HAPTIC MODELING OF STOMACH FOR REAL-TIME PROPERTY AND FORCE ESTIMATION

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Robotic devices are being employed in gastrointestinal endoscopy procedures for diagnostics and surgery. However, force measurement, a very important factor for control and haptic feedback, becomes very challenging due to the strict size limitation of such devices and the flexible nature of the endoscope. This paper focuses on the modeling of the interior stomach wall for tool–tissue interactions from two perspectives: (1) If the interaction force between the robotic tool and the tissue can be measured, we utilize the force information to estimate the mechanical property of the stomach wall in real-time; given the force and position information, we would derive mathematically the only system model that can guarantee identifiability under arbitrary manipulation; (2) in the worst case scenario where force measurement is not available, we propose a viscoelastic model to restore force information solely based on position and motion information available from the robot. Ex-vivo experiments were performed on porcine stomach specimens to demonstrate the performance of the proposed models. Based on these findings, generalization and implementations of the modeling in real-time applications were discussed.

Keywords: Tissue property; haptic modeling; real-time; robotic surgery.

1. Introduction

Over the past decades, there have been a number of studies on mechanical models of collagen fibers, blood vessels, and other human tissues.1–11 A common approach for the early studies was to conduct experiments on the tissue/organ of interest, take measurements, and model or characterize the mechanical properties afterwards. Despite their off-line nature, existing studies have provided valuable knowledge to researchers and surgeons for medical applications such as surgical training with virtual reality simulators, surgical planning, as well as pathological diagnosis.
With the development in haptics, robotic devices have been widely adopted as sensing and actuation devices; with different types of energy sources; the requests for tissue/organ modeling have shifted towards real-time capable approaches. Therefore, the modeling of the tool–tissue/organ interaction was studied, specifically aiming to enable new functionalities or improve the performance of robotic devices in medical applications. The majority of these studies focus on organs which are solid and of relatively high stiffness, such as the liver. Due to the small deformations ranging from 2–6 mm in their corresponding applications, the viscous properties of the tissue were ignored without losing generality.

Distinct from the other organs in the peritoneal cavity, the stomach is hollow and highly elastic. In many medical interventions, tool–tissue interaction may result in large deformations, in which the viscoelastic behavior of the tissue cannot be ignored. With the recent development in surgical device and technology, the stomach has demonstrated its potential in playing a strategic and critical role in paving the future of intraperitoneal surgery. For example, the idea of NOTES (Natural Orifice Transluminal Endoscopic Surgery) suggests accessing the peritoneal cavity through one of the viscera, such as the stomach, to perform surgical interventions with the help of a flexible endoscope. The robotic approach appears to be a promising solution to provide the surgeon with essential maneuverability and accuracy. In such procedures, without directly touching the tissue, the surgeons are not able to sense the interaction force, which could be very important for ensuring the efficacy and safety of surgical interventions. For a better understanding of tissue manipulation, it is advantageous to investigate the modeling of the viscoelastic tissue behavior of the stomach.

With the stomach as the organ of interest, while extendable to other organs, the following two questions are tackled in this study:

1. Given full haptic (force, motion) measurement data, how is real-time mechanical property estimation obtained in the arbitrary manipulation of the robotic device?
2. If force measurement is not available, is it possible to adopt a mechanical property model of the corresponding organ, such that the missing force information can be restored using the motion information?

The potential applications for the two approaches are rather straightforward. If force measurements are available, the estimated mechanical model parameters can be used to improve the performance of the robotic device. The estimated mechanical parameter set can be used in developing high-level controller algorithms for robotic assistance. Moreover, with insufficient tactile information, it is difficult for the surgeon to discern the existence of abnormal tissues. By providing real-time mechanical property information of the target, it may assist the surgeon in diagnostical procedures.

On the other hand in many applications, force sensors might not be mounted onto the tool-end due to technical constraints such as size, sterilizability, and...
disposability, hence direct force information may be unavailable. Yet, it may be helpful to have this information fed back to the surgeon to give him/her a resistant force relevant to his/her motion input, as a safety guideline. In such cases, a simple but straightforward mechanical property model could be applied to enable partial force feedback to the user even without force sensors.

In this paper, we address the first question primarily by deriving the worst case input signal in the sense of information richness for parameter estimation. Based on this worst case scenario, a suitable mechanical model was proposed for real-time estimation, guaranteeing competent parameter estimation results in arbitrary manipulation.

2. Methods

2.1. Model for real-time parameter estimation

Assuming that both force and motion measurements, together with their time derivatives, are available to the system, we can utilize mathematical techniques to identify the parameters of the predefined mechanical property model of the stomach in real-time. Pioneered research works could be found in Yamamoto et al.’s paper, where performances of soft tissue properties estimation using different real-time estimation techniques were discussed and compared.

The convenience of real-time property parameter estimation comes at a cost — it brings constraints to both the input signal and the predefined mechanical property model between force and motion. Here, we present the problem in the following two aspects:

1. What is the worst case input excitation signal class in terms of information richness?
2. What mechanical property model could still guarantee estimation results when the worst case input signal is applied?

The findings of a recent publication on the information richness in real-time parameter estimation is adopted for discussions in the remainder of this section.

2.1.1. Persistent excitation

Input signal selection is crucial to estimation performance. It is necessary that the input signal is persistently exciting; in other words, it contains enough information to excite the system, so that all parameters concerned could be identified properly. It has been reported that information richness of the input signal is related to the structure of the system to identify; foundation work can be found in Green and Moore’s paper. Recently, essential and sufficient conditions of persistent excitation were given for least squares identification in Gevers et al.’s paper.

To maintain generality, we used the ARMAX (autoregressive moving average model with exogenous inputs) model, a very commonly encountered system model,
for our discussion. An ARMAX system is defined as:

\[ A(q^{-1})y(t) = B(q^{-1})u(t) + C(q^{-1})e(t), \]  

where

\[ A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}, \]
\[ B(q^{-1}) = b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b}, \]
\[ C(q^{-1}) = 1 + c_1 q^{-1} + \cdots + c_{n_c} q^{-n_c}, \]

\( q \) is the forward-shifting operator, \( y(t) \) is the measured output signal, \( u(t) \) is the input signal, and \( e(t) \) is noise.

**Proposition 1 (SRn).** A quasi-stationary scalar signal \( u(t) \) is Sufficiently Rich of order \( n \) (SRn) if

\[ \bar{E}[\psi_n(t)\psi_n^T(t)] = \lim_{\tau \to \infty} \frac{1}{\tau} \int_0^\tau E[\psi_n(t)\psi_n^T(t)]dt > 0, \]  

where

\[ \psi_n(t) \triangleq \begin{bmatrix} u(t-1) \\ u(t-2) \\ \vdots \\ u(t-n) \end{bmatrix} = \begin{bmatrix} q^{-1} \\ q^{-2} \\ \vdots \\ q^{-n} \end{bmatrix} u(t). \]

**Proposition 2 (SREn).** In addition, \( u(t) \) is Sufficiently Rich of Exact order \( n \) (SREn), if it is SRn, but not SR\((n+1)\).

Here, a necessary and sufficient condition of system identifiability is given regarding the information richness of the input signal for an open-loop system identification problem.

**Theorem 1.** For an ARMAX model structure (Eq. (1)), the open-loop model structure is identifiable if and only if

\[ u(t) \text{ is SR}_k, \quad k = n_b + \min\{n_a, n_c\}. \]  

An important corollary of (3) is:

**Corollary 1.** Equation (1) is identifiable if \( u(t) \) is SRn, where \( n > n_b + \min\{n_a, n_c\} \).

The proof of this corollary is not included in Gevers’ paper, but is rather straightforward:

**Proof.** If \( u(t) \) is SRn, \( n > n_b + \min\{n_a, n_c\} \), followed by the definition of Sufficient Rich of order in Eq. (2), \( u(t) \) must be SRk, \( k = n_b + \min\{n_a, n_c\} \). Consider Eq. (2), we have Eq. (1) identifiable.
Theorem 1 of Eq. (3) and Corollary 1 are very important deductions concerning the information richness property of excitation signals. On one hand, they provide a quantitative measure of input signal information richness, while on the other hand, they reveal the relationship between the SR order of input signal and the orders of identifiable ARMAX models. They are used in selecting the worst case input signal and the corresponding model structure in the following sections.

2.1.2. Excitation signal selection

It is desirable to select appropriate input signals according to the system structure. However, in this work, the discussion is made in reverse. Aiming to estimate the mechanical properties of a specimen during indentation, the algorithm is expected to provide decent estimation results at all times. This implies that whatever operation the probe is conducting, the resulting input signal to the system should always be persistently exciting for the selected model. Following this guideline, the system model structure should be simple enough, such that the worst case input signal (the least information rich), could still excite the system and provide competent estimation results.

Following the definition in Eqs. (2) and (3), the simplest excitation signals are the ones with the lowest SR order. It can be derived easily from the definition that the impulse signal

$$\delta(t) = \begin{cases} 1, & t = 0 \\ 0, & \text{else} \end{cases}$$

is SRE0, since there is no $n$ that could make $\psi_n(t) > 0$. However, in real-world manipulation, impulse signals are not practical in real life. Instead, general excitation signals are commonly decomposed into a series of sinusoidal signals of different frequencies. A sinusoidal signal of constant frequency is SRE2. However, here we argue that a simple human movement could be even simpler. For instance, during the indentation of the stomach, the trajectory of the device could follow a constant speed to a desired location, and then stop for a certain amount of time until being moved again to a new location. This very basic poke-and-hold trajectory, and yet very common in real-world manipulation, results in an excitation signal that consists of ramp ($u_1(t)$) and constant ($u_2(t)$) segments:

$$u(t) = \begin{cases} u_1(t) = kt, & t \in [0, T] \\ u_2(t) = kT, & t > T \end{cases}$$

In the excitation signal defined by Eq. (5), the probe first follows a contour with a constant velocity $k$ for a time period $T$, and then stops and remains in the final position afterwards. Although $u_1(t)$ is not stationary, it is only involved in the beginning of the process, while the rest of the process involves a constant value, which is SRE1. Here, an important property related to persistent excitation of $u(t)$ is given, which is also essential to later on discussions.

**Proposition 3.** $u(t)$, as defined in Eq. (5), is SRE1.
Proof. It takes two steps: first, \( u(t) \) is SR1; second, \( u(t) \) is not SR2. Taking \( u(t) \) as defined in Eq. (1), it follows immediately that

\[
\psi_1(t) = u(t - 1) = \begin{cases} 
  k(t - 1), & t \in [0, T + 1] \\
  kT, & t > T + 1 
\end{cases},
\]

\[
\bar{E}[\psi_1(t)\psi_1^T(t)] = \lim_{\tau \to \infty} \frac{1}{\tau} \int_0^\tau E[\psi_1(t)\psi_1^T(t)]dt = \lim_{\tau \to \infty} \frac{1}{\tau} \int_0^\tau u^2(t - 1)dt,
\]

and

\[
\frac{1}{\tau} \int_0^\tau u^2(t - 1)dt = \frac{1}{\tau} \int_0^{T+1} k^2(t - 1)^2dt + \frac{1}{\tau} \int_{T+1}^\tau k^2T^2dt = \frac{k^2}{\tau} [T^2 + g(T)] = k^2T^2,\]

where \( g(T) \) is a polynomial function of constant \( T \). Since \( kT \neq 0 \), \( \bar{E}[\psi_1(t)\psi_1^T(t)] \) is SR1.

Next, consider \( \psi_2(t) = [u(t - 1) u(t - 2)] \), similarly to above, but now in matrix form we have

\[
\bar{E}[\psi_2(t)\psi_2^T(t)] = \lim_{\tau \to \infty} \frac{1}{\tau} \int_0^\tau E[\psi_2(t)\psi_2^T(t)]dt = \lim_{\tau \to \infty} \frac{1}{\tau} \int_0^\tau \begin{bmatrix} u^2(t - 1) & u(t - 1)u(t - 2) \\
  u(t - 1)u(t - 2) & u^2(t - 2) \end{bmatrix} dt.
\]

Considering Eq. (4), with finite \( T \) and non-zero \( k \), we obtain

\[
\bar{E}[\psi_2(t)\psi_2^T(t)] = \begin{bmatrix} (T - 1)^2 & (T - 1)(T - 2) \\
  (T - 1)(T - 2) & (T - 2)^2 \end{bmatrix}.
\]

Hence, \( \det(\bar{E}[\psi_1(t)\psi_1^T(t)]) \) = 0, which means \( \bar{E}[\psi_1(t)\psi_1^T(t)] \) is only positive-semidefinite instead of positive-definite. Therefore, \( \bar{E}[\psi_1(t)\psi_1^T(t)] > 0 \) is not true. Following the definition of Eq. (2), \( u(t) \) is not SR2. Since \( u(t) \) is SR1 but not SR2, we have \( u(t) \) is SRE1.

\[
\square
\]

Natural human motion consists of signals with a certain number of different frequencies. As controlled by humans, more sophisticated probe motions could also be decomposed into a series of sinusoidal signals with different frequencies. It can be shown that a sinusoidal signal with constant frequency is SRE2. Therefore, any input signals that can be decomposed into sinusoid components will at least guarantee SRE2. By Corollary 1, we can easily conclude the following proposition.

**Proposition 4.** If the system model structure Eq. (1) can be persistently excited by SRE1 signals (such as \( u(t) \) as defined in Eq. (5)), it can also be excited by more sophisticated input signals.

Here, we aim at selecting a practical input signal with the lowest order of SR. Starting with SR0 signals, such as the impulse signal, the discontinuity could
not be realized in real life. SRE1 signals are the next desirable candidate. Although a step signal is SRE1, the sharp rising edge is not realizable in experiments. $u(t)$ consists of a ramp component and a subsequent constant component. It is composed in this way to remain SRE1, but becoming practical. In a normal indentation task, it is also natural to probe with a certain speed, then stop for a while before moving to a further point. Therefore, our selection of the excitation signal is $u(t)$ as shown in Eq. (5).

2.1.3. Model selection

Consider $u(t)$ the practical excitation signal with the least information richness. Recall the ARMAX system model structure in Eq. (1). As shown in Theorem 1, $u(t)$ imposes constraints on the orders of the characteristic polynomials of Eq. (1), such that

$$nb + \min(n_a, n_c) = 1.$$ 

In this work, we focus mainly on the mechanical properties of the stomach; hence, the historical information of the input signal is more of a concern, rather than the output force signal. Hence, we could assume $n_a = 0$. On the other hand, the noise applied to the output measurements are mainly sensor noises of the force/torque sensor, which could be regarded as white noise. Hence, $n_c = 0$. Therefore, we have the following constraint of the system model structure:

$$n_a = 0, \quad n_b = 1, \quad n_c = 0. \tag{6}$$

Note that here, the ARMAX model is defined using the classification definition in Eq. (1), not the extended FIR representation widely considered in discrete-time control. Here, $B(q^{-1}) = b_1 q^{-1} + \cdots + b_{nb} q^{-nb}$, the $q^0$ term is missing from the polynomial. This follows the argument that the current time input could only affect the output in the next step. This does not necessarily conflict with the FIR representation where B-polynomial contains the zero-order term of $q$. The only difference lies in the handling of subscripts.

Combining Eq. (6) with Eq. (1), we obtain the main contribution of this section:

**Theorem 2 (minimum identifiable system).** The system, identifiable with the input signal as in Eq. (5), has the structure of:

$$y(t) = b_1 u(t - 1) + e(t). \tag{7}$$

Considering the system structure in Eq. (7), the matching mechanical property model is Hooke’s law between force and displacement:

$$f = kx, \tag{8}$$

applied with the 1-step minimum time-delay convention of ARMAX model (Eq. (1)), and measurement noise on the force signal. Here, $k$ is the stiffness. Therefore, Hooke’s law is taken as the mechanical model of the stomach for real-time parameter estimation.
2.2. Model for real-time force estimation

In the previous section, we have shown that only a very simple model could be guaranteed to be identifiable given the worst case input signal in real-time parameter identification. This is based on the assumption of time-varying parameters of the stomach.

For real-time force estimation, however, the assumption is different. In robotic endoscopic surgery or NOTES, the workspace is normally highly constrained. The end effectors have to be very small in size for their safe introduction to the stomach through esophagus. If there is no physical force sensor that could be applied for haptic information acquisition, the surgeon can only operate the robot purely based on visual feedback. In order to provide haptic feedback, a mechanical property model of the stomach tissue could be used to calculate forces using the input motion signal. Pre-operational calibration will be needed to characterize the property model, following which the pre-characterized time constant parameter set could be used in the model to estimate the tool–tissue interaction force according to the motion inputs. In this force estimation process, no force measurement will be required. As the robot is controlled by the surgeon, the real-time force estimation could reflect the current tissue response with respect to the corresponding robot motions, hence assisting and benefiting the surgeon in decision-making when operating the robot.

Viscoelastic models are commonly adopted in related studies as force/motion models. In this section, several commonly used viscoelasticity models are compared. It is shown that they have limitations in modeling the characteristics of the stomach tissue. To address the limitations of these viscoelastic models, a modified force/motion model is proposed at the end of the paper.

In order to compare the performance of different approaches, the same ramp-and-hold input signal as defined in Eq. (5) is used throughout the paper.

2.2.1. Overview of viscoelastic models

Combinations of linear springs and dashpots are commonly used to describe the viscoelastic behavior of materials. Three typical models are the Maxwell model, the Voigt model, and the Kelvin model (also known as the standard linear solid model). The mechanical schematic and mathematical representations are shown in Table 1.

In Table 1, $f$ represents the force, $x$ represents the indentation distance, $E$ is the stiffness of the spring, and $\eta$ is the viscosity of the dashpot. Their responses to the ramp-and-hold input are shown in Figs. 1(a)–1(c).

For the Maxwell model, the ratio of change in force decreases as the force increases to maintain constant indentation velocity. When there is no more deformation, the force decays in an exponential way until zero, for the dashpot will absorb all the energy.

For the Voigt model, the force experiences linear increment as the indentation distance increases. When there is no more deformation, the force drops immediately to the level of the force exerting on the spring.
For the Kelvin model, a similar interpretation is applicable as a combination of both former models. However, it is notable that all three models suffer from discontinuity at the moment of impact (when \( t = 0 \), the indentation distance is zero while the velocity is not zero). In reality, both elastic and damping forces should be initially at zero at the beginning of impact.

Table 1. Mechanical schematic and mathematic representations.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Schematic representation</th>
<th>Mathematical representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maxwell model</td>
<td><img src="image" alt="Maxwell model diagram" /></td>
<td>( f(t) + \frac{1}{\eta} \frac{df(t)}{dt} = \frac{dx}{dt} )</td>
</tr>
<tr>
<td>Voigt model</td>
<td><img src="image" alt="Voigt model diagram" /></td>
<td>( f(t) = E \frac{dx}{dt} + \frac{\eta}{E} \frac{dx}{dt} )</td>
</tr>
<tr>
<td>Kelvin model</td>
<td><img src="image" alt="Kelvin model diagram" /></td>
<td>( f(t) + \frac{\eta}{E_2} \frac{df(t)}{dt} = E_1 \frac{dx}{dt} + \frac{\eta}{E_2} (1 + \frac{E_1}{E_2}) \frac{dx}{dt} )</td>
</tr>
</tbody>
</table>

Fig. 1. Behavior illustration of a viscoelastic material with ramp-and-hold input described by four different models.

For the Kelvin model, a similar interpretation is applicable as a combination of both former models. However, it is notable that all three models suffer from discontinuity at the moment of impact (when \( t = 0 \), the indentation distance is zero while the velocity is not zero). In reality, both elastic and damping forces should be initially at zero at the beginning of impact.
To address this problem, another model to be considered is the Hunt–Crossley model. In this model, the damping coefficient is made dependent on the indentation distance. It has been shown by Warhefka and Orin that the Hunt–Crossley model has better physical consistency as compared to linear contact models such as other Kelvin model. The mathematic representation of the Hunt–Crossley model is

\[ f(t) = kx^n(t) + b x^n(t) \frac{dx}{dt}, \quad (9) \]

where \( k \) is the spring constant, \( b \) is the damping constant, and the exponent \( n \) is a real number usually close to unity, which is mentioned to depend on the surface geometry of the contact.

In Fig. 1(d), the force shows a nonlinear profile as the indentation distance increases due to the exponent component, although the curvature could be rather flat if the exponent coefficient \( n \) is close to unity. Although it is mentioned in several papers, that the exponent coefficient in the Hunt–Crossley model could refer to different contact geometries, there are no quantitative results in analysis. The only example commonly used is that when \( n = 1.5 \) (as used in the figure here), the elastic term exactly matches the force resulting from the Hertz theory for spheres contacting in static conditions. Their studies focused on the contact between the tool and infinite elastic body, which might not be applicable to thin-wall soft tissues such as the stomach. In addition, excess force at the impact moment is avoided, but the stress relaxation part when the indentation stops has the same profile as the Voigt model.

To obtain a better representation of the viscoelastic response of the thin-wall soft tissue of the stomach, a modified model is introduced in the following section. The proposed mechanical property model is based on the existing viscoelastic models, while addressing their limitations in stomach modeling.

2.2.2. Proposed mechanical property model

After reviewing the response of these viscoelastic models to the ramp-and-hold inputs, we found that these models could not represent the full nature of the soft tissue due to their simplicities or restrictions, which are insufficient to describe the soft tissue behavior under the condition of large deformation. Based on these four commonly recognized viscoelastic models, a modified model for force indentation relation is proposed to closely describe the nonlinear response of the stomach wall:

\[ f(t) + \tau_1 \frac{df(t)}{dt} = k_1 x(t)^3 + k_2 x(t)^2 + k_3 x(t)^3 + \tau_2 x(t) \frac{dx}{dt}, \quad (10) \]

where \( \tau_1 \) is the relaxation time coefficient, \( k_i \) \((i = 1, 2, 3)\) are the nonlinear elastic coefficients, and \( \tau_2 \) is the nonlinear damping coefficient.
A few remarks are made on the proposed model:

**Remark 1 (Relaxation phenomenon).** The historical term of force \( df(t)/dt \) is considered in the proposed model. This inclusion is to yield the relaxation of force once indentation is finished and the probe holds its position.

**Remark 2 (Nonlinearity).** For the viscous component, a nonlinear term is included in the proposed model, namely the multiplication of displacement and velocity. This is to avoid the unnatural shock force at the moment of impact as shown in three linear models (Maxwell, Voigt, and Kelvin). In such an arrangement, the force response could start from zero even with a non-zero impact velocity. For the elastic component, to describe the highly nonlinear response under large deformation, a third-order polynomial term is selected. The three coefficients could allow more flexibility in fitting the dramatic change in force with the increasing indentation distance.

**Remark 3 (Specimen dependency).** The aimed application of this model is estimating contact force using a preassigned parameter set and the real-time measured tool tip position during stomach indentation. Although in most surgical applications the stomach is already inflated, the inter-specimen variations and even the inflation differences are potentially influential to the force estimation result. The effect of inaccurate parameters to the force estimation result will be discussed in Sec. 4.2.

### 3. Results

Two different approaches regarding stomach mechanical property modeling have been proposed. They differ significantly due to different applications. However, they have at least one thing in common: given the same specimen, the same input signal and the calculated force output should converge to the true force signal in the ideal case. Following this, in order to verify the above estimation approaches, experiments were conducted on explanted porcine stomachs. Although it was shown in the literature that significant differences do exist between the tissue properties measured *in-vivo* and *ex-vivo*, it was also shown that the force-displacement response of both conditions could be closely curve-fitted by the same phenomenological model by adjusting the parameters set. The scope of this reported study is to identify an appropriate model to describe the tissue behavior, rather than offering accurate characterization for the live tissue. Thus in this paper, all the experiments were conducted on *ex-vivo* porcine stomachs.

#### 3.1. Experimental setup

The indentation apparatus was designed to measure the forces on the tip of the probe during the indentation. Figure 2 shows a overview of the experimental setup. The
interaction tool was chosen to be a 12-mm outer diameter blunt probe with a hemisphere-shaped head. The position and velocity of the device were driven by a linear motion slider (EZS3-15 from EZlimo™), while the force data was collected by a load cell (Entran™) with a sampling rate of 100 Hz. The stomach specimen was placed and held at the end of the indentation device. An incision opening was first made on one side of the stomach body to inflate the specimen; a plastic frame was then inserted inside to prop up and expand the surface of the stomach body, and the specimen was clamped at the back to close up the incision. Indentation was performed on the center of the stomach body.

3.2. Experimental protocol

All indentations were made with respect to the same initial reference position, which was labeled by a marker on the slider base. When the experiment started, the probe was driven to indent into the stomach body at a fixed velocity until the desired displacement, following the input signal profile as defined in Eq. (5). The probe then remained at the final position, while force acquisition was continued for the stress relaxation to reach a steady state. After that, the probe returned to its equilibrium position and was prepared for the next trial.

The same indentation depth of 3 cm was tested with different velocity values (0.75 mm/s, 1.5 mm/s, and 3 mm/s) for different specimens. In total, five specimens were tested in the experiment.

Both position and force signals were recorded during each experiment trial. For real-time parameter estimation, force and position were used to estimate parameters, while for force estimation, only position was used to calculate force, and the measured force was used to characterize and evaluate the estimation result.

3.3. Real-time parameter estimation

As shown in Sec. 2.1, the worst case input signal (Eq. (5)) could only guarantee identifiability for a system structure as simple as in Eq. (7), which matches the Hooke’s law of position and force, as in Eq. (8). The problem then shrinks down
mathematically to the real-time estimation of environmental stiffness:

\[ f(t) = kx(t) + e(t), \]

which is a rather well-studied problem, where standard estimation methods could be applied (see Ljung’s book on system identification\(^{36}\)).

However here, the discussion is held from a different aspect: with mathematical performance not of major concern, we focused on how to extract more information from the worst information rich excitation signal. We adopted the worst case excitation signal as input, and assessed the performance of real-time tracking by using the proposed system model as in Eq. (7).

Here, fast real-time impedance estimation method proposed by Wang \( et \ al.^{37} \) is adopted. This method is a widely used approach for robotic applications in pattern recognition and parameter estimation tasks involving robotic arms,\(^{38}\) as well as human–machine interaction scenario applications\(^{39,40}\) and evaluation\(^{11,42}\) was adopted. The modified recursive least-squares (RLS) algorithm was performed with time-varying forgetting factors to achieve fast tracking, while maintaining good noise rejection. By tuning the forgetting factor function properly, the RLS algorithm handled real-time parameter estimation very well. The result of one typical trial is shown in Fig. 3(a) and to further illustrate the tracking performance, a closed-up view is shown in Fig. 3(b). In the experiment, the probe moved at a constant speed of 0.75 mm/s to a total indentation distance of 3 cm. Then, it stopped moving and held this position. It could be seen from the measured force response that the force increased faster as the indentation distance increased. After the movement stopped, the force on the probe decayed until a steady state level. Throughout the whole process, the estimated force was able to efficiently track the measured force, even in the presence of sensor noise. As can be observed from Fig. 3, allowing time-varying stiffness parameter results in a very good tracking performance with the force output signal. The output error was kept below 0.5 N. The mean and standard deviation of output tracking errors for eight trials on the same stomach specimen are shown in Table 2. The results show good tracking capability for real-time identification by using the proposed system model as developed in Eq. (7), when the excitation signal is of least information richness as derived in Eq. (5). More discussions regarding the performance and application are presented in Sec. 4.1.

### 3.4. Real-time force estimation

By using the same sets of experimental data, we sought to characterize the force model by using the nonlinear least squares method (such as “lsqcurvefit” function in MATLAB) to best fit the data. The Voigt model, the Kelvin model, and the Hunt–Crossley model were also used to describe the response in comparison with the proposed model. The Maxwell model was not considered because it would eventually decay to zero during the stress relaxation procedure.
As shown in Fig. 4, it is found that both the Voigt model and Kelvin model obtained a negative damping coefficient to best fit the curve. This is because their linear elastic response could not match with the measured highly nonlinear force profile. Even though parameter characterization could be achieved by using the

Table 2. Output tracking errors for eight trials.

<table>
<thead>
<tr>
<th>No. of tests</th>
<th>Error mean</th>
<th>Error standard deviation</th>
</tr>
</thead>
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<tr>
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<td>0.0968</td>
</tr>
<tr>
<td>2</td>
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<td>0.0874</td>
</tr>
<tr>
<td>3</td>
<td>-0.0015</td>
<td>0.0686</td>
</tr>
<tr>
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<td>0.0841</td>
</tr>
<tr>
<td>5</td>
<td>0.0003</td>
<td>0.1009</td>
</tr>
<tr>
<td>6</td>
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<tr>
<td>8</td>
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</table>

Fig. 3. Parameter estimation results using RLS algorithm. (a) Real-time estimation result with error. (b) Period from 28 to 42 s for a clearer view of tracking performance.
The nonlinear least squares method was used to find the optimized parameter set to minimize the sum of squares of the estimation errors. Therefore, for the Voigt model and the Kelvin model, the parameter set obtained using this method returns a negative value for the damping coefficient. Even by assigning a positive damping coefficient, the estimation error will be very high. This is known as the drawbacks for these two models for not capable of modeling the nonlinear response. Based on the highly nonlinear elastic response of the stomach, it could be concluded that Voigt model and the Kelvin model are not suitable for the stomach.

On the other hand, though the Hunt/C0 Crossley model could fit the ramp stage, it fails to describe the stress relaxation in the hold stage. As a result, the proposed model outperforms the Hunt—Crossley model in both mean and standard deviation of the estimation error (0.279 N and 0.440 N, respectively for the Hunt—Crossley model).

The results have shown that the proposed model, which was derived on the foundation of the common viscoelastic models, is capable of interpreting the tissue behavior of the stomach. Further discussion about the generalization of the proposed model are presented in Sec. 4.2.

Fig. 4. Force estimation results by parameter characterization using different models, where the dashed line is the experimental data and the solid line is the characterized model prediction.
4. Discussion

The proposed algorithms for real-time parameter estimation and force estimation have been validated using experimental data. In the remainder of this section, discussions are held from several aspects on the generalization, relation, and application of the algorithms.

4.1. Generalization of the real-time parameter estimation algorithm

The real-time parameter estimation approach shows promising performances in output force signal tracking. Before comparing its performance with the other approach, the following remarks are made regarding the performance and results of this approach:

**Remark 1 (Repeatability).** While having a good tracking performance, the algorithm also presents very good repeatability. The result shown in Fig. 3 is of one trial. Table 2 shows the tracking performance of the real-time estimation in a series of tests. For example, No. 4 corresponds to the result shown in Fig. 3. In practice, the averaged error is found to be under 0.1 N, approximately at the force sensor noise level. It exhibits a good convergence property and robustness with an initial value of zero for the estimated parameter $k$.

**Remark 2 (Inter-specimen differences).** As has been discussed in Remark 3 of Sec. 2.2.2, the performance of the force estimation algorithm with time constant parameters is potentially dependent on the specimen in use. The same statement is true for the real-time estimation approach. However, the inter-specimen difference reveals new information which could lead to a new application. When the specimen is changed, resulting in different force levels, the estimated parameter could converge to the new settling point with negligible error. The results of four experiments on two specimens, two from each specimen, were plotted for comparison, as shown in Fig. 5(a). The corresponding estimated parameter $K$ is shown in Fig. 5(b). It could be observed that for each specimen, the parameter $K$ converges to a similar value for different trials, while the two converged values of $K$ are significantly different for different specimens. This is also true for the first half of each trajectory, where the profile is similar for same specimen, while differing among specimens.

This observation suggests that the estimated parameter contains properties of the stomach. In the result shown in Fig. 5, it may appear to be related to the force profile. However, note that here, a same input signal is used for all trials. In the case of different input signals, the force signal alone could not reveal the property of the specimen since it contains the influences of the input signal.

**Remark 3 (Physical meaning of $K$).** In the first 20 s of Fig. 5(b), the estimated parameter $K$ values vary significantly, with the highest value around 500 N/m. Here, we argue that the $K$ is a mathematical representation of the force and position relationship resulting from the estimation algorithm. Hence, although it has a unit of
N/m, it does not necessarily indicate the physical quantity of stiffness. In other words, it is the first-order approximation result to the force signal in a least-square sense, although mathematically it is a bit more sophisticated than linear curve fitting because of the forgetting factor RLS. It is possible to use this argument to explain the large variation of K in the first 20s: there is/are other dynamic factor(s) not considered by the current simplified model. Thus the effect of such factor(s) is force-included into K values, since the algorithm only provides optimal estimations in a least-square sense, resulting in irrational variations. While contributing to the robustness of real-time identification, the simple model also limits the information obtained of mechanical properties. The estimated parameter with the simple model is in fact an artificial term consisting of all higher-order system dynamics. Although the
output error was kept small, the estimated parameter $K$ was not the true stiffness of the specimen, but also contained influences introduced by the RLS algorithm mathematically.

On one hand, this finding supports the necessity of introducing more complex models to describe the system; thus, to get a better representation of the specimen, higher-order models are desired, while on the other hand, we aim to develop an algorithm that guarantees identifiability under all circumstances. The worst case input signal constrains the system model complexity for real-time parameter estimation. To this end, we have considered different input excitation signals as described in Sec. 2.1.2. With parameter estimation in concern, the signals were classified by the order of information richness. SRE0 signals, such as the impulse signal, required the mathematical expectation to be zero at all times; in the real-world, this means the probe should almost always be staying in the starting point. Assuming the continuous motion of the probe, this is clearly not practical. Hence, we claimed that SRE0 signals are not considered as real-world feasible inputs. Next, we considered SRE1 signals. Such as the poke-and-hold case of Eq. (5) discussed in Sec. 2.1.2, a composition of SRE1 signals forms the most basic operations encountered in the real-world. Hence, we argue that to guarantee identifiability under all circumstances, the system model needs to be identifiable at least for SRE1 inputs. The reasoning is straightforward: if a model structure can only be identified with SRE2 inputs, the estimation results are not reliable if an SRE1 input signal is applied.

In a nutshell, given full haptic (force, motion) measurement data, it is possible to retrieve the mechanical properties of soft tissue. However, the generalization of the real-time parameter system is subjected to the input signal information richness. If a higher-order system model is desired, we have to apply constraints such that the input signal needs to be SRE2 at all times.

4.2. Generalization of the real-time force estimation algorithm

The main concern with the stomach tissue is its viscoelastic behavior. Thus, starting from a few commonly used viscoelastic models, we proposed a modified viscoelastic model to directly relate the two important features in robotic surgery — motion and force. It has been empirically shown that the proposed model is able to depict the force response of the stomach tissue. However, it is inevitable that the stomach tissue properties would be patient-specific and inhomogeneous. Even the extent of inflation during the operation might also affect the tool—tissue interaction force. Thus, the main challenge of the real-time force estimation algorithm is the time constant nature of the proposed mechanical property model, which is to use one pre-defined parameter set to fit multiple input and multiple specimens in force estimation.

In this work, the concern of specimen dependency is addressed from two aspects. First, we discussed the performance of using one parameter set on different input signals with a same specimen. Then, we analyzed the effect of using one parameter set on different specimens.
In the first comparison, two different input signals were applied to the same specimen. The input signals had different velocities during the ramp phase, while keeping the same indentation displacement. The velocity was 3 mm/s for the first input, and 1.5 mm/s for the second input. The indentation displacement was 3 cm for both inputs. The parameter set of the force estimation model was calculated using the first input. It was then applied to the second input data for force estimation. The results are shown in Fig. 6. As can be observed from the figure, the estimated force of the second input does not match the measured force as well as the first input. However, the degrading is only significant during the beginning of the relaxation phase. During indentation and the late relaxation phase, the performances of both input signals are similar. Hence, we concluded that it is possible to generalize a parameter set obtained from one specimen to different input signals using the same specimen, while still yielding similar force estimation performance.

In practice however, it is very unlikely to pre-characterize the model in-vivo with the tissue/organ to be operated on; to do this, one needs to either have a force-sensor on the tool, or perform ex-vivo parameter characterization using force-sensing devices. The first case violates the pre-assumption of no force-sensor available; for the second case, it is not feasible to biopsy a part of the tissue/organ to perform ex-vivo tests. Only a parameter set characterized from different specimens could be applied for estimation. Therefore, it is necessary to validate inter-specimen performances for the real-time force estimation approach. In the second comparison, we take the same parameter set obtained in the first comparison, and apply it to a wide range of different trials measured from two different specimens (one used to obtain the

![Fig. 6. Force estimation results using different velocity inputs (Velocity 1 = 3 mm/s, Velocity 2 = 1.5 mm/s) on the same specimen. The parameters are characterized by the measured data of Velocity 1.](image-url)
parameter set another for a foreign set) using different input signals. To cope with the condensed information, time profiles of the trials are not shown. Instead, each trial is represented by an ellipse in the $f - e$ coordinate system. Here, $f$ denotes the measured force, while $e$ stands for the estimation error. The center of each ellipse is defined by the force after relaxation (measured force after relaxation of 30 s) and the averaged force estimation error. The horizontal radius is defined as the amount of relaxation in the first 10 s, while the vertical radius is defined as the standard deviation of the estimation error. The $f - e$ plots are shown in Fig. 7. Specimen A is used to characterize the parameters of the model. As a comparison set, same experiments were performed on Specimen B, but estimations were based on the parameters that were characterized from Specimen A.

It should be noted that for the same specimen (Specimen A), the relaxation forces decay faster with a larger indentation velocity (0.75 mm/s, 1.5 mm/s, and 3 mm/s). In spite of that, the estimation errors for different velocities were still kept within similar ranges. Besides, the steady state force, as shown by the center of the $f - e$ plot, were around the same value of 2.3–2.5 N, which is in accordance with the results shown in Fig. 6. The $f - e$ plot offers a comparable illustration to show that the performance of the proposed model in response of different motion inputs.

Fig. 7. Force estimation results using different specimens. The parameters are identical to those used in Fig. 6. The coordinate of the center of $f - e$ ellipse is defined by the relaxation steady state force and averaged force estimation error, respectively. The horizontal radius refers to the amount of relaxation in the first 10 s, while the vertical radius refers to the standard deviation of the estimation error.
For different specimens, the estimation error for Specimen B is much larger than Specimen A. The mean estimation errors are within 50% of the relaxation steady state force level, which is indicated as the dashed line in the figure. This suggests high specimen dependency of the model. One possible reason for the large differences observed in different specimens would be due to the different initial condition introduced by the fixation of the specimens. Even under the same initial condition, the differences are still inevitable since here, we attempted to fit our pre-defined model to the specimen, which might have slightly different mechanical properties. However, it is noticed that the amount of relaxation in the first 10 s of Specimen B is comparable to that of Specimen A. This suggests that the viscous properties of the tissue are quite consistent even for different specimens. Since the proposed model can characterize this behavior, it could still fit the measured data of Specimen B by adjusting some of the parameters.

It is also noted that there is a trend of decrease in the relaxation settling force for Specimen B. This could be referred as phenomenon of pre-conditioning; as the same stimuli input applies to the specimen repeatedly, the relaxation force level would decrease to a steady state at which no further change will occur unless the stimuli signal is changed. It is commonly perceived that the tissue will not be typically preconditioned during surgery. Thus, it is not necessary to describe this phenomenon in the modeling.

In summary, if force measurement is not available, the force information could be restored from the motion input precisely using the proposed model. Although due to the inter-specimen differences, the estimation error would not be eliminated. The main goal here is to identify a mechanical property model which could describe viscoelastic behavior or in particular, the force—motion profile of the stomach tissue. The changes in the tissue properties can be reflected by changing the parameter set, rather than changing the whole model structure.

### 4.3. Comparison of two approaches and implementation

It is argued here that the two approaches were developed aiming at completely contrasting applications, such that solely comparing the output error does not represent their true performances. On one hand, no matter how accurate the parameter estimation algorithm is, it cannot be performed without a force sensor. On the other hand, the force estimation model would suffer from inter-specimen variations despite the sophistication of the model itself. Subject to the presence of force measurement, two proposed approaches could then be adopted for different applications to improve the user experiences of surgeons.

For the parameter estimation approach, where the force measurement is available, it is recommended to implement the proposed system model in a consistent examinable protocol, for example, a fixed motion routine such as palpation. Correspondingly, the tissue property at different locations could be identified in real-time. With prior knowledge on the tissue property, the real-time parameter estimation approach could
help to improve current diagnostics experiences of the surgeons. The surgeon would not only feel the tool–tissue interaction force, but also obtain an indicative index related to the tissue property for examining abnormalities such as embedded tumor.

For the force estimation approach, where the force measurement is missing, the proposed viscoelastic model can provide a relative haptic feedback as a guideline for the surgeon, where the assumption of homogeneity of the tissue could be accepted. To deal with the inhomogeneity of the tissue, it would take further steps to develop a real-time tracking system, such as the interventional navigation system,32,43 such that the spatial orientation of the surgical robot relative to the organ/tissue of interest could be acquired to update the parameter set accordingly.

5. Conclusion

This paper is dedicated to model the tool–tissue interaction behavior of the stomach, targeting real-time applications in surgical operation, especially for endoscopic surgeries. Two approaches are taken to tackle the problem in real-time applications — (1) proposing a system model for real-time parameter estimation when force information is available and (2) proposing another model for real-time force estimation when force information is missing. For the parameter estimation approach, we aimed to obtain reliable results under arbitrary robotic surgical operations. By classifying and analyzing the possible input signals relating to their information richness, we obtained a surprisingly simple conclusion that only the first-order relationship between force and displacement, the Hooke’s law, could be identified by arbitrary input signal. For the other approach, when force information is not accessible, we proposed a straightforward phenomenological model to provide real-time force estimation based on the current motion input. The proposed model considers the advantages of several existing models; it is customized for the tubular and viscoelastic characteristics of the stomach.

Although the model structure and parameter values are based on the stomach, the major proportion of the contribution of this paper can be generalized to other organs. For instance, the real-time parameter estimation constraint is true for any estimation problem; the only model guaranteeing universal identifiability is the Hooke’s law between force and motion. The discussion of inter-specimen variance also holds for other organs, when similar technical constraints and concerns apply. Possible future directions include the implementation of the proposed approaches into surgical applications, as well as further investigation in remedies for the specimen-dependency for the force estimation algorithm. So far, the discussions are made with one degree-of-freedom indentation. Further investigations could be carried out to exploit multi-directional results.

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References


