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Using Heterogeneous Sensory Measurements in a Compliant Magnetic Localization System for Medical Intervention

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***Abstract*— In many medical intervention procedures, passive magnetic tracking technology has found favor in continuous localization of medical instruments and tools inside the human body. By utilizing a small permanent magnet as a passive source, it requires no dedicated power supply or wire connection into the body. Past researches usually adopt rigid structures to restrict the movement of sensors, as the precise positional information of the homogeneous magnetic sensors play an important role in the accuracy of traditional inverse optimization algorithms. In this paper, we investigate methods to enable the sensing system to be used for the nasogastric (NG) tube localization in a compliant setting, such that the device can conform around the patient for improved ergonomics and comfort. Such a system, which now contains additional sensors required to sense the active compliance, will contain a non-homogeneous sensor assembly producing heterogeneous sensory information. Two methods are proposed and evaluated: one is a modified inverse optimization method using a deformation model in series with the magnetic field model; the other is a direct forward Artificial Neural Network (ANN) method. The efficacy of both methods were evaluated and compared by numerical simulation and experiments. Advantages and disadvantages of both methods were discussed at the end.**

I. INTRODUCTION

Magnetic tracking technology has been an emerging trend in many localization and navigation applications. It utilizes the phenomenon that the instantaneous amplitude and orientation of the local magnetic field will vary according to its position and orientation from the magnetic source. Thus, it is able to provide three-dimensional up to six degrees-of-freedoms (DOFs) positional information without the need for line-of-sight. Besides the non-contact nature, a major advantage is that the permeability of the human biological tissues (such as meat, fat and even bone) is almost the same as that of the air. This means the presence of human body poses minimal interferences on the tracking accuracy, making it ideal to be used in medical interventions [1].

There are several commercially available systems in the market taking advantage of electromagnetic (EM) tracking. The approach undertaken by these devices includes associating the targeted object with either a small sensor coil placing in a controlled time-varying magnetic field to induce currents (e.g. AURORA system, NDI Medical, US), or an EM transmitter generating signals to be detected by a receiver unit (e.g. CORTRAK system, Corpak Medsystems, US). Such systems require external power to generate the magnetic field. As a result, the targeted object must be tethered by wires to supply power or transmit electrical signals, sometimes making it obstructive and cumbersome for bedside clinical usage. There is also passive transponder technology using EM as wireless power supply to generate radio frequency signal for localization (e.g. Calypso system, Varian Medical Systems, US). However,a single transponder could not provide multiple DOFs positional information, limiting its usefulness in localization applications.

Another approach is to use miniature, low-cost magnetic sensors to track small permanent magnet (PM). This approach utilizes the magnetic field from the PM as a passive source and does not require wiring and external power. With the rapid development of the magnetic sensing technologies in increasing accuracy and resolution, the passive magnetic tracking approach has drawn significant attention in the field of medical localization. Sclageter used a 2D-array of Hall sensors to obtain five DOFs of a PM [2]. The sensing system consisted a 4×4 array of 16 cylindrical Hall sensors with integrated flux-concentrators on a rigid plane. This system was tested as noninvasive verification of nasogastric (NG) tube placement [3]. Wang and Hu also developed a three-axis magnetometer 2D array system for tracking of endoscopy capsule [4], [5]. Sensor arrangement optimization were also reported to be a factor for tracking accuracy [6], [7]. To the best of authors' knowledge, all systems reported in the literature only used measurements from the a homogeneous array of magnetic sensors which are fixed on rigid surfaces in 2D or 3D structure. However in medical interventions, the sensing system is to be used on different patients; planar rigid structure appears to be cumbersome and it is impractical to have one-size to fit all. It will be highly desired to have flexible/compliant structure, such that the size could be adjustable for better ergonomics and comfort to the patients. In order to do so, heterogeneous type of sensor information is to be included to simultaneously monitor and compensate for the deformation in the flexible/compliant structure.

Hence, in this paper for the first time we present and discuss the challenges in magnetic localization when incorporating heterogeneous sensory information. In the following, the traditional inverse optimization algorithm is first discussed which harnesses additional flexure sensors to measure the geometry deformation of the compliant system. Then a direct forward ANN (Artificial Neural Network) algorithm is proposed which processes the heterogeneous sensory inputs at once rather than sequentially. Taking the design of a compliant sensing system for localization of a nasogastric tube as an illustrative example, numerical simulations and

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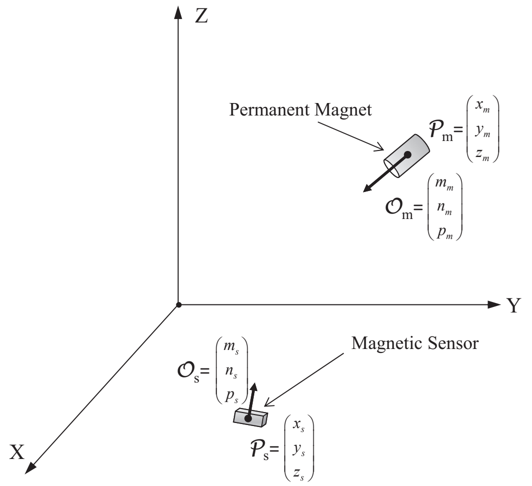


Fig. 1. Tracking a permanent magnet using magnetic sensor.

experimental tests using both algorithms are performed and evaluated.

II. MATERIALS AND METHODS

A. Conventional Inverse Optimization Method

Passive magnetic tracking traditionally requires solving an inverse problem by using a magnetic field model for the forward problem and approximating the measured data by the chosen model [8]. As shown in Fig. 1, two vectors $\mathcal{P} = [x, y, z]$ and $\mathcal{O} = [m, n, p]$, are used to describe the position and orientation respectively, for both the PM and the sensor in the defined coordinate system. The orientation vector $\mathcal{O}$ is a unit vector with the constraint of

$$m^2 + n^2 + p^2 = 1. \tag{1}$$

For the magnet, the orientation refers to its magnetization axis; for the sensor, the orientation refers to its sensing axis (in case of three-axis magnetic sensor, the orientation can be defined as its z-axis).

A forward magnetic field model is used to predict the magnetic field measured at the sensor,

$$\mathcal{B}_{model} = [B_x, B_y, B_z]^T = \mathcal{M}\{(\mathcal{P}_s - \mathcal{P}_m), \mathcal{O}_m, \mathcal{O}_s\}. \tag{2}$$

The magnetic field model $\mathcal{M}$ can be an ideal Dipole Model, where the PM is modeled as a single dipole in space. For better accuracy in concern of the magnet geometry, other complex models can also be used, such as the distributed multipole model (DMP) [9], or the hybrid model [10]. Then a nonlinear optimization algorithm, such as the Levenberg-Marquardt Algorithm (LMA), is used to approximate the positional information of the PM by minimizing the error between the modeled and the measured magnetic fields, $\mathcal{B}_{model}$ and $\mathcal{B}_{measurement}$ for all sensors:

$$C = \sum_{i=1}^{n} ||\mathcal{B}^i_{model} - \mathcal{B}^i_{measurement}||^2, \tag{3}$$

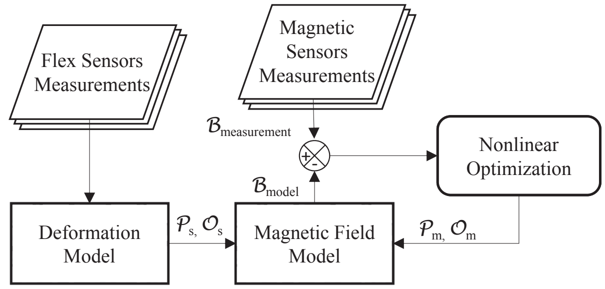


Fig. 2. Sensing scheme of the inverse optimization method.

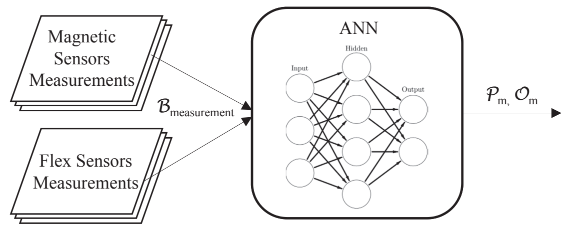


Fig. 3. Sensing scheme of the ANN method.

where the index i indicates the i^{th} sensor of the total n sensors.

In a rigid system, the positional information of the sensors is fixed. The only parameters to be solved are the six spatial parameters of the PM. The minimum sensor measurements required for solving the nonlinear optimization are five. However, in a compliant system, the positional information of the sensors can also change. It is impossible to approximate the parameters of both the PM and sensors by only using the magnetic sensors measurements alone. Therefore, an additional sensor such as resistance-based flex sensor, must be used to assess the deformation of the compliant structure from its original configuration. Illustration of the sensing scheme of the inverse optimization method can be expressed as in Fig. 2. On top of the traditional inverse optimization method, a deformation model based on the geometry of the sensing system structure needs to be used to update the positional information of the sensors.

Note that in this sensing scheme, despite the noise existing in the sensors measurements, there are three instances that might introduce modelling and approximation errors into the system: both the magnetic and deformation models and the optimization algorithm itself.

B. Direct Artificial Neural Network Method

To bypass the physical model-based approach, Artificial Neural Networks (ANN) are often used to approximate nonlinear functions. Especially when the data to be processed is huge, the ANN model is able to significantly reduce the computational complexity and improve the calculation speed. Previously, Foong et al. applied ANN in the design of a

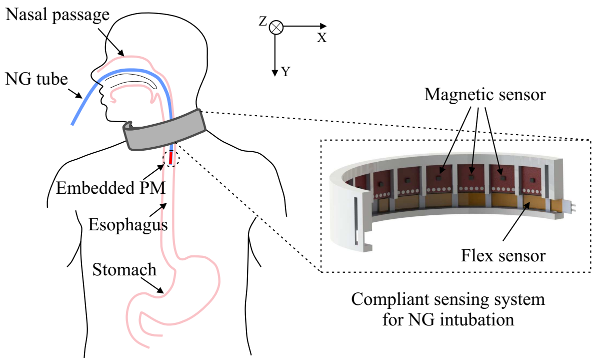


Fig. 4. Compliant sensing system for NG intubation.

magneto-elastomeric force sensor by mapping the sensors measurements to exerting forces, instead of modelling the physical model of the system [11]. Wu et al. adopted ANN as magnetic field model to address the shortcoming of the Dipole Model in describing the near field of the PM. It is reported that the ANN model is able to capture the magnetic field even if the PM is in irregular shape [12], [13].

Basically, the ANN consists of sets of adaptive weights, which requires supervised learning by training. Once the training is done, the outputs can be directly obtained by performing linear transformation of the inputs using the weights. However, the data sets for training must be carefully selected to avoid underfitting or overfitting during supervised learning. Since the ANN gives non-parametric function for approximation, it is desired that the training data should be as comprehensive as possible; otherwise its robustness is not guaranteed.

In the localization for medical interventions, the workspace is usually confined and the intervention trajectories are normally of low variance even on different patients [14]. Therefore, it is possible to design procedure-specific sensing system by performing prior training over the desired workspace. In the case of compliant structure, the flex sensors measurements can be directly used as one of the input feature for the ANN as illustrated in Fig. 3, eliminating the need to use two separate models. Comparing to the inverse optimization method, ANN method allows to retrieve the positional information of the PM directly from the heterogeneous sensors measurements.

C. Compliant Sensing System for Enhanced NG Intubation

In order to evaluate both approaches, the positional accuracy of a compliant localization system for tracking nasgoastric tubes is presented here and is based of a previously presented design in [15]. By using passive magnetic tracking technology, a PM is embedded in the tip of a NG tube, and magnetic sensors are arranged in a semicircular-shape structure attaching to the patient's neck to track the PM position. In such a manner, any erroneous placement during the intubation can be identified immediately by continuously monitoring the tip of the NG tube in real-time.

In this system, the PM used is a grade N52 Neodymium (Nd-Fe-B) cylindrical magnet (K&J Magnetics Inc, US) with the dimension of Ø $1/8\times$ length $3/8$ inch, which can fit tightly into the inner diameter of a Fr 13 NG tube. And 11 tri-axial magnetometers Xtrinsic MAG3110 (Freescale^{TM}, US) are used to measure the changes in the magnetic field. A resistance-based flex sensor (Spectra Symbol, US) is used to measure the bending of the structure. A Wheatstone bridge circuit is used to measure the resistance of the flex sensor. These two heterogeneous sensors are used together to determine the positional information (both position and orientation) of the PM, as well as the sensors, as proposed in the conventional inverse optimization and direct ANN methods. The compliant structure which is 3d-printed, can be deformed to ergonomically conform to the patient's neck. The diameter of the designed semicircular structure is 130 mm. Symmetrical design is adopted in the distribution of the slots to hold both type of sensors. Illustration of the design is shown in Fig. 4. Based on this design, numerical simulations are performed and presented.

III. NUMERCIAL SIMULATION AND RESULTS

The two methods using heterogeneous sensory information are numerically evaluated and investigated. For the inverse optimization method, magnetic field model and the deformation model is first decided and calibrated; for the direct mapping ANN method, the region of interest is defined and sampled for training. The details of the preparation for each method is elaborated in the following sections.

A. Inverse Optimization Method

Considering the computation complexity, the Dipole Model is selected for the magnetic field model. It models the cylindrical PM as a single magnetic dipole at the center of its geometry. It describes the magnetic field at the sensor $\mathcal{P}_s$ due to the magnetic source at $\mathcal{P}_m$ as

$$\mathcal{B} = \frac{\mu M}{4\pi}\left(\frac{3(\mathcal{O}_m \cdot \mathcal{P}_{sm})\mathcal{P}_{sm} - R^3 \cdot \mathcal{O}_m}{R^5}\right) \tag{4}$$

where

$$\mathcal{P}_{sm} = \mathcal{P}_s - \mathcal{P}_m$$

is the vector from magnetic source to the sensor and R is its magnitude. μ is the permeability of the medium, and it is constant for biological tissue and air, which is usually taken as $4\pi\times10^{-4}$ H/mm. In the Dipole Model, only the parameter M, which is the constant strength of the dipole moment, is magnet-specific and needs to be predetermined. Calibration was performed by fitting the measurements to the model as defined in (4), and the value of M is measured at 6.88×10^4 A$\cdot$ mm^2.

Since the structure is printed with homogeneous material and symmetrically designed, the Circle Model as defined in [15] is employed to approximate the structure after deformation. It approximates the deformed structure still in the shape of a circle but with different radius. The flex sensor measures the corresponding arc angle of its active length. The arc angle for original semicircular shape is $\theta = \pi/2$. Based any

TABLE I
ROI PARAMETERS

	Parameter	Range
Training Volume	X-axis	[-10,10] mm
	Y-axis	[-50,50] mm
	Z-axis	[40,75] mm
	resolution	1 mm
	Number of points	76356
PM Orientation	m	[-0.1,0.1]
	n	[0.88, 1]
	p	[0, 0.47]
Arc Bending Angle	θ	[90°, 100°]

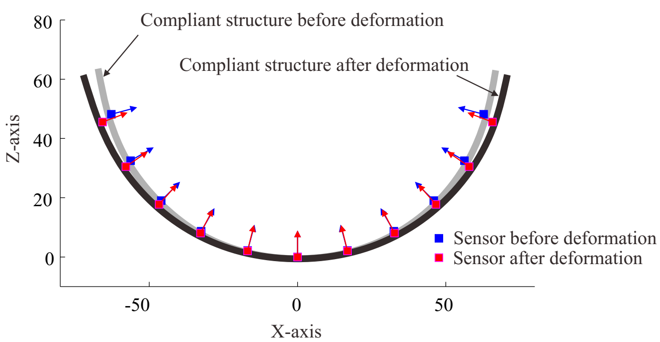


Fig. 5. Illustration of the changes in the positional information of magnetic sensors due to the deformation of the compliant structure.

consequent changes in the angle $\Delta\theta$, the compliant structure can be replotted.

In the simulation, the magnetic field measurements are corrupted by applying 1μT RMS (root-mean-square) noise to the modeled data. The positional information (both position and orientation) of the sensors can be retrieved from the deformation model. Then the cost function in (3) is minimized using the *lsqnonlin* function from the Optimization Toolbox of MATLAB (MathWorks, US), to obtain the positional information of the PM.

B. Artificial Neural Network Method

In order to simulate the measurement data for training the ANN, the Dipole Model is adopted as the field model with corrupted noise. For each training set, the inputs contain 33 magnetic field measurements from the 11 tri-axial magnetometers, and 1 arc bending angle measurement from the flex sensor; the outputs contain the 3-element position coordinates and 3-element orientation unit vector for the PM. The resolution of the training volume decides the number of training data sets. The higher the resolution, the larger the training data, the more the training complexity. Based on the profile of the intervention trajectory, in this case the NG tube intubation trajectory into the esophagus, the Region of Interest (ROI) is determined for training. In order to include as much variations as possible in the compliant setting, the arc bending angle θ and PM orientation $\mathcal{O}_m$ are randomly assigned for the training data set at each point. Detailed range

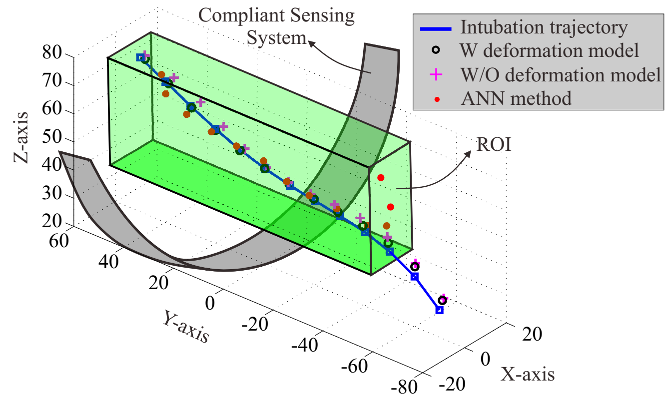


Fig. 6. The NG intubation trajectory with reference to the ROI (region of interest) for ANN training; one example of tracking results of the inverse optimization method and ANN method are shown when $\theta = 98°$.

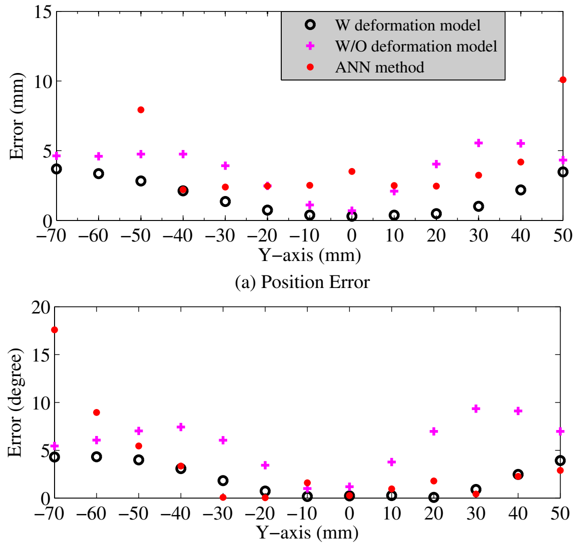
of the parameters are summarized in Table I.

Before the training, feature scaling is performed to both the inputs and outputs to ensure that the objective function is optimized equally on all features.Then the training data sets are trained by a back propagation ANN (single hidden layer and 10 neuron nodes per layer) with Levenberg-Marquardt Algorithm, using the *nntraintool* function from the Neural Network Toolbox of MATLAB. The trained ANN model is used in the simulation to process the sensor measurements directly to obtain the positional information of the PM.

C. Trajectory Tracking Comparison

In the simulation, the compliant structure is set to deform outward. Because of the deformation, the positional information of the magnetic sensors changes as shown in Fig. 5. The trajectory tested is a representative NG tube intubation trajectory with varying PM orientation. As shown in Fig. 6, the compliant sensing system is placed perpendicular to the Y-axis at $Y = 0$; the PM moves along Y-axis from -70 mm to 50 mm with a total of 13 data points; 2 points fall out of the ROI. The inverse optimization method and ANN method are tested concurrently on the same data sets. Three tracking results are compared, inverse optimization method with and without deformation model, and ANN method. In the case where there is no deformation model used, there will be no update on the positional information of all the magnetic sensors, resulting further tracking errors. Graphical plots of the tracking results and corresponding positional errors are presented in Fig. 6 and Fig. 7 respectively, where the arc bending angle θ is at 98°. Position error is calculated as the Euclidean distance between the actual and estimated position, while orientation error is calculated as the deviation angle between the actual and estimated orientation unit vectors.

It is shown that by using the deformation model, inverse optimization method is able to track the trajectory well. As expected, without updating the positional information of the sensors, tracking errors in both the position and orientation are much larger. For the ANN method, it is shown that the position tracking errors are below 4 mm, and the orientation



(a) Position Error

(b) Orientation Error

Fig. 7. Positional errors of both methods ($\theta = 98°$).

tracking errors are below 3° within the ROI. But once the PM moves out of the ROI, even at the ROI boundary (at −50 mm and 50 mm for example), the position and the orientation tracking errors can increase as large as 46.8 mm and 25.6° (at −70 mm). This is to be expected as the ANN was only trained within the ROI.

Multiple simulation tests are performed at different arc bending angle θ within the training range. The root-mean-square errors (RMSE) of the tracking results are summarized in Table II. It is shown that both position and orientation tracking errors will increase as the deformation of the compliant structure increases if the inverse optimization method is performed without using the deformation model to update the positional information of all the magnetic sensors. In comparison, once the deformation model is used, both position and orientation tracking errors are reduced and remain consistent even there are deformation changes in the compliant structure. Same consistency is also observed in the ANN method. Using the ANN method, the position tracking errors appear close to the results using inverse optimization method with the deformation model; the orientation errors are the lowest among all three trajectory tracking results.

One thing to take note here is that the magnetic field model and deformation model used by the inverse optimization method is assumed ideal in the simulation, but not the case in real scenario. In practical applications, the imperfection of the models may introduce slight errors in depicting the magnetic field data, leading to cumulative deteriorated tracking performance. On the contrary, ANN method is trained based on the empirically obtained actual measurements, which does not depend on the models. By selecting the features and ROI for training strategically, the ANN method is able to predict the targets accurately. In a nut shell, it is proven in the simulation results that the proposed ANN method with heterogeneous sensory information is able

TABLE II

TRACKING RESULTS OF BOTH METHODS WITH REFERENCE TO DIFFERENT DEFORMATIONS

	Position RMSE (mm)			Orientation RMSE (°)		
θ	92°	95°	98°	92°	95°	98°
With deformation model	2.0	1.9	2.2	2.5	2.3	2.7
Without deformation model	2.5	3.5	4.6	3.5	5.3	7.2
ANN method (within ROI)	2.8	2.8	3.0	2.0	1.7	1.5

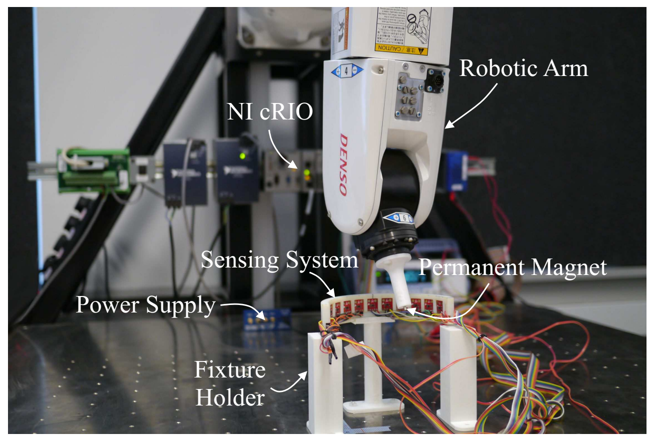


Fig. 8. Setup of the robotic platform and the sensing system for experiments.

to capture the variations of the magnetic field in a compliant structure. In the following, experimental results are presented for validation.

IV. EXPERIMENTAL TESTS

Experiments were designed and conducted on the compliant sensing system as described in Fig. 8. A six-axis articulated robotic platform (VS-068, Denso Robotics, Japan) was used to perform the trajectory with the magnet mounted on its end-effector. The magnetic sensors and the flex sensor were powered by an ultra-low noise power supply module (ABPSM-ULN-A, ABRACON Corp., US) at 3.3 V and 5 V, respectively. A reconfigurable control and monitoring system NI CompactRIO (National Instrumens, US) was used together with DENSO toolkit (ImagingLab, Italy) for LabVIEW (National Instrumens, US) to control the robot. And two types of I/O modules were used on the CompactRIO to collect data from the sensors: NI 9205 (Analog Input Module) for the flex sensor, and NI 9403 (Digital I/O Module) for the magnetic sensors.

Data were firstly collected in the ROI for ANN training. The ground coordinates of the robotic platform were first registered to the sensing system by moving the end-effector in contact with the magnetic sensor in the center. Then the offset was performed by moving the PM far away from the sensing system to measure the static environmental

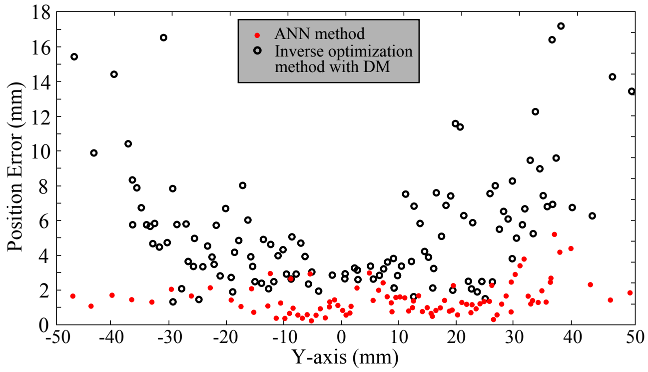


Fig. 9. Experimental results of the tracking performance for the inverse optimization method and ANN method.

magnetic field. The robotic arm was programmed to move the PM to different positions within the ROI. It prolongs the calibration time to include orientation adjustment at each position. Therefore, for simplicity, the orientation of the PM was fixed along the positive Y-axis this preliminary test. And the sensing system was fastened on the fixture holder with a fixed arc bending angle during the calibration. Even though, the data acquisition for training still took more than five hours.

In order to test the tracking capability of the ANN method, the PM was moved to random positions within the ROI. Measurements from the sensors were then used to estimate the position of the PM using both methods. A total number of 129 data points was sampled as shown in Fig. 9. It is found that the RMSE of the tracking result for ANN method is below 2 mm, while that for inverse optimization method with Dipole Model is greater than 6 mm. Inverse optimization method is able to give comparative performance when the PM places closer to the center of the system, but poorer as the PM moves further from the sensing system. This could be because the decrease in the singal-to-noise ratio (SNR).

V. DISCUSSIONS AND CONCLUSIONS

In this paper, we proposed and investigated two different methods to incorporate compliant sensing system in passive magnetic tracking by using heterogeneous sensory information. The results suggest that the deformation in a compliant structure could deteriorate the tracking performance. But with additional flex sensor assessing the deformation, both proposed methods are able to provide consistent and enhanced tracking performance. The inverse optimization method requires much less pre-tracking preparations than the ANN method. In the implementation of the inverse optimization method, it requires an initial guess of the parameters (or their bounds). The algorithm may fail to give the correct global optimum if there are large errors in the initial parameters. And the computation time for solving the inverse problem slows down the tracking update rate, which was about 10Hz in the experiment. In comparison, the ANN method appears to be more robust as the training were performed based on the actual measurements. In the aspect of real-time application, the output from the ANN method was almost instant. However, the ANN method can only work within the trained ROI, while there is no specific spatial limitations on the inverse optimization method. In summary, the choice of tracking method between the two will depend on the actual requirements in the specific medical interventions. The studies presented in this paper shed light on incorporating heterogeneous sensory information in the passive magnetic tracking technology, which may pave the way to build compliant sensing systems in medical applications for the benefit of patients.

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