupled force estimates obtained from the Maxwell model. This strategy enables simultaneous control of both interaction points, allowing the system to minimize undesired forces at the fulcrum while precisely regulating contact forces at the operative site.

For all three strategies, the control objectives are defined as follows: at the abdominal wall (fulcrum point), the desired force is set to 0 Newtons to minimize any unintended overload or pressure that could cause patient discomfort or tissue trauma. At the internal tissue, the desired force is set to 4 Newtons, representing a typical force specification for delicate surgical tasks that require controlled contact without causing tissue damage. These objectives reflect realistic surgical requirements where the instrument must pass safely through the trocar without exerting excessive force while maintaining appropriate contact with the operative tissue.

Figure 11 shows the results for each control strategy. From top to bottom, it shows: measurements on the Y-axis in the abdominal wall; measurements on the Z-axis in the abdominal wall; and Z-axis force measurements in the tissue. The spots marked as “1” and “2” indicate the moments in which the instrument presses on the abdomen in a harmful way due to poor estimation of the fulcrum position. Besides, the spot marked as “3” after 25 s marks the moment when the tip of the instrument touches the soft tissue.

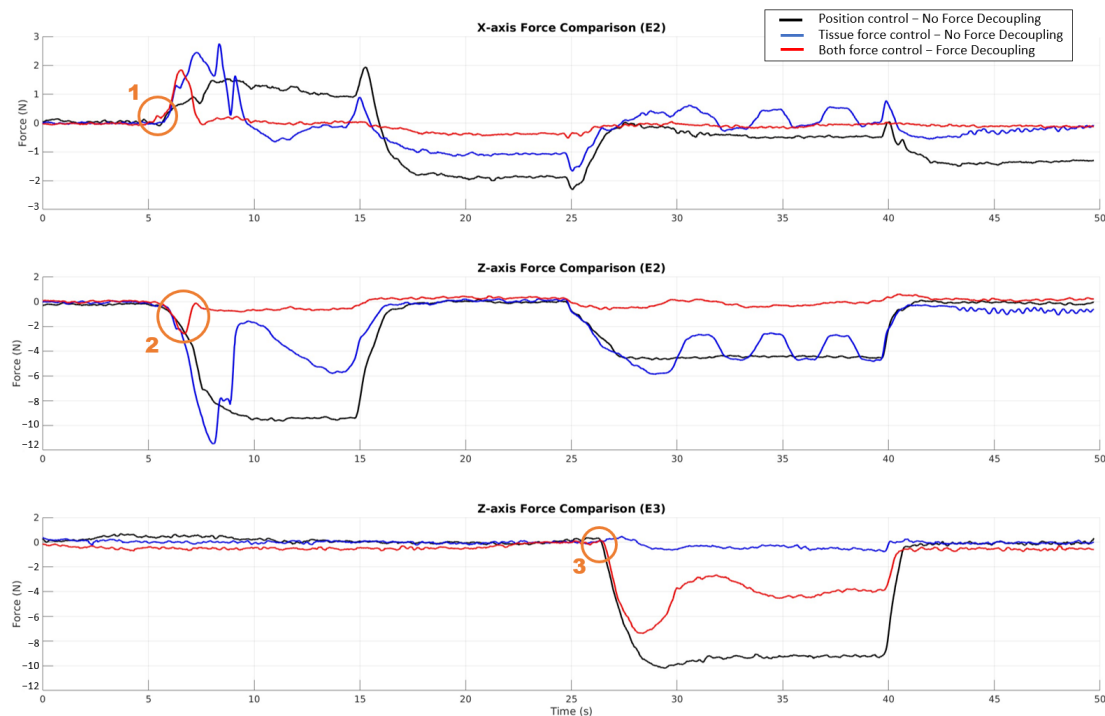


Figure 11. Comparison of forces for the three control strategies. The black line shows the force measurements when only position control is used. The blue line shows the measurements when position and force control are used, but only force control at the tip of the instrument. The red line shows the results of the proposed control strategy with force separation and force control in the abdominal wall and soft tissue.

The upper graph in Figure 11 shows the forces measured along the Y axis at the abdominal wall by sensor E2 for the three evaluated control strategies. The red curve corresponds to the proposed dual-force control with force decoupling, while the other two curves represent pure position control and tissue-force control without decoupling. The abdominal force obtained with the proposed method remains much closer to the desired reference of 0 N, showing that the fulcrum point is effectively regulated and that undesired contact with the abdominal wall is minimized. In contrast, the two baseline strategies produce significantly larger interaction forces. In both cases, force peaks exceed 2 N and remain above this level for more than 5 s, reflecting sustained and potentially harmful loading of the abdominal wall due to the mislocated fulcrum and the inability of the controller to compensate for it.

The middle graph in Figure 11 presents the forces measured along the Z axis at the abdominal wall. In the pure position control and in the just tissue-force control without decoupling, the abdominal force rises to values close to 10 N, indicating severe and sustained loading of the abdominal wall caused by the mislocated fulcrum. In particular, when tissue force control is applied without decoupling (blue curve), the controller interprets the total force as tissue contact and attempts to regulate it. However, because it cannot distinguish between tissue and abdominal forces, it generates incorrect corrective actions that amplify the abdominal interaction, producing a pronounced overshoot around the desired tissue force of 4 N, although it didn't apply here. By contrast, the proposed dual-force control with decoupling (red curve) limits the abdominal force to a peak of approximately 2 N and rapidly drives it back toward the 0 N reference. This fast and well-damped response demonstrates that the controller is able to accurately identify abdominal contact and to compensate for the fulcrum misalignment in real time, effectively protecting the abdominal wall while maintaining stable tool motion.

Finally, the lower graph in Figure 11 shows the Z-axis interaction force at the soft tissue measured by sensor *E3* for the three evaluated control strategies. In the absence of force control (black curve), the instrument applies forces of up to 10 N to the tissue, reflecting uncontrolled penetration and potentially unsafe loading. When tissue-force control is applied without decoupling (blue curve), the measured force at the tissue remains close to 0 N. This occurs because the controller, unable to distinguish between abdominal and tissue forces, incorrectly interprets the abdominal wall contact as tissue interaction and reacts by retracting the instrument, preventing it from reaching the tissue surface. In contrast, the proposed dual-force control with force decoupling (red curve) successfully regulates the tissue interaction force around the desired reference of 4 N. The force quickly converges to this target and remains stable, demonstrating that the controller can maintain appropriate contact with the tissue while simultaneously compensating for abdominal wall interactions. This result confirms that force decoupling enables accurate and safe tissue manipulation even in the presence of fulcrum misalignment.

By comparing these three strategies under identical trajectory and force objectives, the experiment demonstrates the necessity and effectiveness of force decoupling for achieving safe and precise dual-site force regulation in laparoscopic surgery. Therefore, separating forces allows for precise control of both the abdominal wall and the tissue.

4.3. Interpretation of Results and Comparison with State of the Art

The experimental validation demonstrated that the proposed single-sensor decoupling method achieves an RMSE of 0.35 N for abdominal forces and an estimation error of 9.0% for soft tissue interactions. To contextualize these results, it is useful to compare them with recent indirect force estimation approaches. For instance, deep learning-based methods using vision, such as those by Chua et al. [36], report an RMSE of approximately 0.521 N for tool-tissue interaction forces. Our viscoelastic modeling approach achieves a lower RMSE (0.35 N), suggesting that physical sensing combined with model-based decoupling can offer superior precision compared to purely data-driven visual estimation, without the computational overhead of image processing.

Furthermore, while studies like Masui et al. [35] focus on classification accuracy (reaching 86.4%) to provide visual pseudo-haptic feedback to surgeons in teleoperation, our approach goes a step further. The quantitative accuracy of our estimation is sufficient to close the control loop, allowing the robot to actively compensate for errors rather than provide the surgeon with pseudo-haptic feedback. This distinction is critical for the transition from Level 1 (Assistance) to Level 3 (Task Autonomy) in robotic surgery.

4.4. Limitations of the Study

While the results demonstrate the feasibility of the proposed decoupling method, several limitations inherent to the experimental design must be acknowledged. First, regarding the mechanical environment, the validation was performed in an *in vitro* setup where the abdominal wall phantom and the tissue sample were mechanically isolated. In a realistic *in vivo* scenario, connective tissues (fascia, peritoneum) physically couple internal organs to the abdominal wall. Consequently, organ manipulation could transmit tensile forces to the trocar, challenging the additive decomposition assumption. Although our analysis suggests that such coupling forces, along with unmodeled trocar friction and stick-slip effects, can be effectively managed by the controller as lumped abdominal disturbances, this hypothesis requires validation in *ex vivo* or *in vivo* models to ensure that the safety margins remain sufficient under physiological coupling conditions.

Second, regarding the sensorization, the experiments were conducted at force magnitudes (up to 8 N) higher than typical delicate laparoscopic interactions (1–2 N). This

adjustment was necessary due to the limited resolution of the industrial force sensors used (± 0.8 N), which would result in a low signal-to-noise ratio at clinical force levels. While this affects the direct clinical applicability of the current hardware setup, the decoupling algorithm itself is scale-independent. The translation to clinical practice would require replacing the current sensors with high-fidelity sensor, but the underlying viscoelastic estimation logic would remain unchanged.

Finally, the current tissue model focuses primarily on the indentation axis (Z_{tool}). This design choice relies on the assumption that palpation and puncture tasks are dominated by normal forces, whereas lateral forces (X, Y) on the tissue surface often result in sliding (friction) rather than viscoelastic deformation. However, for complex tasks such as suturing or knot tying, where lateral tissue dragging is significant, the current 1D model would be insufficient. Future iterations must extend the estimator to 3D to account for shear stress and multi-axis tissue dynamics.

5. Conclusions

The proposed force-decoupling method successfully separated the tissue and abdominal forces measured during robotic tool–tissue interaction. Among the evaluated viscoelastic models, the single-element generalized Maxwell model proved to be the most suitable, achieving an estimation error of 9% for soft tissue forces and 13% for abdominal wall forces while maintaining low computational complexity. The identified parameters indicate that the soft tissue exhibits high stiffness and strong viscous damping, characteristics that justify the model's ability to reproduce the experimental force response with high fidelity.

The experimental validation further demonstrated that the estimated abdominal forces closely matched the measured data, with an R^2 of 0.9817, an RMSE of 0.35 N, and a mean error of -0.295 N, all of which remain well below clinically relevant thresholds. Importantly, the method maintained stable performance even under sensor limitations and modeling uncertainties, supporting its suitability for real-time deployment. By enabling the reliable separation of abdominal wall and soft-tissue interaction forces using only a single force sensor, the proposed approach overcomes a major limitation of current robotic surgical platforms.

Moreover, embedding the viscoelastic force-decoupling model into a force-controlled robotic system demonstrated its practical utility by improving force regulation and interaction safety during tool motion. This is especially relevant for autonomous and semi-autonomous laparoscopic robots with non-fixed or virtual remote centers of motion, where fulcrum misalignment can generate undesired interaction forces. Accurate force separation allows the controller to simultaneously protect the abdominal wall while regulating contact at the surgical site, leading to smoother, safer, and more precise manipulation. Overall, this work provides a computationally efficient solution that strengthens the sensing and control foundations required for advancing surgical robot autonomy in minimally invasive procedures.

Limitations and Future Work

Although the results are promising, this study has certain limitations. First, the experiments were conducted in a controlled environment with a limited amount of data, which may restrict the model's generalization capability. Second, only forces along the Z-axis of the tissue were considered.

Future work includes:

- Expanding the dataset with scenarios closer to real surgical practice, and validating this architecture in ex vivo biological tissues to assess the robustness of the Maxwell model against greater biological variability.
- Exploring hybrid viscoelastic models or models that can be adjusted online during operations.
- Extending the model to estimate forces along the X and Y axes of the tissue. We aim to extend the estimator to infer lateral forces (X, Y) at the tissue tip, enabling fully decoupled 6-DOF force control for complex suturing tasks.

In conclusion, the developed methodology is considered valid for force estimation in surgical contexts, offering a sufficiently accurate and stable approach despite the limitations imposed by sensor resolution, and it represents an advance in force estimation for minimally invasive robotic surgery, providing a solid foundation for future clinical applications and technological improvements in safe and precise robot–patient interaction.

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Data Availability Statement: The dataset used in this study can be made available by the corresponding author upon reasonable request.

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