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Needle Deflection Estimation using Fusion of Electromagnetic Trackers*

H. Sadjadi, K. Hashtrudi-Zaad, and G. Fichtinger

Abstract— **We present a needle deflection estimation method to compensate for needle bending during insertion into deformable tissue. We combine a kinematic needle deflection estimation model, electromagnetic (EM) trackers, and a Kalman filter (KF). We reduce the impact of error from the needle deflection estimation model by using the fusion of two EM trackers to report the approximate needle tip position in real-time. One reliable EM tracker is installed on the needle base, and estimates the needle tip position using the kinematic needle deflection model. A smaller but much less reliable EM tracker is installed on the needle tip, and estimates the needle tip position through direct noisy measurements. Using a KF, the sensory information from both EM trackers is fused to provide a reliable estimate of the needle tip position with much reduced variance in the estimation error. We then implement this method to compensate for needle deflection during simulated prostate cancer brachytherapy needle insertion. At a typical maximum insertion depth of 15 cm, needle tip mean estimation error was reduced from 2.39 mm to 0.31 mm, which demonstrates the effectiveness of our method, offering a clinically practical solution.**

I. Introduction

Percutaneous needle insertion is involved in many clinical diagnostic and therapeutic procedures, such as biopsies, regional anesthesia, neurosurgery, and prostate brachytherapy [1]. Contrary to casual observation, needle-based interventions can be extremely complex, especially when needle deflection and tissue deformation exacerbate needle placement error.

Over the past two decades, prostate brachytherapy has been established as a definitive treatment for early stage prostate cancer [2]. The process of a typical brachytherapy treatment starts with computerized planning to identify the optimal locations for the implanted radioactive sources (seeds), such that an adequate radiation dose is received by cancerous prostate cells, while no more than a tolerable dose is received by the surrounding tissues. During the implantation process, with the patient in lithotomy position, needles are inserted into the prostate through which 50 to 120 small radioactive seeds are permanently implanted at preplanned target positions, under the real-time transrectal ultrasound (TRUS) guidance. The seeds remain permanently in the prostate and continue to emit radiation until eventually becoming inactive.

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H. Sadjadi is with the Department of Electrical and Computer Engineering, Queen's University, Ontario K7L 3N6, Canada (phone: +1-613-484-0508; fax: 613-533-6513; email: h.sadjadi@queensu.ca)

K. Hashtrudi-Zaad is with the Department of Electrical and Computer Engineering, Queen's University, Ontario K7L 3N6, Canada (email: khz@queensu.ca)

G. Fichtinger is with the School of Computing, Queen's University, Ontario K7L 3N6, Canada (email: gabor@cs.queensu.ca)

Despite the popularity of brachytherapy and its emerging technological improvements, accurate needle placement still poses a major challenge. It is shown that the dosimetric quality of the implant degrades with needle divergence [3], and needle deflection is considered a major source of error contributing to such inaccurate needle placements [1]. Current clinical brachytherapy needles are relatively rigid, and made of steel with a thickness of 17 or 18 Gauge (1.47 mm or 1.27 mm). However, their bevel tips cause the needles to experience asymmetric tip forces, causing unwanted bending during insertion, and increasing targeting error [4].

To reduce placement errors, physicians adjust the needle tip position by retracting, and then repeatedly reinserting the needle from slightly different initial positions. However, multiple reinsertions may lead to excessive trauma, which in turn may increase the severity of edema and swelling. Tissue swelling may increase prostate volume significantly, often as much as doubling the original volume. As the half-life of the swelling is comparable with the half-life of the implanted isotope, the prostate may become severely under-dosed, which may lead to failure to control the cancer and recurrence of the disease. Therefore, it is imperative to reduce prostatic trauma caused by multiple insertions.

Reliable and accurate needle deflection estimation can help compensate for needle bending before and during insertion and thus reduce tissue trauma by reducing the number of reinsertions.

II. Related Work

There are a number of static (or quasi-static) needle deflection models available. For example, in [5], a series of rigid bars connected by angular springs was used for simulation of needle deflection. In [6], linear beam theory was used to estimate the deflection based on the needle insertion depth. However, the estimated deflection was less than the actual deflection, and the authors suggest the existence of additional degrees of freedom acting on the needle. Therefore, to compensate for such estimation error, in [7], [8], [9], the needle was modeled based on beam theory, and the amount of deflection was estimated based on the insertion depth as well as measurements of forces and torques on the needle base. In [10], model parameters were estimated in real-time to support needle steering with the use of a linear beam-based needle model.

For flexible needles, lateral manipulation of the base can affect tip motion; therefore, a kinematic relationship between the base and the tip motions can be established. For example, [11] demonstrates the use of the Jacobian matrix to correlate the tip velocity to that of the base. Also, [12] models the kinematics of a flexible bevel tip needle as a nonholonomic system and validates the results through several experiments. As the interaction between needle and tissue is stochastic in nature, identical multiple insertions of a flexible needle into soft tissue results in varying trajectories [13]. In order to better represent the interaction in [14], a noise model was introduced to tune the parameters of the nonholonomic model.

These attempts on improving needle deflection modeling share one basic limitation: sensitivity to model parameters. In this approach, in order to accurately estimate the deflection, the model parameters are required to be precisely quantified based on simulation and/or experimental data.

Consequently, the resulting estimate is highly susceptible to variations of these parameters. In a true clinical setting, neither the biomechanical properties of the soft tissue, nor the mechanical properties of the needle can be precisely quantified *a priori*. For example, during a prostate brachytherapy procedure, the needle flexibility varies with the number of seeds loaded within the needle shaft, causing intermittent changes in the model parameters of the needle. As a consequence, estimates relying on a deflection model that is based solely on *a priori* known parameters are inherently unreliable and thus clinically impractical.

III. Fusion of the Electromagnetic Trackers

Needle tip estimation error caused by uncertainty in the needle deflection model parameters can be reduced using measurements taken directly from the needle tip. Available clinical instrumentation to localize the needle tip produces noisy and inaccurate results. At the same time, needle base movements can be measured with less noise and greater accuracy using sensors, such as optical trackers, encoders, camera, etc.

The needle tip position can be estimated using accurate needle base measurements and needle deflection models, but it is subject to parameter uncertainties. The needle tip position can be directly measured, but it is subject to measurement noise and inaccuracies. It is posited in this paper that an appropriate combination of these will substantially reduce overall needle tip position estimate error.

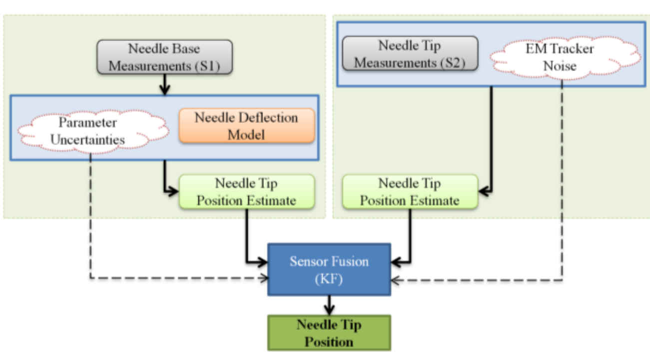

Figure 1: Proposed system block diagram. The KF combines both estimates of the needle tip position, and provides a more reliable prediction of the needle tip position.

In this work, electromagnetic (EM) trackers are considered to take measurements from both the needle base and the needle tip, and a Kalman filter (KF) is used to fuse this sensory information. Given both sets of measurements, the KF reduces the needle tip position estimation error at each time step, and continually provides a reliable estimate with minimum estimation error variance. The block diagram of the proposed system is presented in Figure 1.

A. EM Trackers

Although EM trackers are relatively new in medical applications, their popularity is increasing, primarily due to their minimal size, lack of line-of-sight restrictions, and ability to track surgical instruments inside the body. Unfortunately, they are susceptible to distortion by metallic objects, including some surgical instruments, and are less accurate than other tracking devices, such as optical trackers.

In brachytherapy, EM-tracking of both the needle base and the needle tip is clinically feasible in combination with any of the standard after-loading techniques, where the needle is inserted first, then the central trocar (housing the EM tracking coil) is retracted, and the radioactive sources are loaded into the needle [15].

In this work, in order to realistically simulate sensor measurement errors, an experiment is performed to study the accuracy and precision of the EM tracker. The experiment uses an Ascension trakSTAR EM tracker to collect sensory information from the base and tip of the needle. An 8 mm (Model 800) sensor is attached externally to the base, and a 0.55 mm (Model 55) sensor is placed internally within the lumen at the tip. Due primarily to the difference in sensor size, the tip sensor has considerably more noise and is less precise than the base sensor. A sample of measurement error from the tip sensor is illustrated in Figure 2.

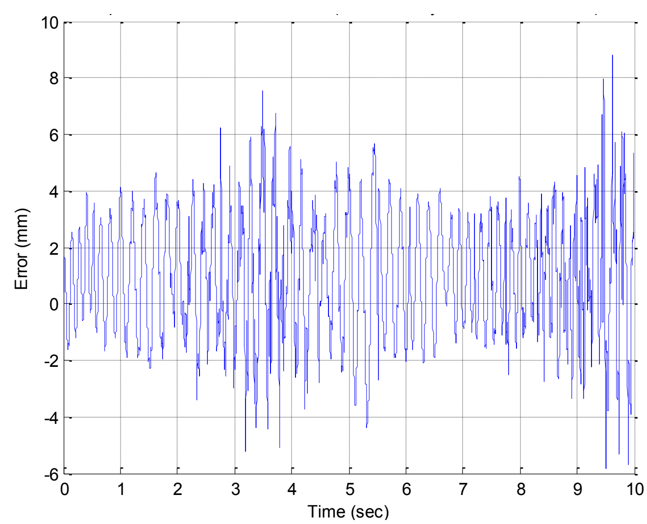

Figure 2: Tip sensor measurement error at 300 mm from the transmitter.

The accuracy and precision of both sensors are experimentally measured, using a 3 by 6 grid as the ground truth. At each grid point more than 2,000 samples are collected, and the mean and variance are calculated, as illustrated in Figure 3.

These experiments suggest an optimum operation range of 100 mm to 300 mm from the transmitter. Based on this experimental data, the accuracies of the two sensors are modeled for this range, as illustrated in Figure 4. Furthermore, to represent the precisions of the sensors, variance for each sensor is also derived and modeled from this data. In this operation range, as the sensor moves away from the transmitter, the standard deviation increases from 0.0 mm to 0.2 mm for the base sensor, and from 1.5 mm to 3.0 mm for the tip sensor, as can be observed in Figure 4.

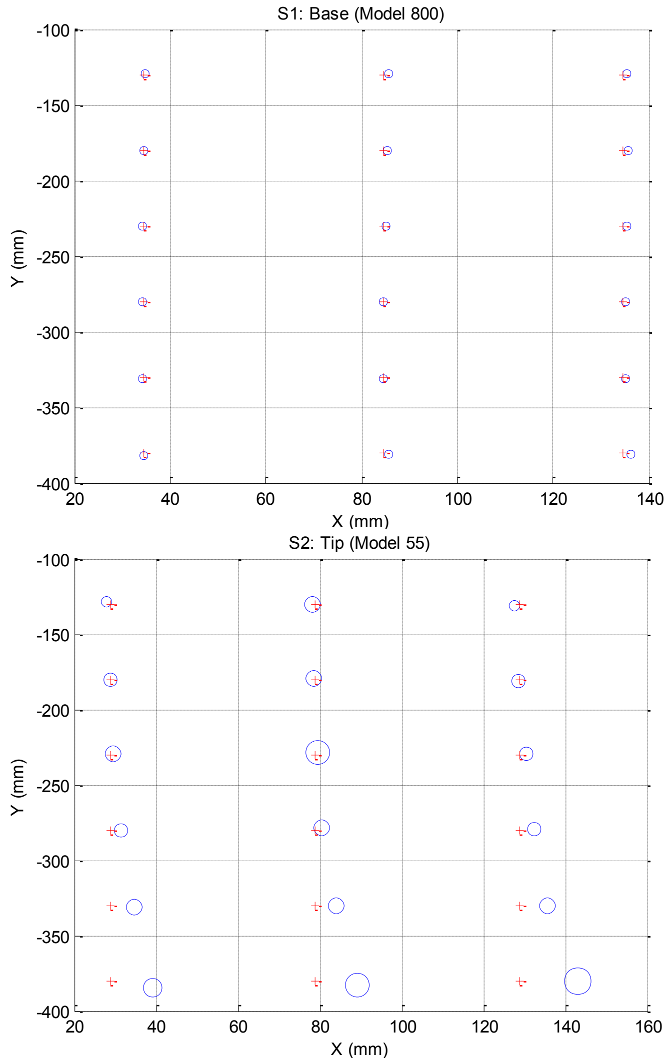

Figure 3: Accuracy and precision test of the EM trackers. The + signs show the known grid points. Each circle represents a set of measurements, centered at the mean, with the radius proportional to variance. X and Y are the coordinates of the sensors with respect to the transmitter.

B. Kalman Filter Formulation

The filter was formulated as follows:

$$x_k = Ax_{k-1} + w_{k-1} \tag{1}$$

$$z_k = Hx_k + v_k \tag{2}$$

Equation (1) represents the linear stochastic difference equation of the process model with the state $x_k = [x \quad \dot{x}]^T$ where x is the 3 degrees of freedom (DOF) coordinates of the tip at discrete time steps of $k = 1, 2, 3, \ldots$. The process is modeled with $A = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix}$ where dt is the sampling time(s), and acceleration terms are considered as a Gaussian process noise as denoted by $w_k \sim \mathcal{N}(0, Q)$.

Equation (2) represents the measurements $z_k = [x_b \quad x_t]^T$, where x_b is the tip position estimated using the base measurements combined with a deflection model, and, x_t is the tip position estimated using the direct tip measurements, with $H = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}$, and a Gaussian measurement noise as denoted by $v_k \sim \mathcal{N}(0, R)$.

The process noise covariance, Q, is considered constant, while the measurement noise covariance, R, changes at each time step. For both EM trackers, R is a function of the sensor signal quality, as provided by the tracking device. Also for the EM tracker installed on the base, the tip position estimate accuracy degrades due to deflection model uncertainties; therefore, R increases with insertion depth.

In this work, a quadratic polynomial kinematic deflection model provides estimates of the tip position, based on the orientation of the needle tip bevel angle. This angle is estimated, given the base angle measurements combined with a model for the torsional lag along the needle. As shown in [16] the torsional lag can be approximated by a first order system. The time constant was experimentally established to be τ=0.08d (ms), where d is the insertion depth (mm).

IV. Simulation Results

This proposed method was implemented to compensate for needle deflection during a simulated prostate cancer brachytherapy needle insertion.

At each distance from the transmitter, the sensor measurement error was assumed to have a Gaussian distribution, with the mean and variance derived from the experimental data collected (Figure 3). For each sensor, the error model was simulated accordingly, as illustrated in Figure 4.

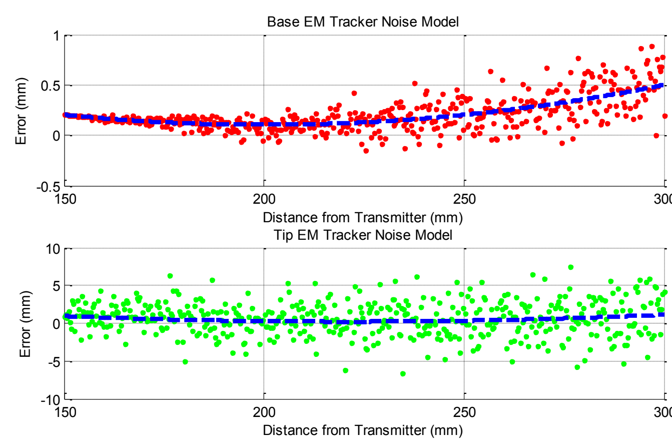

Figure 4: Simulated sensor error models. Points in each graph show the simulated measurement data, and the measurement mean is represented by the dashed lines.

To validate the effectiveness of the KF, the simulated quadratic polynomial deflection model included a 50% perturbation in parameters. Given the deflection model and the KF formulation, the sensory information from both EM trackers was fused to continually provide a reliable estimate of the tip position, with minimum estimation error variance, as illustrated in Figure 5.

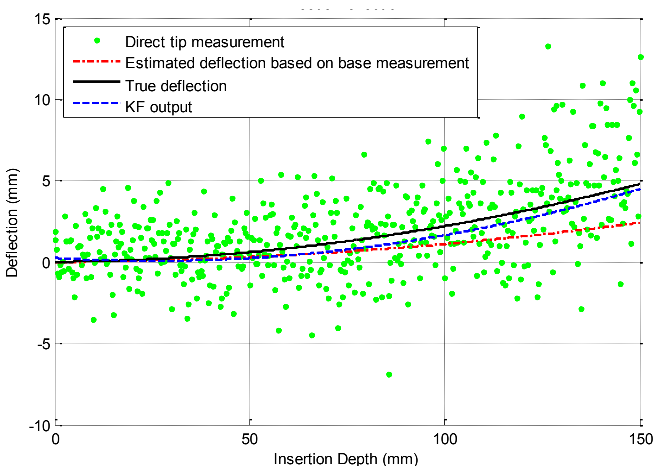

Figure 5: Simulated prostate cancer brachytherapy needle deflection.

Simulations with several different random initial conditions showed that at a typical maximum brachytherapy insertion depth of 15 cm, this method reduces the needle tip mean estimation error from 2.39 mm to 0.31 mm. It can be seen that the complementary sensory information provided by the tip EM tracker significantly contributed to a reduction of the estimation error, despite noisy and inaccurate measurement data.

Moreover, this KF formulation isolates the deflection model from the process model, allowing this filter to be applied to any needle deflection model. An alternative approach would be to integrate the needle deflection model with the process model, and use an extended Kalman filter (EKF) formulation for nonlinear deflection models, as illustrated in Figure 6.

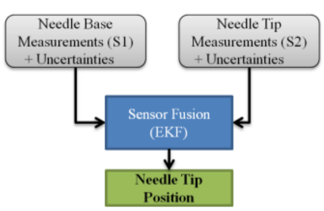

Figure 6: Alternative system process formulation of the Kalman filter.

V. CONCLUSION AND FUTURE WORK

In prior works, needle deflection models estimated the needle tip position given various measurements taken from the needle base. However, these estimates relied heavily on the exact quantification of the model parameters, and did not account for the unavoidable uncertainties found in clinical settings. Therefore, deflection models relying exclusively on known parameters are inherently unreliable. However, using a simulated prostate cancer brachytherapy needle insertion, we showed that the parameter quantification uncertainties discussed in this work can be successfully compensated for by the introduction of an additional needle tip EM tracker in conjunction with sensor fusion.

Presently, we continue to theoretically examine the performance of our approach using various needle deflection models, and to experimentally verify the simulation results through prostate brachytherapy phantom studies.

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