# The Development of a Virtual Simulator for a Novel Design Non-Permanent Magnetic Needle Based Eye Anesthesia Training System 

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#### Abstract

Ophthalmic anesthesia plays a crucial role in eye surgery. However, the conventional practice of this process is a blind procedure, in which a needle is inserted blindly into the cadaver. This paper introduces a needle tip tracking system for ophthalmic anesthesia training focusing on the Retrobulbar block procedure. The study presents a development in a prototyped system using Hall effect sensor arrays to track a 5D magnetized needle tip (X, Y, Z, $\theta, \varphi$ ). The orbital structure is fabricated with embedded Hall effect sensors. The extended Kalman filter and least square method are developed to select the observation model from multiple training sets and to estimate the needle tip coordinates. The robotic manipulator (ABB YUMI) is used to model the training set between the distance and the initial angle of the magnetized needle. The developed system provides the needle tip position with an RMS of Euclidean distance error up to $1.7398 \pm$ 0.5288 mm . As a result, the system is capable of providing the needle tip positions with an acceptable error comparing the system's accuracy with the size of the retrobulbar target space and important anatomies.


INDEX TERMS Educational robots, hall effect devices, medical robotics, simultaneous localization, mapping.

## I. INTRODUCTION

One of the essential preparations of ophthalmic surgery is eye anesthesia [1], [2]. The challenge is inserting an anesthetic needle into an area behind an eye globe where the most sensitive part of the human body abounds with important muscles and nerves [3], [4]. Retrobulbar block, the most common procedure of eye anesthesia, uses a cavity between an eye globe and an orbital structure to enter a retrobulbar space. A needle (22-27 Gauge) is inserted at an inferolateral space of the orbit cavity and penetrated until it reaches the area behind the eye globe [5], [6]. The needle is then pointed medially to enter the retrobulbar space. Since the human anatomy is unique, physicians have to abide by only their experience to estimate the movement and location of the needle. A very slight aberration from the correct process can cause muscle hemorrhages, globe penetrations, blindness,

[^0]and lethal damages [7]. Therefore, in practical cases, ophthalmologists must go through extensive practices before operating. In general, the type of practice for eye anesthesia is a cadaveric training system [8], [9], [10]. After the fresh cadaver is acquired, the expert physicians supervise the trainees in the practice procedures, focusing on their postures and the remaining needle length [9], [10]. This information will allow the experienced inspectors to prognosticate the needle tip position in the cadaver. However, the needle's trajectory is still predicted without empirical evidence. As a result, the trainees will not receive feedback if they enter the wrong target area, or damage crucial eye anatomies [11], [12]. Although the complication rate of expert physicians for eye anesthesia is rare ( $0.1 \%$ ), the rate of injuries from non-experienced doctors tends to have a significant number around $4 \%$ [13], [14]. This issue elucidates the non-effective system for eye anesthesia training. Moreover, the cadaveric training system requires a soft cadaver, which is significantly more challenging to acquire than a typical cadaver [15], [16].

## II. RELATED WORK

Many training systems have been developed to provide position feedback to the trainees [17], [18]. Back in 1996, the ophthalmic retrobulbar injection simulator or ORIS, which uses embedded ultrasonic sensors in manikin's skull, was introduced to provide a trainee with a needle tip position [19], [20]. This system has a high success rate in delivering the correct needle tip coordinates. However, the characteristic of the ultrasonic sensor limits the system's capabilities by only providing an accurate position when no obstacle is present between the needle tip and sensor [20]. In 2001, the ophthalmic anesthesia simulation system (OASiS) developed by researchers from the Indian Institute of Technology Madras used a different concept to detect the needle tip position. They selected the electric field-based tracking system to capture the needle position in a manikin [21], [22]. Although the system provided a precise needle tip position, the needle was required to be attached with an additional circuit that could potentially cause difficulty during operation [22].

An eye anesthesia simulator (EATS) has been developed using an electromagnetic detection system [23]. The advantages, such as the non-contact detection, sensitivity with metallic parts, and appropriated workspace, are ideal for this application [24]. First, a commercial active magnetic tracking system (Aurora V2 System) was selected as the primary device [25]. The ability to detect an accurate position of this system provided trainees with a needle tip position calculated from a sensor attached to the syringe [26]. Despite the system's high precision, the difficulty in use, larger size, and price prevented most from gaining access to this system. Moreover, the NDI system requires calibration after transporting, which requires an engineer in the installation process [27], [28]. The modification on the syringe with an extensional sensor also presents this system with an extra layer of impracticality. As a result, the system was redesigned with passive magnetic sensors (Hall effect sensor) to capture the magnetic flux emitted from a magnetized needle.

The Hall effect sensor is a commonly used positioning sensor [29]. It provides counts of detecting signals from a nearby magnetic source, which are transformed into the distance or position of an object [30]. However, the Hall effect sensor is also utilized as a localizing sensor, using the conversion of magnetic flux intensity into the real-time position of an object. Many studies have developed an array of Hall effect sensors to localize metallic materials in 3D coordinates with known characteristic parameters [31], [32], [33]. The previous studies on the relationship between magnetized needle and Hall effect sensor in a perpendicular direction illustrated the potentiality of using the Hall effect sensor to detect the magnetized needle [23]. Experimental results indicated that there are several advantages of the Hall effect detecting system, which consisted of the consistent sensing data ( $\mathrm{p}<0.5$ in each interested distance), appropriate halflive activity ( $>2$ hours), and suitable sensing area ( $\approx 13 \mathrm{~mm}$ ). Additionally, the maximum detecting workspace between the needle tip and a sensor is confined to 13 mm radius, a distance
more significant than the average size of a human's globe in an orbital structure. However, further studies show that the perpendicular model used in the calculation cannot provide a precise needle tip position even when the actual needle is located inside the detecting space. This paper introduces the development of the eye anesthesia training system in various aspects, including the multiple angular training set, the multiple angular model selection algorithms, and the localization technique from the multiple angular models.

## III. SYSTEM ARCHITECTURE

The EATS gives trainees exceptionally reliable needle tip positions in the simulation of orbital anatomy. The system components consist of the human manikin, orbital structure model, solid stainless-steel needle (27G), magnetizer, and magnetic magnitude checker, as shown in Fig 1.


FIGURE 1. The system architecture of EATS to practice or examine the trainee.

The current study focuses on the training system for retrobulbar block, which is one of the standard processes for ophthalmic surgical preparations [34]. Using an inferolateral quarter of the orbital structure model from the CT scan as a starting structure, a Hall effect sensor array is inserted into the model. The sensor array comprises 26 high-resolution Hall effect sensors [35]located in 4 columns, the same as the previous study prototype [23]. The Hall effect sensors capture the strength of the magnetic field emitted from a magnetized needle. The magnetizer induces the charges on the needle. The sensing voltages are aggregated by an analog multiplexer (model ADG732). The data is then conveyed to a digital-analog converter (DAC). The 12-bit DAC (ADS1115) is used in transforming the sensing voltage into digital data [36]. The Arduino Mega is selected as the central controller to convey the digital data to a computer using the UART protocol. Extended Kalman filter (EKF) and Least Squares Estimation (LSQ) have been developed to localize the needle tip positions using activate sensing data and experimental models [37], [38]. The GUI has been developed under the Unity engine to illustrate the 3D coordinates of needle tip position [39]. The GUI has been developed under the

Unity engine to illustrate the 3D coordinates of needle tip position [40].

## IV. MATERIALS AND METHODS

## A. PRINCIPLE OF A MAGNETIZED NEEDLE

Due to the shape of the anesthetic needle, a cylindrical dipole model is selected to simulate a characteristic of magnetic intensity around the magnetic source. The needle passes through magnetizer-induced positive charges to one end of the needle while pushing negative charges to another end. This circumstance creates a material called ferromagnetic material, as shown in Fig. 2a. Additionally, the magnetic flux tends to travel from the positive end to the opposing end, as shown in Fig. 2.

The strength of a magnetic field at the target area ( $\mathrm{B}(\mathrm{r})$ ), where coordinates are defined with a distance from the center of needle (r) and angle from the magnetization direction $(\theta)$, is denoted by $\mu_{0}$ and $\vec{m} \cdot \mu_{0}$ is the permeability of vacuum and $\vec{m}$ refers to the magnetic moment of the magnetic source. In this study, the orientation in x and y axis $(\varphi)$ is assumed to be equal with the magnetization direction $\vec{m}$ as shown in (1) and Fig. 2b [41].

$$
\begin{equation*}
B(r)=\frac{\mu_{0}}{4 \pi}\left[\frac{3 \vec{r}(\vec{r} \cdot \vec{m})-\vec{m}}{r^{3}}\right] \tag{1}
\end{equation*}
$$

Equation 1 can be rewritten in a team of field strength in the x and y directions by removing dot products and cross vectors. Besides, the strength in the z -direction is equal to zero.

$$
\begin{align*}
B(r)_{x} & =\frac{\mu_{0}}{4 \pi r^{3}}[3 \sin (\theta) \cos (\theta)]  \tag{2}\\
B(r)_{y} & =\frac{\mu_{0}}{4 \pi r^{3}}\left[3 \cos ^{2}(\theta)-1\right] \tag{3}
\end{align*}
$$

Equations 1-3 denote that the magnetic strength in the target coordinate is mainly dependent on the distance (r) and angular $(\theta)$ between the magnetic source and target area. Since the stainless needle is the composite material, the characteristic values of conductive material (m) remain undefinable. However, these parameters can be modeled by the experiments in the next section.

## B. THE LOCALIZATION TECHNIQUE FROM THE MULTIPLE ANGULAR MODELS

The sensor array is designed with n number of Hall effect sensors. Each Hall effect sensor $\left(s_{i}\right)$ captures the strength of the magnetic field from the needle $\left(e_{i}^{k}\right)$ at frame k , integrating with the covariance of sensing data $\left(\epsilon_{i}^{k}\right)$. Each sensor is denoted by sensor state $\left(\hat{s}_{i}\right)$, which consisted of position $\left(P_{i}\left(X_{i}, Y_{i}, Z_{i}\right)\right)$ and orientation in the quaternion system $\left(q_{i}\left(x_{i}, y_{i}, z_{i}, w_{i}\right)\right)$ relating to the system's origin $(X, Y, Z)_{O}$ rigin as shown in Fig. 3.

$$
\begin{equation*}
\hat{s_{i}}=\left(P_{i}, q_{i}, e_{i}^{k}, \epsilon_{i}^{k}\right) \tag{4}
\end{equation*}
$$

Time of arrival (TOA) is involved in aggregating a data set $\left(E^{k}\right)$ from each sensing data and calculating the covariance value at frame k . The sensing data is then applied with MSL

Stainless Steel Needle Vertical Section


FIGURE 2. The characteristic of positive and negative charges in ferromagnetic materials after passing the magnification process (a). The frame diagram between the magnetized needle ( $X, Y, Z$ ) Needle and the world coordinates ( $X, Y, Z$ )Origin, which can be represented in a term of the spherical coordinate system ( $\mathbf{r}, \theta, \varphi$ ) (b).


FIGURE 3. The magnetized needle and the Hall effect sensor array with different sets of distance and angle in the planar of vector direction (d).
to calculate the direction of the magnetic needle $\left(\vec{d}^{k}\right)$. The system uses the Least Square Estimation technique (LSQ) to
select the initial angle of the magnetized needle $\left(\theta_{0}\right)$ from training models $T\left(\theta_{0}^{i}\right)$. The needle tip state $\left(\vec{x}^{k}\right)$ is acquired by applying the Extended Kalmar Filter (EKF) with sensing data, training model, previous belief state, and initial angle as the input data of system, as shown in Fig 4.


FIGURE 4. The simplified localization algorithm of EATS estimates the needle tip coordination using the training data set based on LSQ and EKF algorithms.

## C. MAGNETIC NEEDLE LOCALIZATION (MSL)

MSL calculates a unit vector, representing a direction of magnetic source in the Hall effect sensor array, and registers the sensing data to the exact original coordinates in the system. First, the sensing data is captured from each observation at frame k by an active magnetic source, without a false detection, which is obtained from $e_{i}^{k}$ and the threshold T. The threshold filter is defined as (5).

$$
e_{i}^{k}= \begin{cases}e_{i}^{k}, \text { Activated sensor, } & \text { if } e_{i}>T  \tag{5}\\ 0, \text { Inactivated sensor, } & \text { if } e_{i} \leq T\end{cases}
$$

The threshold is set as a result from the first experiment. The filtered data is then applied with the directional vector of the activated sensors. The directional vector is denoted by (6).

$$
\begin{equation*}
\vec{d}=\frac{e_{i}^{k}}{\left|\sum\left(E^{k}\right)\right|} \tag{6}
\end{equation*}
$$

where $\vec{d}$ is a directional vector, $\sum\left(E^{k}\right)$ stands for the summation energy of activated sensing data.

Additionally, the strength of magnetic flux, due to the principle of the dipole model, fairly emits from a positive side to a negative side. Thus, the system supposes that the directional vector represents a projection of the needle in a planar plane (x and y axis $(\varphi)$ ), as shown in Fig. 3. Besides, the position and orientation of sensor states are defined during the fabrication process. A relationship of sensing data and
distance in the planar plane leading to (7)-(10).

$$
\begin{align*}
e_{i}^{k} & =\frac{\mu_{0}}{4 \pi}\left[\frac{3 \vec{r}(\vec{r} \cdot \vec{m})-\vec{m}}{r^{3}}\right]  \tag{7}\\
r_{i} & =\sqrt{\left(x^{2}+y^{2}+z^{2}\right)}  \tag{8}\\
\theta_{i} & =\arccos \frac{z}{\sqrt{\left(x^{2}+y^{2}+z^{2}\right)}}=\arccos \frac{z}{r}  \tag{9}\\
\varphi & =\arccos \frac{1}{|\vec{d}|} \tag{10}
\end{align*}
$$

where $r_{i}$ denotes the distance between the magnetic source and sensor number i , while $\theta_{i}$ is an orientation between them. $\mathrm{x}, \mathrm{y}$ and z are the coordinates of needle tip referring to the position of sensor number i.

Although the distance and angular of the magnetized needle can be calculated by (7)-(10) and the given initial angle $\left(\theta_{0}\right)$, the initial angle affects the magnetization direction $(\vec{m})$, which affects the system unable to calculate the needle tip coordinates with (7). Therefore, we select the 3rd degree polynomial regression between the sensing data and known distance from the first experiment as the transfer function, which is denoted in (11).

$$
\begin{equation*}
r_{i}\left(\theta_{0}\right)=a e_{i}^{3}+b e_{i}^{2}+c e_{i}+d \tag{11}
\end{equation*}
$$

where $\mathrm{a}, \mathrm{b}, \mathrm{c}$ and d are the constant parameters of 3rd degree polynomial regression from the different initial angles in first experiment (Table 1). The experiment sets to collect the data between the sensor and the posture of the magnetized needle will be discussed in the experimental chapter.

TABLE 1. The set of parameters in transfer function $\mathbf{f}\left(\theta_{0}\right)$.

| $\theta_{0}$ | a | b | c | d |
| :--- | :---: | :---: | :---: | :---: |
| 0 | -0.05748 | 1.673806 | -16.2656 | 58.1814 |
| 15 | -0.05528 | 1.596507 | -15.3475 | 55.86132 |
| 30 | -0.04972 | 1.464136 | -14.4502 | 52.86515 |
| 45 | -0.05797 | 1.679811 | -16.0747 | 56.26305 |

## D. THE STATE OF MAGNETIZED NEEDLE TIP

The system calculates the needle tip position as the state $\left(\vec{x}^{k}\right)$ at frame k in a term of the cartesian coordinate system, where the direction of unit vector $\vec{d}$ refers to the direction in $x$ and y axis, while the output of (8), (9), and (10) denotes the coordinates in $\vec{d}$ and z with the orientation of the needle $\left(\theta_{0}\right)$. The transfer function in (11) also applies to the covariance of sensing data $\left(\epsilon_{i}^{k}\right)$ to calculate the covariance of needle tip position ( $\sigma$ )

$$
\begin{equation*}
\hat{x}^{k}=\left(P_{\text {needle }}, \sigma\right)^{k}=\left((X, Y, Z)_{\text {needle }}, \varphi, \phi, \theta_{0}, \sigma\right)^{k} \tag{12}
\end{equation*}
$$

Nevertheless, the initial angle of the magnetized needle remains unknown. Therefore, Least Squares Estimation (LSQ) technique involves selecting this angle from training data sets.

## E. TRAINING MODEL OF OBSERVATION WITH INITIAL ANGLE ( $\theta_{0}$ )

Due to the robotics experiment, the robot arm is assigned to generate an observation model between coordinates and sensing data named as a training set. This training set is represented as a set of a needle tip's coordinates ( $P_{\text {needle }}$ ) and magnetic intensity (e) as in (13). The training data consists of the needle tip's state in 4 different initial angles in the current study $0,15,30$ and 45 degrees, respectively.

$$
\begin{equation*}
T\left(\theta_{0}\right)=\left\{P_{\text {needle }}, e\right\} \tag{13}
\end{equation*}
$$

## F. LEAST SQUARES ESTIMATION (LSQ) WITH THE MAXIMUM LIKELIHOOD TRAINING MODEL

The needle tip state was estimated in a term of Bayesian learning techniques. The distances and angle between the needle tip and sensor are modeled as (14). Thus, the needle tip position and orientation directly affect the state of the sensor array.

$$
\begin{equation*}
H\left(\hat{s}_{n}, T\left(\theta_{0}\right)\right)=Z^{k}=(\mu, \sigma)^{k} \tag{14}
\end{equation*}
$$

where $Z^{k}$ is an observation state at frame k , consisting of the mean and covariance of the needle tip position referring to the world coordinate $(P)_{\text {Origin. }} \mathrm{H}$ denotes the transfer function between the sensor state and the observation state. $T\left(\theta_{0}\right)$ is the training model of initial angle $\theta_{0}$. Localization algorithm from training model with initial angle $\theta_{k}$. The magnetic strength of all sensors is captured in frame k as shown in Fig. 5.


FIGURE 5. Localization algorithm from training model with initial angle $\theta_{\boldsymbol{k}}$. The magnetic strength of all sensors is captured in frame $\mathbf{k}$.

The localization algorithm with observation data estimates the needle tip state $\left(\vec{x}^{k}\right)$ using the training set. The sensing data is compared with all training sets $T\left(\theta_{0}\right)$ to calculate a set of feasible sensing states. The possible coordinates from sensor number i $\left(P_{i}^{t}\right)$ are then plotted refer to the sensor position as shown in Fig. 6a. We multiply the possible coordinate with the homogenous transform $\left(H_{0}^{i}\right)$ of each sensor to set the origin coordinates as the world coordinates, as in Fig. 6b.

```
Algorithm 1 The Needle Tip Localization With Observation
Set \(\theta_{0}^{i}(H)\)
```

Input: Sensor State: $\hat{s}_{n}$, Training Set of Needle with Initial
angle k: $T\left(\theta_{0}^{i}\right)$
Output: The estimated position of Needle tip:
$P_{o}^{\text {needle }}=(\mu, \sigma)$

1) Select coordinates with sensing data equal to the training set $\theta_{i}$ and covariance $\epsilon_{n}$ as shown in Fig. 6a. $p\left(P_{i}^{\text {needle }} \mid e_{i}^{k}\right)=P_{\text {needle }}$ where $e_{i}^{k} \pm \epsilon_{i}=e$
2) Add possible coordinate with the reference position as shown in Fig. 6b.
$P_{0}^{\text {needle }}=$ Homogenous Transform $_{o}^{i} P_{i}^{\text {needle }}$
3) Add weight to the possible coordinates. $w\left(P_{0}^{\text {needle }}\right)=\forall\left(P_{o}^{\text {needle }}\right)+1$
4) Check overlap area from with coordinates' weight as shown in Fig. 6c.
$w\left(P_{o}^{\text {needle }}\right)>$ Threshold, where the threshold is activated sensors -2
5) Calculate the observation state $Z^{k}$ from center $(\mu)$ of the overlap area and its covariance $(\sigma)$.

The LSQ technic involved estimating the angle of the needle to the origin $\left(\theta_{0}\right)$ from the training set. Then, a maximum likelihood model selects the observation model from the minimum output from the subtraction between the observation model and calculation as in (15). Besides, equation (7)-(11) leads to the transfer function $f\left(E^{k}, \theta_{0}\right)$.

$$
\begin{align*}
& \theta_{0}=\operatorname{argmin}\left\|\left(\theta_{0}\right)\right\| H\left(\hat{s}_{n}, \|\left(\theta_{0}\right)\right)-f\left(E^{k}, \theta_{0}\right) \|^{2}, \\
& \theta_{0}=0,15,30,45 \tag{15}
\end{align*}
$$

## G. NEEDLE TIP LOCALIZATION SYSTEM BASED EXTENDED KALMAR FILTER (EKF)

After LSQ selects the observation model and initial angle of the needle, the system resamples and updates the needle state with the observation model to estimate the belief of needle state using an Extended Kalmar filter. Fig. 7 illustrates the concept of the needle tip tracking system using EKF using N units of the Hall effect sensor. The magnitude and observation vectors are converted to possible distances and orientations from the sensor's coordinates in the frame (k).

EKF provides the system to functionally estimate the 3D position of the needle tip in a term of probability density function (PDF). The needle tip's coordinates are initially modeled with a first-order Markov chain with the sensing data as an independent condition. This chain can be written as:

$$
\begin{align*}
\hat{x}_{k} & =f_{k}\left(\hat{x}_{(k-1)}, \hat{s}_{n}, \theta_{0}, E^{k}\right), u(t)  \tag{16}\\
z_{k} & =h_{k}\left(\hat{s}_{n}, T\left(\theta_{0}^{i}\right), \hat{x}_{k}\right)+v_{k} \tag{17}
\end{align*}
$$

where $u(t)$ is the control function of the needle, which does not consider in this EKF system because human gesticulation is unpredictable. $v_{k}$ denotes the covariance parameters from algorithm 1. $z_{k}$ represents the observation model with the


FIGURE 6. (a) The plot of needle tip's coordinates using the training models with different initial angles ( 0 to 45 degrees) in sensor number 3. (b) The registration of needle tip coordinates using all active sensors and the training model with different initial angles ( 0 to 45 degrees). (c) The estimated needle tip state from the calculation of overlap space by weight parameter (Intensity).


FIGURE 7. The concept diagram of EKF using MSL and LSQ with the training observation models and previous beliefs of the needle tip state.
initial angle from algorithm 1 . Besides, we do not consider the control function (u) in the prediction state of EKF because human gesticulation is unpredictable.

## Algorithm 2 Extended Kalman Filter to Estimate the Needle Tip State [42]

Input: State of Needle Tip Position:
$\hat{x}_{(1: k-1)}=\hat{x}_{1}, \hat{x}_{2}, \ldots, \hat{x}_{(k-1)}$
Sensor State: $\hat{s}_{n}$, Training Set of Needle with Initial angle i: $T\left(\theta_{0}^{i}\right)$ Covariance of Sensing Data: $\epsilon_{k}$, Covariance of Observation Data: $v_{k}$ Initial angle from LSQ: $\theta_{k}$, Previous covariance error: $\sigma_{(1: k-1)}$
Output: Needle Tip State: $\hat{x}_{(k \mid k)}$, Covariance error: $\sigma_{(k \mid k)}$

```
Prediction Step:
1) Predicted state estimate: \(\left.\hat{x}_{( } k \mid k-1\right)=f\left(\hat{x}_{( } k-1 \mid k-\right.\) \(\left.1), \hat{s}_{n}, \theta_{0}, E^{k}\right)+\epsilon_{i}^{k}\) where \(\mathrm{u}(\mathrm{t})\) is set to be 0 in this system since the hand gesticulation is unpredictable.
2) Predicted estimate covariance:
\(\left.\left.\sigma_{( } k \mid k-1\right)=f\left(\sigma_{( } k-1 \mid k-1\right)\right)\)
Update Step:
3) Measurement residual:
\[
\tilde{y}_{k}=z_{k}-h_{k}\left(\hat{s}_{n}, T\left(\theta_{0}\right), \hat{x}_{k}\right)+v_{k}
\]
4) Optimal Kalman gain:
\[
\left.\left.K_{k}=\left(\sigma_{( } k \mid k-1\right)\right) h_{k}\left(\sigma_{( } \mid k-1\right)+v_{k}\right)^{-1}
\]
5) Update State:
\(\left.\hat{x}_{( }(k \mid k)=\hat{x}_{( } \mid k-1\right)+K_{k} \tilde{y}_{k}\)
6) Update covariance:
\[
\sigma_{( }(k \mid k)=\left(\left(I-K_{k} h_{k}\right) \sigma_{(k \mid k-1)}\right)
\]
```

where $K_{k}$ denotes Kalman gain at time $k$. f is the MSL calculation model of needle tip coordinate and activated sensor positions. $h_{k}$ is the needle tip localization based on observation models at time k .

## V. EXPERIMENTAL SETUP

## A. EXPERIMENT FOR MULTI-DIRECTIONS CHARACTERIZATION

A robotic manipulator (ABB Yumi) was assigned to precisely move an end effector integrated with a magnetized needle to target positions. A needle holder and sensor socket were fabricated by 3D printing, as shown in Fig. 8, while the needle


FIGURE 8. The multiple angles characterization experiment between a Hall effect sensor and magnetized needle using a robot arm. The modified needle holder with ABB Yumi gripper. The Hemisphere command was set in the first experiment with $\mathbf{4 5 1}$ commands in each radius.


FIGURE 9. The $\mathbf{3 \times 3}$ array of Hall effect sensors and their sensor state ( $\hat{\boldsymbol{s}}_{\boldsymbol{i}}$ ) in MATLAB.
holder was modified with a socket for the robotics finger to grasp. The robot system set the gripping force as 12 Nm to grip the holder while moving to the designed coordinates. The needle tip coordinates, representing an end of the effector in the system, were registered and calculated by the 4-Points tool tip calibration procedure [43]. This process generates the parameter set that refers to the needle tip property in a coordinate system. We defined the minimum error per motion as 0.1 mm and maximum velocity as $5 \mathrm{~mm} / \mathrm{s}$.

The sensor position was set as the origin of the system $\left((P)_{O}\right.$ rigin $)$, as shown in Fig. 8. The sensor position was fused with a set of commands to generate the target coordinates in a hemisphere shape. 4 command sets, which have different initial angles between the needle and Hall effect sensor from 0 to 45 degrees ( 15 degrees per each set), were created by MATLAB. Each command set consisted of the hemispherical coordinates with the specific orientation varying radius from 0.5 mm to 14.5 mm ( 1 mm per step), which have an origin at the incipient position. Additionally, each radius of the hemisphere contains 452 coordinates. The robot arm was programmed to move the end effector to all coordinates in the anticlockwise direction, as shown in Fig. 8. The robot arm moved from the inside hemisphere ( 0.5 mm ) to the outside hemisphere ( 14.5 mm ), respectively. We recorded the coordinates together with sensing data from the Hall effect sensor. At the end of each experiment, the automated


FIGURE 10. (a) The fully assembled orbital structure with embedded sensors (left). (b) The Experiment of magnetized needle localization in orbital structure (right).


FIGURE 11. The 8 target points and pathway of motion (red) in the validation system related to the anatomical landmarks of orbital structure.
tool was reinitiated to the center of the Hall effect sensor. The manipulator stopped for 2 seconds in each movement, while the sensing data was sampled 20 times. The system used a standard I/O system from ABB YUMI as a state indicator. 24 V output from the robot was stepped down by Programmable Automation Controllers (PLC) to 5 V before being sent to the digital input port of the microcontroller. We used this signal to indicate the stop state of the robot arm and started sampling the data.

Additionally, when the manipulator approached the target position, the state indicator was set for 2 seconds. The sensing data was passed LPF and averaged to plot a mean as the intensity of magnetic flux in each coordination system. The system also calculated the SD (standard deviation) of sensing data in each command. Finally, the filtered data was applied
with a threshold classification for determining the sensing workspace. The threshold was defined as 4 Gauss from the maximum SD in the last shell of the command set.

## B. EXPERIMENT FOR MULTI-MODEL PREDICTION AND LOCALIZATION WITH HALL EFFECT SENSOR ARRAY

The array of 9 Hall effect sensors was fabricated in a $3 \times 3$ square shape as shown in Fig.9. The sensor sockets were fabricated by a 3 D printing technique using PLA material, which provides a resolution of around 0.1 mm . The center of sensor number 1 was assigned as the origin of the measurement system $\left((P)_{\text {origin }}\right)$. The distances between sensors were 8 mm in both the x and y axes due to the workspace from the first experiment. The command set, which consisted of 9 coordinates, was generated randomly in


FIGURE 12. The box plot between the sensing data and the distance from the sensor in the hemisphere shape (from 1.5 to 13.5) of 4 different initial angles.


FIGURE 13. The SD plot of the training set with the initial angle of 30 degrees varying by different distances.


FIGURE 14. The error bar plot of the training set with $\mathbf{3 0}$ degrees as an initial angle in different distances from the origin.
the workspace. The robot arm was commanded to move the needle tip from point 1 to 9 , respectively, while the sensing data was captured with a sampling rate of around 10 Hz ,

TABLE 2. Range of position coordinates for 8 target points.

| Deviation in System Coordinate <br> $(\mathrm{mm})(\mathrm{max}, \mathrm{min})$ |  |  |  | z |
| :---: | :---: | :---: | :---: | :---: | | Mean and SD |
| :---: |
| of Euclidean Distance |
| $(\mathrm{mm})$ |

as shown in Fig. 9. We set the velocity of this experiment as constant velocity ( $2 \mathrm{~mm} / \mathrm{sec}$ ). The experiment was repeated 4 times with different command sets and different initial angles from 0 to 45 (as defined in training data). The LSQ and EKF techniques were applied to estimate the needle tip position based on the training set from the first experiment. We generated the ground truth using the position feedback from the robot arm every 0.2 seconds. The Euclidean distance between the ground truth arm and estimated needle states was calculated to illustrate the accuracy of the developed system.

## C. EXPERIMENT FOR NEEDLE TIP LOCALIZATION IN ORBITAL CAVITY

As a result of both experiments, the maximum detection range of this new version of the Hall effect sensor was


FIGURE 15. The 2D plot of the needle tip coordinates (side view), which has to sense over the threshold, in 4 different initial angles. The black line illustrates the workspace of the Hall effect sensor with the magnetized needle.


FIGURE 16. The needle tip localization with known initial angle experiment ( 0 Degree). The robot arm moves the needle tip from origin to 9 targets (blue marks) with constant velocity ( $2 \mathrm{~mm} / \mathrm{s}$ ). The ground truth pathway (black line) is compared to the estimated coordinates of the needle tip from the developed system (red marks) every 0.2 seconds. Sensor number 1 is set as the origin of this experiment.


FIGURE 17. The plot of RMS error of Euclidean distance (blue line) with the ground truth of needle tip coordinates ( $X, Y, Z$ ) from the robotics end effector in 4 different initial angles ( $0,15,30$, and 45).
almost the same as the space in the human's orbital cavity ( $12.0-14.0 \mathrm{~mm}$ ) [3], [44]. Therefore, the system was
designed with the same sockets' position from previous studies [45]. The orbital structure was embedded with 24 sensors,


FIGURE 18. The plot of Euclidean distance error (blue line) and the output state (red mark) with the ground truth of needle tip coordinates (black line) from the robotics end effector in 15-degree as the initial angle in 9 different target points.


FIGURE 19. In the needle tip localization model with known initial angle experiment, the ground truth pathway (black line) is compared to the estimated coordinates of the needle tip from the developed system (red marks).
separated into 3 rows and 7 columns, as shown in Fig. 10. The electronic wires passed through the holes behind the sensor sockets to the backside of the phantom. We generated 8 target coordinates in orbital structure from the 8 positions
of anatomical landmarks as the target command of the robot arm (the exact command set with the experiment in the previous study [23]), as shown in Fig. 11. Besides, the motion velocity was set as non-constant velocity due to human
gesticulation [45], by integrating constant velocity and random acceleration $(5 \pm 2 \mathrm{~mm} / \mathrm{s})$. We registered all target positions with the same reference in the robot arm and set it as the origin. The robot arm respectively operated from points 1 to 8 and stopped at each point for 2 seconds. The state of the needle tip, which consisted of coordinates and orientation, was calculated by the sensing data. We measure the root mean square (RMS) of the Euclidean distance between all estimated needle tip coordinates with the target points to validate the system's accuracy.

## VI. RESULTS

## A. MULTIPLE DIRECTIONAL APPROACH FOR MAGNETIZED NEEDLE CHARACTERIZATION

The result shows that the variety of initiate angles influences sensing output. As can be observed from Fig. 12, the average value (red trick) of sensing data from the different initial angles at the same distance is almost the same, but there is a difference in SD (range of the box graph) of the sensing data. The SD of the sensing data decreases when the initial angle increases at the same distance from the origin. Besides, the SD also reduces when the needle tip is pointed far away from the sensor. On the other hand, it is found that the SD of observations at the same coordinate is significantly low compared to the mean of sensing value ( $\mathrm{P}<0.05, \mathrm{n}=20$ ), as shown in Fig. 13. Fig. 14 illustrates that the SNR between sensing data and the coordinate of the needle tip is significantly low, particularly in distances (r) lower than 4.5 mm .

According to Fig. 12, we applied the third polynomial regression between the mean and distance of each initial angle in training sets to calculate the set of parameters in (11), as shown in Table 1. Moreover, we applied the sensing data of each coordinate with the threshold classification filter as in (5) with T equal to 4 . The result illustrates that the changes in the initiate angle contort the detecting area of the system, as shown in Fig. 15. The initiate angle also affects the transfer function between sensing data and the captured needle tip coordinates.

## B. MULTI-MODEL PREDICTION AND LOCALIZATION WITH HALL EFFECT SENSOR ARRAY

The output states of the magnetized needle were compared to the ground truth from the robotics system, as shown in Fig. 16. We calculated the Euclidean distance between the position feedback from the robot arm and the calculated position at the same time frame (k). The position feedback from robot arm was plotted together with the Euclidean distance error, as shown in Fig. 17. The result illustrated that the system has RMS error of Euclidean distance of around $1.7398 \pm 0.5288 \mathrm{~mm}$ (the maximum error less than 4 mm ), depending on the distance of needle tip (r) and the number of activated sensors. Besides, the result shows that the z -axis primarily influences the error in the experiment. For instance, the second graph in Fig. 17 shows a significant increase in the error when the needle tip is raised in the z -axis (after


FIGURE 20. The practicing day of trainee medical doctor (1st year) with the developed EATS model.

40 samples). On the other hand, the X and Y axis motion has a lessened effect on the Euclidean distance error. Further investigation on the results shows that the error in the localization system was accumulated over the increasing time frames, as in Fig. 17 and 18, which is the common problem in EKF system. Moreover, there is no remarkable error from the different initial angles as shown in Fig. 17.

## C. ACCURACY OF THE DEVELOPED SYSTEM

The reference coordinate was registered to the phantom position as the origin of the validation system. The experiment was repeated 10 times with the same target sequence ( 1 to 8 ). The output state was calculated 2 times in each step. The estimated coordinates were compared with the target points as shown in Fig. 19. We calculate the Euclidean distance between target points and estimated coordinates. Besides, all errors in the $\mathrm{x}, \mathrm{y}$, and z axis were recorded as in Table 2. The RMS error of the Euclidean distance involved describing the accuracy of the system. The result illustrates that the system has accuracy of around $1.958 \pm 1.060 \mathrm{~mm}$ with the maximum error in z -axis around ( 4.5739 mm ).

## VII. CONCLUSION AND DISCUSSIONS

In the first experiment, the result illustrated that the maximum detection area of the sensor is around 13.5 mm , which is similar to the output from previous studies. The change in the sensor model enhances the detected resolution between
the magnetic field and sensing data, while detection space remains the same. The difference in the sensing model provides a more accurate needle position. The SD in each coordinate denotes that the T system has an acceptable signal-to-noise ratio from the new sensor ( $\mathrm{P}<0.05$ ). Consequently, the initial angle of the needle affects the shape of detection and the initial transfer function (f) as shown in Fig. 15. The magnetic field strength is still related mainly to the angle and distance between the needle and sensor.
The second experiment shows an increase in precision compared to the previous studies with the same initial angle. We found that the development in the variety of the observation model can enhance the system accuracy of the prior research $(1.80+-0.8370 \mathrm{~mm})$ to $1.7398 \pm 0.5288 \mathrm{~mm}$. The system that employs the pathway localization method shows the capability to track the needle tip with the constant velocity in real-time with an acceptable error. Moreover, the system can use the training set from the first experiment to classify the initial angle by MSL and LSQ.

After the integration of the system with the orbital phantom, there was an increase in the error of needle tip estimation from $1.7398 \pm 0.5288$ to $1.958 \pm 1.060 \mathrm{~mm}$. This error was caused by the mismatch between sensor states and actual positions in the orbital structure, affecting the LSQ for model selection. The other source of error was caused by the non-constant velocity of the robot arm, which is crucial in reducing the EKF algorithm's accuracy. The result denoted that the x and y -axis error is comparatively lower, maximizing at 3.4 mm compared to 4.5 mm of the z-axis. The occurred errors are also dependent on the position of detection. The error margin rises significantly when the needle tip position reaches the edge of the workspace. For instance, in target positions 1, 3, 5 and 6, the RMS error increases over 2 mm . The orientation of the sensor affects the accuracy of the system. In target point number 6, the primary activated sensor is not parallel to the orbital skull, inducing more errors in the z -axis. However, the system error is smaller than the significant structure in Ophthalmic anatomies.

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