NEEDLE INSERTIONS MODELLING : IDENTIFIABILITY AND LIMITATIONS

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Abstract: Soft tissues modeling is a very present preoccupation in different scientific fields, from computer simulation to biomechanics or medical robotics. In this article, we consider the interaction of a needle with living tissues, which is a particularly complex modeling problem since it is characterized by inhomogeneity and nonlinearity properties. We propose a robust method to online estimate the interaction between living tissues and a surgical needle. The ability to obtain physically consistent models during *in vivo* insertions is discussed.

Keywords: soft tissue modeling, online robust estimation, *in vivo* needle insertion.

1. INTRODUCTION

Interventional radiology is a developing medical field in which specialists use medical imaging techniques (CT-scan, C-arms, Ultrasound) to insert surgical needles, in order to reach internal organs. It allows to achieve minimally invasive local treatments, from simple biopsies to cancer treatments, as stated in Rhim et al. (2001). Unfortunately, this procedure has two main drawbacks. Firstly, it is difficult to precisely place the needle tip in the target organ, whereas this has an important influence on the success of the treatment. Secondly, during a CT-scan guided operation, the radiologist is exposed to harmful X-rays radiations.

For a few years, the modelling of the interaction forces during needle insertions has become a challenging task. Pioneer works recently appeared, principally in the medical robotics context (DiMaio and Salcudean (2004); Okamura et al. (2004)). Indeed, they have been motivated by the development of systems to robotically assist needle insertion training, guidance or teleoperation (Stoianovici et al. (1997); Maurin et al. (2004)).

To characterize the interaction between a needle and soft living tissues, let us first describe a puncture into a single layer sample. We assume that the needle tip is initially motionless and in contact with the surface of the tissue. The needle insertion is a 3 phases procedure illustrated by figure 1:

- Phase 1: The needle pushes the tissue surface which becomes deformed.
- Phase 2: When the force applied by the needle on the tissue reaches a given energetic threshold (see Hervely et al. (2005)), the nee-

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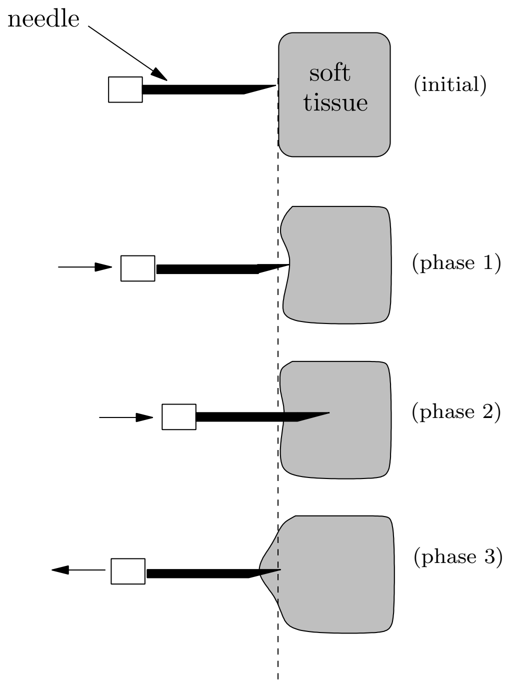

Fig. 1. Needle insertion into a single layer soft tissue

dle penetrates into the tissue by cutting its surface. While the needle is inserted, the friction forces attract the skin along the needle shaft.

- Phase 3: The needle is extracted from the tissue. Again, the tissue is attracted in the needle motion direction. Consequently, the position of the needle when it is extracted does not correspond to the initial position.

The first phase corresponds to a viscoelastic interaction as described in Fung (1993). In accordance with Okamura et al. (2004) the interaction forces during the second phase are due to the effects of cutting, friction, and to the relaxation of the skin after the puncture. In the third case, the interaction between the needle and the tissue is only due to friction. It is particularly difficult to study the mechanics of the insertion in living tissues because:

- the different tissues in interaction with the needle are inhomogeneous;
- these tissues exhibit nonlinear properties;
- their contributions to the interaction are superimposed.

For all these reasons, needle insertions modelling is a challenging task.

Okamura et al. (2004) study the forces involved in the needle penetration and withdrawal. The insertion is controlled by a robotic translator and the associated forces and displacements measurements are obtained for bovine livers. The characteristic properties of needle insertion forces are identified and a methodology is given to separate the contributions of stiffness, friction and cutting forces in order to derive a complete force model. Though suitable for the characterization of efforts and haptic simulation, the previous methodologies involve different specific *ex vivo* tests to adjust parameters to patient variability. The rheological characterization of tissues, proposed in Kobayashi et al. (2004) has the same limitations.

In the following, we will assume for obvious reasons that the insertion of the needle in a patient should be strictly limited to the necessary medical task. From this point of view, the identification of a needle insertion model from data collected during the medical act itself is required. DiMaio and Salcudean (2004) estimate an elastostatic linear model derived from the needle tip force and position measurements and from the deformation of the pierced material. The deformations are given by markers placed on the surface of the material. It is difficult to use this procedure in the clinical conditions, specially in the case of internal organs. In the context of the interaction of robot with a soft environment, Diolaiti et al. (2005) focus on the online estimation of viscoelastic linear and nonlinear models. The proposed methodology is of interest though results are given for small motions of a translator system in contact with thin layers of stiff (polycarbonate) and soft (silicone gel) samples. Since it is applied to artificial materials and viscoelastic stimuli, *i.e.* without cutting, it does not directly adapt to the problem of needle insertion. Nevertheless, this approach undoubtly shares similar motivations with our study.

In this article, we analyze the modeling and identification of needle insertion interactions during *in vivo* experiments. The limitations of the modeling and identification procedure are discussed. In section 2, the estimation techniques and the experimental setup are presented. Section 3 presents modeling issues and the results of online estimations obtained during *in vivo* experiments. Finally, the conclusion summarizes the main contributions of this work.

2. METHODS

2.1 Experimental Setup

As already stated, the aim of this paper is to model the needle insertion from measurable informations in operating conditions. We consider that the tissues in which the needle is inserted are not equipped with particular fiducials that may allow to capture the organs motions, as in DiMaio and Salcudean (2004). We suppose that the only informations at disposal are the position or the velocity of the needle tip and the interaction forces measured by a force sensor. They can be obtained if the needle is instrumented or hold by a robotic assistant.

To estimate needle insertion models we use a PHANToM haptic device from Sensable Technologies as an instrumented passive needle holder. The PHANToM end effector is equipped with an ATI Nano17 6 axis force sensor. A needle holder is mounted on the force sensor, so that needles of different sizes can be attached (see figure 2). The PHANToM encoders are used to measure the motions of the needle, with a precision of 30 μm. During a manual insertion, the velocity

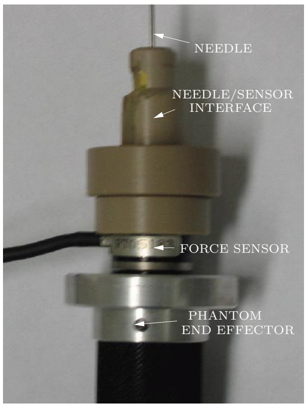

Fig. 2. Instrumented needle

of the needle tip is generally very low. Since it is derived from position encoders, it is corrupted by an important quantization noise. To reduce its effect we estimate the velocity with a standard Kalman filter. Measurements are acquired at a frequency rate of 1 kHz, under real-time constraints imposed by the software implemented on Linux RTAI operating system.

2.2 *Online Estimation Method*

We use a recursive estimation method in order to identify a model of the tissue. This method is based on *a priori* models, that will further be discussed. Recursive parametric estimation algorithms are based on a discrete time linear parameterization of the system output (see Goodwin and Sin (1984)):

$$y_{k+1} = \varphi_k^T \theta_k^* + w_{k+1}$$

where θ_k^* is the vector of unknown parameters to be estimated, φ_k is the regression vector build from the measured signals and y_{k+1} is the measured output signal, at time $k+1$. The output measure noise is represented by the signal w_{k+1}.

From the estimation $\hat{\theta}_k$ of θ_k^* at time k, we can estimate the output signal at time $k+1$ as:

$$\hat{y}_{k+1} = \varphi_k^T \hat{\theta}_k.$$

We define the *a priori* prediction error as the error between the measured output and the estimated output:

$$e_{k+1} = w_{k+1} + \varphi_k^T(\theta_k^* - \hat{\theta}_k).$$

Finally, we define the *a posteriori* prediction error:

$$\hat{e}_{k+1} = y_{k+1} - \varphi_k^T \hat{\theta}_{k+1}.$$

We use Recursive Least Squares (RLS) algorithm which is probably the most used technique for online estimation. The RLS algorithm writes:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + \frac{F_{k-1}\varphi_{k-1}e_k}{\frac{1}{\alpha_{k-1}} + \varphi_{k-1}^T F_{k-1}\varphi_{k-1}}$$

$$F_k = F_{k-1} - \frac{F_{k-1}\varphi_{k-1}\varphi_{k-1}^T F_{k-1}}{\frac{1}{\alpha_{k-1}} + \varphi_{k-1}^T F_{k-1}\varphi_{k-1}}$$

where α_k is a weighting function ($\alpha_k = 1$ corresponds to the classical RLS algorithm). Note that the gain factor F_k is recursively adapted.

Additionally to the standard algorithm we use a dead-zone function (Ioannou and Sun (1996)) so that the estimation may remain robust when the absolute value of the error signal is under a given threshold, denoted as N_0. Its value is chosen so that $N_0 > \nu_0$, with ν_0 the magnitude of the noise w_k. The resulting algorithm is obtained by premultiplying F_k by $\delta(e_k)$, with:

$$\delta(e_k) = \begin{cases} 1, & \text{if } |e_k| \geq 2N_0 \\ \frac{|e_k|}{N_0} - 1, & \text{if } N_0 \leq |e_k| < 2N_0 \\ 0, & \text{if } |e_k| < N_0 \end{cases}$$

The parameters adaptation freezing allows a sensible robustness improvement.

The variations of the gain factor F_k has some influence on the estimation of varying parameters. Indeed, a persisting excitation of the regression vector, *i.e.* a sufficient level of input measurements, is required for the convergence of the parameters estimation. Nevertheless, in the case of the RLS method, the convergence of the algorithm causes the decrease of F_k towards zero. In this case, the estimated parameters no longer vary. For that reason, the method cannot directly apply to estimate varying parameters. The RLS algorithm with covariance resetting (RLS-CR) solves this problem by resetting the covariance matrix at time k_r with:

$$\{k_r\} = \{k | \lambda_{min}(F_k) \leq \alpha_0^{-1} \leq \lambda_{min}(F_{k-1})\}$$

To reduce the computing complexity of k_r, an equivalent condition on the trace of the covariance matrix can be used:

$$\{k_r\} = \{k | x_k = tr(F_k^{-1}) \geq \alpha_0\}.$$

Indeed, it is shown that x_k can be computed recursively by $x_k = x_{k-1} + \alpha_{k-1}\varphi_{k-1}^T\varphi_{k-1}$. The resetting is achieved by setting $F_{k_r} = F_0$, what implies $x_{k_r} = x_0$.

3. *IN VIVO* EXPERIMENTAL RESULTS

We lead two different tests.

Firstly, we identified the viscoelastic behavior of the tissues occurring in the first phase of the insertion. Since no piercing was necessary, we performed the test on the abdomen of an adult living human. The final part of the needle holder was removed and the force sensor mounted on the end effector directly applied on the abdomen. The corresponding results are given in section 3.1.

The second part of the experiments were performed in operating *in vivo* conditions. Needle insertions in the liver of anesthetized pigs were adopted as benchmarks for two reasons:

- the abdominal tissues of a young pig are rather similar to human ones;
- the properties of the tissues are much more realistic in vivo because of blood irrigation and breathing which considerably influence the mechanical properties of the tissues.

The insertion was done through a small incision on the epidermis (a new one each time), as usually done in interventional radiology. The insertion was then performed through the dermis, the fat and the muscle to finally access the liver. The corresponding results are given in section 3.2.

3.1 Viscoelastic Experiments

Modelling To model the interaction during the viscoelastic phase of the needle insertion, we considered two classical viscoelastic models. The linear Kelvin-Voigt(KV) model is certainly the most common model used in the literature. In our case it writes:

$$f = \begin{cases} -(Kp + Bv), & \text{if } p > 0 \\ 0, & \text{if } p \leq 0 \end{cases} \tag{1}$$

where f is the force exerted on the tissue, p and v represent the position and the velocity of the needle tip, K is the stiffness coefficient and B the damping coefficient. The position p=0 corresponds to the initial contact point. In fact, the representation of living tissues by this linear model is generally not adequate. Indeed, except for very small motions the interaction model varies in an nonlinear way regardless to the tissue motion. The Hunt-Crossley (HC) model intrinsically takes into account the penetration depth between two bodies. It states that the interaction model varies in an nonlinear way regardless to the tissue motion, as presented in Hunt and Crossley (1975):

$$f = \begin{cases} -(\mu p^n + \lambda p^n v), & \text{if } p > 0 \\ 0, & \text{if } p \leq 0 \end{cases} \tag{2}$$

where μ, λ and n are constant parameters that depend on the material properties.

Experimental results From the previous remarks, and from comparative tests between the KV and HC models, we used the HC model for the estimation in the viscoelastic case. Characteristic results are presented on figures 3.

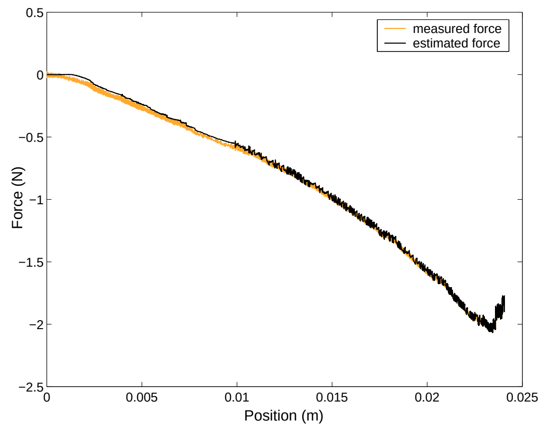

Fig. 3. Force reconstruction with the HC model during the viscoelastic phase

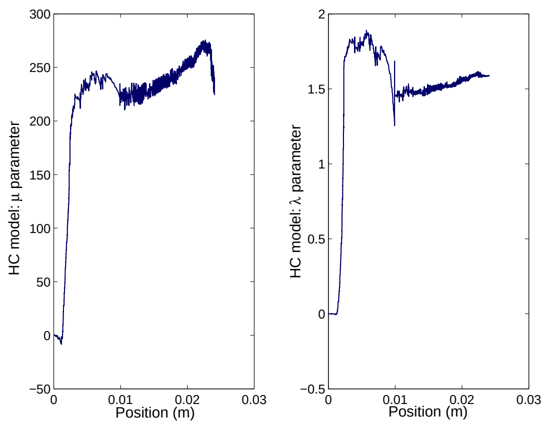

Fig. 4. Estimated parameters of the HC model during the viscoelastic phase

Figure 3 illustrates the quality of the force reconstruction. The absolute mean value of the reconstruction error is 0.0194 N with a standard deviation of 0.0125N. Force is given as a function of the needle tip position.This allows to emphasize the nonlinearity of the model. The HC model allows to obtain quasi constant parameters during the viscoelastic interaction as illustrated on 4. We observe the convergence of the algorithm to: $\mu = 240$ and $\lambda = 1.5$. In that study we assumed that the n coefficient is constant. This is generally assumed in the biomechanics literature. According to Johnson (1989), $n \approx 1.5$ in the case of spheres contacting in static conditions. Diolaiti et al. (2005) established that $n \approx 1.3$ describes accurately the viscoelastic behavior of soft materials and proposed a solution for the simultaneous online estimation of μ, λ and n.

Remarks According to Fung (1993) most living tissues have a viscoelastic behavior, as long as small displacements are considered. In practice, we could observe that the viscoelastic phase during a needle insertion corresponds to relatively large motions. This increases the nonlinear behavior of the tissue. We could also observe an even more disturbing artifact. When the needle is inserted in very viscous organs, they trend to slip in the abdominal cavity. This of course is very difficult to model. In practice, it is avoided by the physician, which often tries to minimize the viscoelastic phase of the insertion by piercing the organs with an abrupt motion of the needle. The effect of speed on the way the needle perforates an organ are studied in Hervely et al. (2005).

3.2 Needle Insertion Experiments

Modelling In order to understand the interactions during a needle insertion we consider the simple case of an insertion into a one layer soft tissue. As underlined previously, the behavior of the tissue during the first phase of the insertion can be approximated by a viscoelastic model. So, if we denote as p_s the position of the entry point on the surface of the tissue, the motion of the tissue can be described by : $p = p_s$. During this first phase the tissue surface becomes shapeless until the penetration of the needle tip. After the puncture the needle tip position is different from the position of the entry point on the surface of the tissue (see figure 5).

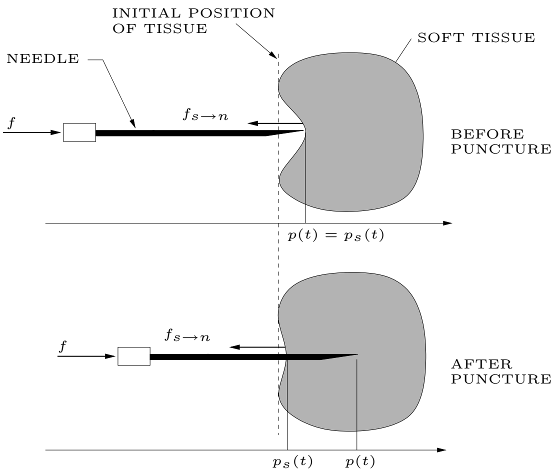

Fig. 5. Descriptive model of the needle insertion

The motions of the needle during the insertion into the tissue and the motion of the tissue can be both modeled by:

$$m\ddot{p} = f + f_{s\to n} + f_f$$
$$m_s\ddot{p}_s = f_{s\to n}$$

where m and m_s are respectively the inertia values of the needle with its holder and of the tissue. $f_{s\to n} = -\mu_{ins}p_s^n - \lambda_{ins}p_s^n(\dot{p}_s - \dot{p})$ in the nonlinear case expresses both the tissue relaxation and its adherence to the needle, and f_f represents the dry friction on the needle.

The online identification of such a model is very difficult in particular because the position of the tissue is not available and the inertia parameters are unknown. Moreover the needle punctures several inhomogeneous layers, which have all different behaviors.

Yen et al. (1996) proposed a model of tissue for needle insertion based on a KV model with piecewise constant parameters. It is also very difficult to online estimate a such model since the organs transitions are not easily detectable. Consequently, we decided to use a model in the form of the KV model, but for which the parameters K and B are varying in time, with the position and the velocity of the needle tip, *i.e.* such that $K = K(p,\ v,\ t)$ and $B = B(p,\ v,\ t)$. In the following we will denote this model as the KV generalized model (KVG). This model is no longer physically consistent since it does not take into account the tissues deformations. However it allows to reconstruct the force with a simple parameters description.

Experimental results The results obtained for the reconstruction of the force based on the estimation of the KVG model are represented on figure 6. The estimation results shown on figure 6 are characterized by a very accurate reconstruction: the absolute error mean value is 0.0486 N for a force amplitude ranging from −5.69 N to 2.45 N. This emphasizes the fact that most of the

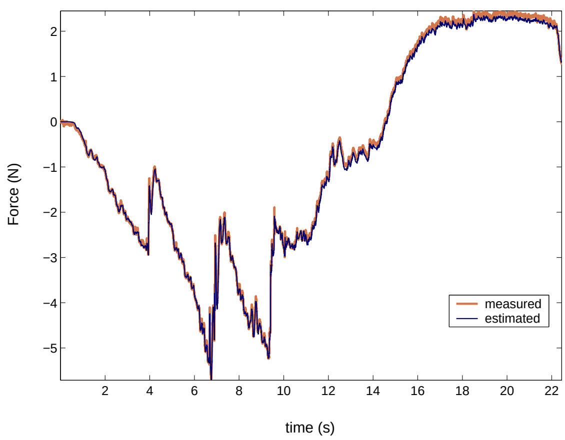

Fig. 6. Force reconstruction with the KVG model during needle insertion

sensed forces that a physician feels while inserting a needle are due to the skin, the fat and the muscles. The main interest of this model is limited to the parameters analysis. The evolution of the estimated parameters of the KVG model during the needle insertion are represented on figure 7. The profile of both parameters of the KVG model

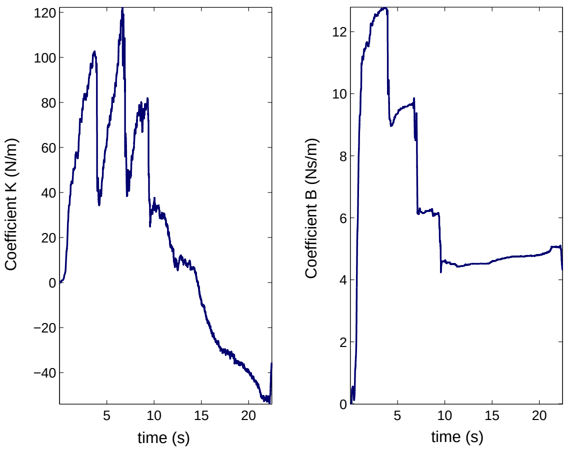

Fig. 7. Estimated parameters of the KVG model during a typical needle insertion

are not continuous, because of the rupture of the different tissues surfaces. Nevertheless, we notice that the parameters are bounded and fluctuate slowly excepted during transitions phases. This may open opportunities in the control of a robotized needle insertion systems.

4. CONCLUSION

In this paper we presented a method to online characterize needle insertions. This method is based on a robust recursive least squares algorithm with covariance resetting. First experiments allowed to evaluate the viscoelastic behavior of the skin and to prove the effectiveness of the estimation technique. The *in vivo* insertion of a needle was then described and the complex behavior of the tissues emphasized. To allow the online characterization of the needle insertion we proposed a varying parameters model. With this model, we achieved the estimation of the interactions with very good tracking properties.

The estimated parameters will further be introduced in the control of a force feedback teleoperated robotic assistant.

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