Electromagnetic Tracking Performance Analysis and Optimization

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***Abstract*— PURPOSE: The purpose of this study is to evaluate the uncertainties of an electromagnetic (EM) tracking system and to improve both the trueness and the precision of the EM tracker. METHODS: For evaluating errors, we introduce an optical (OP) tracking system and consider its measurement as "ground truth". In the experiment, static data sets and dynamic profiles are collected in both relatively less-metallic environments. Static data sets are for error modeling, and dynamic ones are for testing. To improve the trueness and precision of the EM tracker, tracker calibration based on polynomial fitting and smooth filters, such as the Kalman filter, the moving average filter and the local regression filter, are deployed. RESULTS: From the experimental data analysis, as the distance between the transmitter and the sensor of the EM tracking system increases, the trueness and precision tend to decrease. The system's trueness and jitter errors can be modeled as the 3rd order polynomial error equations. After minimizing the positional error and applying smoothing filters, the mean value of error reduction is 36.9%. CONCLUSION: Our method can effectively reduce both positional systematic error and jitter error caused by EM field distortion. The method is successfully applied to calibrate an EM tracked surgical cautery tool.**

I. Introduction

Tracking systems that have been utilized to track the position of devices relative to a patient's body can significantly improve image-guided surgery. Sensors can be attached to medical instruments so that the instrument positions are detected. They have been applied in interventional imaging, minimally invasive surgery, and can be integrated into instruments, such as needles and ultrasound probes. The most popular 6-degree-freedom (6-DOF) tracking systems in medical devices are optical (OP) tracking systems and electromagnetic (EM) tracking systems. Vision-based OP tracking systems are very accurate, but they suffer from a line-of-sight problem between optical markers and tracker cameras. EM tracking systems are relatively inexpensive and more portable. They do not have a line-of-sight problem from sensor coils to field generators, which means that EM trackers are more easily integrated into dynamic procedures such as open surgical navigation.

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An EM tracking system consists of an EM field generator, 6-DOF EM sensors, and an electronics unit. The EM field generator consists of a minimum of three coils in a Cartesian coordinate system. Magnetic fields are created when current flows. The EM sensors contain a minimum of three receiving coils. When the EM sensor is located in the magnetic field, voltage is induced in the sensor coils. The EM system can calculate the position and orientation of the sensor by using the induced voltages in the sensor coils. It can track an object's position and orientation in real-time.

However, as the tracking system depends on an electromagnetic field, the tracking accuracy is affected by excessive electrical noise and magnetic field distortion. When the EM sensor is at rest, the measurement data will contain some random jitters centered on a stable position. The causes of the noise are from both internal and external sources. Internal sources include amplified electronic component thermal activity, variations in measurement timing, algorithm errors, and other sources. External factors have a larger effect on the measurement noise. These factors include metallic objects within the field, noise generated by electrical circuits, fluorescent lighting, power supplies, and wiring with current that varies over time. In addition, magnetic field strength decreases with distance from the generator. Therefore, as the distance between the EM transmitter and the EM sensor increases, the uncertainties including bias and jitter error of the EM system measurement become bigger [1].

In this work, we analyze and reduce the EM tracking error. We introduce the OP tracking system and consider its outputs as ground truth, against which the uncertainties of the EM tracking system will be measured. We model and reduce both positional and jitter errors. We illustrate the practical application of these methods on an EM tracked surgical cautery tool that contains an electric circuit and a small metallic tip that moves in the distorted magnetic field.

II. Related Work

In prior literature, researchers proposed many experimental protocols for the assessment of error in the EM tracking system. For example, Hummel et al. [1, 2] evaluated the EM system by using a precisely manufactured polycarbonate measurement plane. Frantz el al. [3] proposed a system combined with an OP tracking system. They employed a hemispherical calibration device as a phantom which involves reference and registration.

Several researchers have proposed calibration techniques to improve the reliability of EM trackers. Fairly good results can be accomplished with interpolation methods - such as Hardy's multi-quadric interpolation by Zachmann et al. [4], neural networks described by Saleh et al. [5], and high-order polynomial fit [6]. According to the summary of tracker calibration techniques from [6], the polynomial fit method and the Hardy's multi-quadric method produced the best results.

There are some limitations of these prior studies. For example, the precise measurement plane by Hummel et al may not be convenient to evaluate 3D free motion profiles. To reduce the positional error, researchers apply an interpolation method; however, this method cannot provide a certain error model outside the pre-measured range in mathematical expression. Zachmann et al.'s robust method has not tested the effect of small metal changes in the measurement environment. The error model as 3rd or 4th degree polynomial equations is another common way; however, 3rd or 4th degree error modelling is not accurate when the EM senor is near the transmitter. Also, despite tracker calibration (the reduction of positional error) there still exists jitter problems. Researchers have only compensated for positional errors of static distortions, in static non-metallic or static metallic environments only. They have not described the situation where the metal moves together with the EM sensor, with respect to the EM transmitter.

III. Materials and Methods

We designed experiments and analyzed positional errors and jitter problems of the EM tracking system by introducing the OP tracking system as the ground truth measurement. Then we reduced the systematic positional error by the polynomial fitting method. Next, several different smoothing filters were applied to solve the jitter problem. Finally, we tested the practical application of our error analysis and reduction method on an EM tracked surgical tool with a pointed tip.

The main elements in the experiment were the EM tracking system (3D Guidance trakSTAR and sensor 800, Ascension, Burlington, VT), a wooden board with 7×7 drilled holes spaced 50 mm apart, the OP tracking system (Northern Digital Inc., Waterloo, ON), and a needle-point wooden stick combined with an EM sensor and an OP marker. The OP and EM auxiliary software packages were provided by each tracking system, and PLUS (*www.PlusToolkit.org*) provided synchronized acquisition of data. Matlab (Mathworks, Inc, Natick, MA) was used to analyze the data.

A. Measurement Error Analysis

We collected data sets containing transformation matrices of the sensor/marker frame with respect to two tracking system reference frames. There exists some lag between the two sets of measurement data acquired by the software packages of the EM and OP tracking system. We used the cross-correlation method to compensate for the time delay. Then we conducted the least square based pivot calibration in order to calculate the transformation matrices between the tool tip frames with respect to the sensor frame. The tooltip was kept stationary while the combined needle-point tool was pivoted in a cone shape. At least three poses with the combined tool were necessary for computation. After that, the point-based registration by Horn's quaternion method [7] was needed to build the ground truth provided by the OP tracking system in the EM reference frame. Finally, the error analysis of EM tracker and error models, and the reduction of positional and jitter error were accomplished.

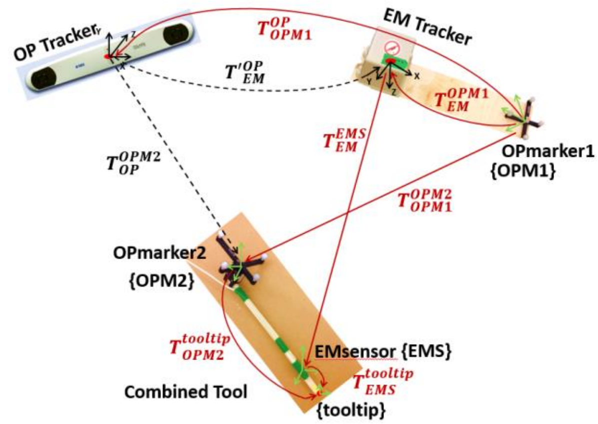

Fig. 1 Experimental Setup Extractions.

Fig. 1 shows the experimental setup. The coordinate frame {OP} is the reference frame of the OP tracking system; {OPM1} is the frame of OP marker1, and {OPM2} is the frame of OP marker2. The coordinate frame {EM} is the reference frame of the EM tracking system; {EMS} is the EM sensor frame. The {tooltip} is the frame of the tooltip. We needed to compute the {tooltip} with respect to {OPM2}, referred to as the unknown homogenous transformation $T_{OPM2}^{tooltip}$ and the {tooltip} with respect to {EMS}, referred to as the unknown homogenous transformation $T_{EMS}^{tooltip}$. The calculation can be accomplished by the pivot calibration process, using the least square method. In addition, the unknown transformation matrix from OP reference frame to EM reference frame should be computed during the point-based registration process. Since the dynamic transformation T'^{OP}_{EM} would change if the OP camera and the EM transmitter were moved relatively, we decided to set OPmarker1 frame as the OP system reference frame and calculate T_{EM}^{OPM1}, which gave a constant transformation from the OPmarker1 to the EM transmitter. Equation (1) shows the tooltip measurement by the EM tracking system in the EM frame and (2) is the tooltip measurement by the OP tracking system in the EM frame:

$$T_{EM}^{tooltip} = T_{EM}^{EMS} \cdot T_{EMS}^{tooltip}. \quad (1)$$

$$T_{EM}^{tooltip} = T_{EM}^{OPM1} \cdot T_{OPM1}^{OP} \cdot T_{OP}^{OPM2} \cdot T_{OPM2}^{tooltip}. \quad (2)$$

The positional error of the EM tracker could be computed as the Euclidean distance between OP measurements and corresponding EM measurements in EM frame. The jitter error, also known as the random error, describes the deviation of the EM measurements at a position over a certain period. It can be represented as the root mean square error (RMSE) between the mean value of all samples for each location and each sample. It represents the precision of the EM tracking system.

B. Systematic Error Reduction

The goal is to calculate the systematic positional error (also unknown as the systematic bias) model of the EM tracker in a certain environment, and then to compensate it in order to improve the reliability of the EM tracking system. In this work, we used the static measurement data set and calculated the systematic error function by the least-square polynomial fitting method. We found the coefficients C that made the overall solution minimized to a function that was a sum of squares, as seen in the following equation:

$$\min_{C} \|F(C, data) - act\|_2^2 = \min_{C} \sum_i (F(C, data_i) - act_i)^2. \quad (3)$$

Here '*data*' is the input data for computing the model. 'C' is the coefficients of the model; '$F(C, data)$' represents the model we generalized; '*act*' is the actual data that we want to fit; '$F(C, data_i) - act_i$' shows the residual, the difference between an actual value and the fitted value provided by the model. The distorted position measurement $(\hat{x}_i, \hat{y}_i, \hat{z}_i)$ from the EM tracking system and the corresponding ground truth location (x_i, y_i, z_i) from the OP tracking system were collected. The equation $Err_i = (x_i, y_i, z_i) - (\hat{x}_i, \hat{y}_i, \hat{z}_i)$ defines the positional error vector for any measured position in the EM system. General equations for the polynomial data fitting can be generated in the form of [8].

C. Random Error Reduction

Through the observation of the static experimental data set, the jitter error ($error_{jitter}$) could be modeled as a 3rd order polynomial function of each tool tip position *(x, y, z)*. This approach is similar to the one used in the positional error model during the tracker calibration procedure. In this step, three filtering methods – Kalman filter, moving average filtering and local regression filtering was applied to the dynamic measurement data so that the noisy data could be smoothed, and consequently, the jitter error was minimized. Kalman filter estimates the current state from noisy observations and the process model. Moving average is dependent on the values of several neighboring measurements both in the past and in the future. Local regression is based on the locally weighted polynomial fitting without prior assumptions of the equations.

Kalman filter estimates the states of a linear system and it can minimize the variance of the estimation errors. The computationally efficient Kalman filter is an optimal recursive least squares estimator for linear systems with zero-mean white Gaussian noise. Kalman filters are commonly used to remove the noise from signal. In the linear process model that we are measuring, process noise covariance and measurement noise covariance are required. The process model can be formed according to the Newton dynamic equations. The state equation and its initialization are explained by [9, 10]. The measurement model: $z_k = \mathrm{H}x_{(k)} + v_{(k)}$, $v_k \sim N(0, R)$. z_k is the measurement output of the EM tracking system, which only contains the position information; therefore, we set the measurement velocity term as $[0\ 0\ 0]^T$, and as a consequence, H matrix, known as the "measurement matrix", relates the state to the measurement data z_k. It is $H = [I_3\ 0_3]$. v_k is the measurement noise. In this part, we need to compute the measurement noise covariance R, defined as the variance of the measurement noise which derives from the EM tracking system's jitter error. $R = [error_{jitter}^2 * I_3]$.

Other commonly used methods for smoothing data in general are moving average and local regression filtering. Moving average filter is optimal for a common problem in time domain. It operates by replacing each point with averaging each y[i] with its N nearest neighboring points in the past and its N nearest neighbors in the future. Moving average is given by the following equation:

$$y_s[i] = \frac{1}{2N+1} \sum_{j=-N}^{N} y[i+j]. \quad (4)$$

where $y_s[i]$ is the smoothed data for the i^{th} point; 'N' is the moving window, the number of neighbors on either side of $y_s[i]$, and $2N + 1$ is the span. Computing the current data requires the measurement time-steps in the past and in the future. The filter cannot be initiated well until several steps measurements have been made. Furthermore, this method emphasises equally on all data points, which means it considers the sensor positions near and far from the EM generator as the equal influence.

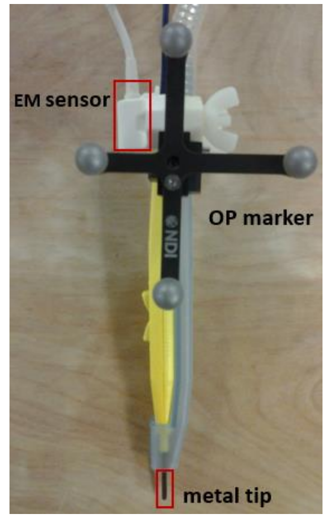

Fig. 2 Experimental setup, application of the EM tracker.

Each smoothed data is provided by the neighboring data within the span in the local regression method. It is assumed that a small group of neighboring points can be fitted as some function, and the points near the estimation have more weight and are more relative to each other. A locally weighted linear least-squares polynomial regression of 1st or 2nd degree was applied in this process. A common tri-cube weight function is described in [11]. We chose 15 to 25 neighborhood points and the linear fit. Only data in the span has weight on the polynomial fit. The local regression is a nonparametric regression method, which means that it does not need the specific function to fit a model, and also it is convenient and flexible for some complex systems without theoretical models.

D. Application

The practical application of the method described above is tested on an EM tracked surgical cautery device that contains metallic parts. The metallic pointed tip of the device distorts the electromagnetic field. As a consequence, the pivot calibration and registration transformation matrices may become unreliable. Additional computational errors should be avoided. Therefore, we used a wooden needle-point stick with an EM sensor and an OP marker in the experiment to evaluate the uncertainty. Once the error caused by EM field distortion is modeled, we can then utilize the surgery tool with an EM sensor, shown in Fig. 2 in further application.

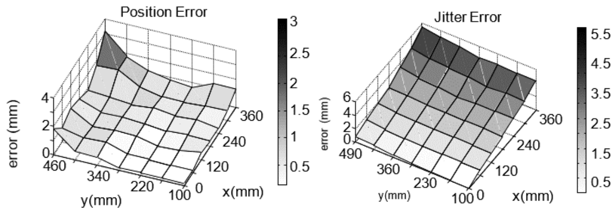

Fig. 3 Positional and jitter error from (76, 166, 37) (mm) to (381, 471, 50) (mm). The EM generator is on the origin (0, 0, 0).

IV. Results and Discussion

Many previous studies assume that there is no error when an OP tracker is introduced. In our study, we discovered that the systematic error from the OP tracking system was quite small so we could neglect it. However, the pivot calibration and the registration experiment processes may create errors. Inevitably, there was some combined error as the OP tracker was registered onto the EM frame as ground truth measurement. Statistically, the combined error was around 0.45 (mm) in this project. It was negligible compared with the error from the EM tracker.

Fig. 3 visualizes the positional and the jitter error, respectively, of the EM tracking system in one z plane. We have three different z planes in total. The EM generator was located on the origin. The grids plotted in the figure are the locations of the tool tip in the EM reference frame. Approximately 900 samples were collected for each location, and the measurement rate was 80Hz. As the tool tip moves further from the EM generator, the jitter error and the systematic positional error increase gradually. According to the plots of the measurement data and the corresponding positional error, we calculated the positional error model as 1st order to 5th order polynomial equations. Our results showed that the model should be a 2nd or 3rd order polynomial equation. A 2nd order polynomial fits especially well when the distance between the EM sensor and the EM transmitter is within 350 (mm). When the sensor moves further, a 3rd polynomial equation is a better fit. Higher-degree polynomials will over-fit the data and introduce more error.

Fig. 4 illustrates the error between the ground truth and the EM measurement of a 3D random motion profile. The measurement data has been down-sampled for clarity. The polynomial error function calculated from the static data set has been tested by a random motion. The error decreased from 66.7% to 16.2%, and the mean value of the error reduction is 36.9%. Our positional error function works very well on the error reduction. However, the models may vary, as they are based on large amounts of static experiment data and the external environment. Fig. 5 represents the error between the ground truth and EM measurements after different smoothing filters. The three smooth filters give similar outcomes overall.

Kalman filter, which relies on the process model and the measurement noise, provides the minimum variance of the estimation error. The filter prefers measurement information when the measurement noise is relatively smaller than the uncertainty of system model; if the measurement error becomes bigger, the filter would emphasize more on the process model. Kalman filter would work perfectly almost

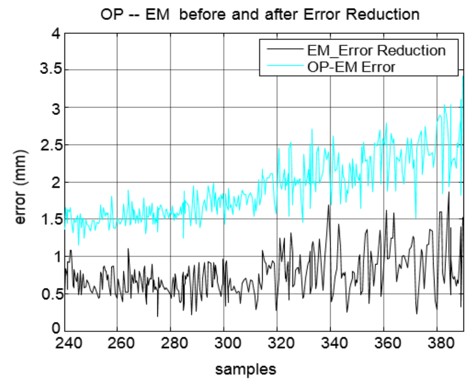

Fig. 4 Error between ground truth and EM measurement before and after tracker calibration and smooth filter.

without the influence of outliers, once the jitter error function is Gaussian and certain.

Moving average and local regression filters are easier to use. However, they consider all measurement points as equally accurate. In our case, we compensated for the positional bias first, and then deployed smooth filters, and they could provide reasonable results. Moving average filter can avoid lags in smoothed measurement caused by using only previous data. However, it may invert the peaks and troughs in the measurement data, unless the window is shortened properly. The number of points chosen affects the smoothness of the result. We initialize the window size as 15 data points.

Local regression method, based on the weighted local polynomial fitting, works well with the proper sample size. Quadratic fit provides less error than linear fit. If the size is too small or too big, or if we choose a higher order polynomial without increasing points, the smoothness decreases. In our case, we chose 15 to 25 neighboring points and the linear fit. This method does not require a specific theoretical equation to fit. However, the outlier in measurements may impact on the smooth result, and the robust version can reduce the distortion by outliers. It is computationally intensive, and it cannot provide a regression function to describe the smoothing process in the mathematical sense.

Therefore, as we compensated the systematic positional error first and then found reasonable noise function, we preferred to use Kalman filter smoothing which is dependent on not only the noisy measurement but also the process model. (Robust) Local regression method is an alternative choice if people do not need a specific mathematical expression or the

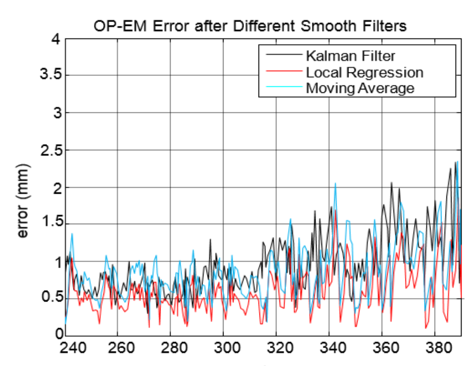

Fig. 5 OP-EM error after different smooth filters.

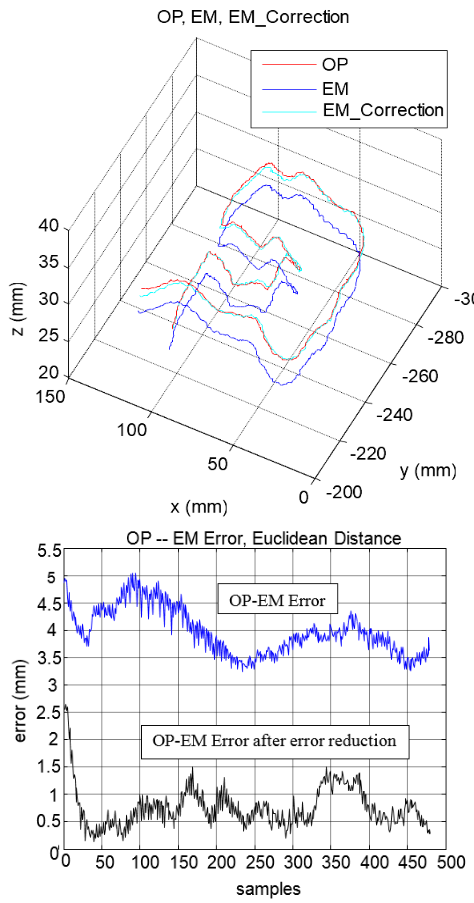

Fig. 6 Random motion before and after tracker calibration.

noise property of the measurement is totally unavailable. Moving average is our least choice since the window size should be chosen carefully and it does not have significantly better results.

Fig. 6 shows the random motion and the error between the ground truth and the measurement from the EM sensor attached on the surgical cautery device, and the error after application of positional error reduction calibration and local regression smoothing filter. We calculated the error functions from a set of static measurement data, then we applied them to the random motion profile. The maximum error is reduced from 4.6 mm to 2.4 mm.

Since the external environment was relatively less-metallic, the distance between the EM sensor and the transmitter, and the metal part of the needle were the main influential elements on the EM tracking performance. Since the metal was not too big, we tried the polynomial method to decrease positional error. From the experimental data, the model can compensate for the EM tracker positional error very well. Compared with the look-up table and trilinear interpolation method, which requires more measurement points with topology information, this method is faster. Moreover, our error model can provide better error values than the interpolation method when the measurements exceed the range of the static pre-measured look-up table. Despite the metallic components of the surgical device, there was a significant reduction in EM tracking error using our method, suggesting the practical application for this method of error reduction.

V. Conclusion and Future Work

Based on the theoretical study of previous works, we designed an experimental setup to measure both the positional and the jitter error of the EM tracking system. The error analysis shows that as the EM sensor moves far from the EM generator, both the trueness and the precision decrease. This conclusion is consistent with the theoretical analysis. The positional and the jitter errors were modeled and reduced successfully. We also applied the similar method to decrease the error by EM sensor combined with cautery device. It is challenging identify a certain method for different environments. The polynomial error models may slightly introduce additional errors in some locations. For smooth filters, the biggest challenge of Kalman filter is to compute the statistical properties of the measurement noise. Moving average and local regression filters consider the whole points within workspace as equal reliability, which is not always reasonable. Our future work is to examine our method for various environments and other applications, to test and compare other modeling methods for the positional error, and to design a faster online error reduction method.

Acknowledgments

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