Underwater Navigation using Geomagnetic Field Variations

Chinmaya V. Kaji, Randy C. Hoover, and Shankarachary Ragi

***Abstract*—Underwater positioning and navigation for autonomous vehicles is challenging because of the GPS-denied environments. We present a novel positioning and navigation method for underwater vehicles using the Earth's magnetic field properties including field intensity, declination, and inclination. In other words, we assume that the underwater vehicle is equipped with magnetometers that can sense the magnetic field properties at the sampling location. Based on the sensor readings, we estimate the geographical location of the vehicle. Specifically, we develop a feed-forward neural network model to estimate the geographical location of the vehicle by mapping magnetometer sensor readings to a unique location on the Earth's surface. To train the neural network, we generate data using the International Geomagnetic Reference Field (IGRF) model.**

***Index Terms*—Underwater navigation, magnetic field, machine learning, GPS denied environments, position estimation.**

I. Introduction and Problem Specification

Positioning and navigation methods for underwater environments have applications including autonomous underwater vehicle motion planning and submarine navigation. Several methods exist for underwater navigation that use Doppler sonars and Inertial Measurement Units (IMUs) [1]. However, these technologies do not provide exact geographical location of the vehicle without a reference location. In most underwater navigation applications, there is a need for absolute positioning and navigation methods without the aid of a reference position.

Electromagnetic waves do not propagate well in underwater environments, and the acoustic waves in sonar-based technologies may have adverse effects on the underwater ecosystems as certain sea mammals use acoustic waves for communication. We develop an alternative navigation method, that uses the geomagnetic field properties to estimate the field sampling location on the global map. The goal of the paper is to develop a method to map the geomagnetic field properties, i.e., field intensity, inclination, and declination, to a unique location on the global map.

We assume that there is an underwater vehicle equipped with magnetometers that provide readings of the geomagnetic field properties. The goal is to estimate the location of the vehicle on the globe given the field property readings from the magnetometers. To achieve this objective, we develop a feed-forward neural network model to approximately learn a mapping function from the magnetic properties to the global locations. We use data generated from the International Geomagnetic Reference Field (IGRF) model [4] to train our neural network.

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A. Literature Review

Global Positioning System (GPS) has revolutionized outdoor navigation and tracking, providing accurate positioning anywhere in the world, but GPS signals do not propagate well into deep sea environments. Various underwater navigation systems exist such as the inertial measurement units, sonar, and acoustics-based positing systems [1]. However, these techniques work in conjunction with GPS, and for these systems to be effective, the underwater vehicle must float on the water surface in a recurring manner to correct any positional errors. There also exist methods [5] that use magnetic compasses to determine the absolute location of the vehicles. In this approach the authors use the 3-axis magnetometer to determine the absolute position using the variations of local magnetic field for indoor and ground vehicles. However, they need to develop a self-building world model beforehand. Without a previously build model, these algorithms would not provide effective results.

The geophysical parameters such as the bathymetry, magnetic field, or gravitational anomaly can also be used to provide localization provided an accurate prior map of the environment [7]. There are also methods present which consist of magnetometer and magnetic field maps measuring the Earth's magnetic field variation for ground vehicle navigation [2]. The magnetic field is also used in navigation models for satellite positing and navigation, which uses the intensity value to determine the altitude and satellite orbit [6].

Indoor navigation methods which use unique fingerprint or profiles of magnetic field data generated from various man-made sources and metals inside the buildings have also been developed [3].

B. Key Contributions

1) We develop a novel underwater navigation and positioning system using the geomagnetic field properties.
2) We develop a neural network model to learn the mapping function from the geomagnetic field properties to a location on the global map.
3) We conduct a numerical study to assess the impact of the neural network parameters (e.g., number of hidden layers) on location estimation performance.

The remainder of this paper is organized as follows: In Section II we discuss the methods used in order to develop our navigation system followed by results and analysis in section

III and conclusion on our findings along with the future scope in Section IV.

II. Methods

The goal of this study is to develop an underwater positioning and navigation method to estimate the position of an underwater vehicle in deep sea environments. Specifically, we use the unique variations in geomagnetic field properties (e.g., field intensity variations) across the globe to determine the location of the vehicle with some uncertainty. Our approach is reliable only in environments with no metallic structures and rock materials, as the geomagnetic field is distorted in the presence of external field sources, e.g., metallic structures.

There exist physics-based models that describe the magnetic field variations across the globe. Specifically, we use a model called International Geomagnetic Reference Field (IGRF), which provides mathematical expressions for the geomagnetic field properties as a function of the geographical location (longitude and latitude) [4].

The IGRF model provides the magnetic field properties as a function of latitude and longitude. The model uses the magnetic scalar potential in the spherical co-ordinates to define the magnetic field $\overrightarrow{B}$ which is given by $\overrightarrow{B} = -\delta V$ where the scalar potential is approximated by [4]

$$V(r,\theta,\phi,t) = a\sum_{n=1}^{N}\sum_{m=0}^{n}(a/r)^{n+1}[g_n^m(t)cos(m\phi) + h_n^m(t)sin(m\phi)]P_n^m(cos\theta) \tag{1}$$

where
r = radial distance from Earth's center
Θ = co-latitude (polar angle)
ϕ = East longitude
t = time
g, h = Gaussian coefficients
$P_m^n(\cos(\theta))$ = Schmidt quasi-normalized associated Legendre function with degree n and order m.

Here, we set a = 6371.2 km and the degree of truncation to N = 13. The 12th Generation IGRF coefficients were computed from candidate sets of coefficients produced by the participating members of IAGA Working Group V-MOD. The equations to calculate the geomagnetic field profiles is given by [4]:

$$H = \sqrt{X^2+Y^2}, F = \sqrt{X^2+Y^2+Z^2}, \tag{2}$$

$$D = \arctan(Y/X), I = \arctan(Z/H). \tag{3}$$

where H stands for the Horizontal Intensity;
F for the Total Intensity;
D for Declination;
I for Inclination and
X, Y, Z represents the geomagnetic field in northward, eastward and radially inwards direction.

IGRF models are standardized for a particular year, reflecting the most accurate measurements available at that time, and indicating a small-scale, slow time variation of the Earth's overall magnetic field. The 12th edition of the IGRF model covers the 2015 epoch.

The above IGRF model estimates the magnetic field properties given the geographical location. We develop an approximate inverse method to estimate the inverse of the above IGRF expressions. In other words, our approximate inverse mapping method estimates the geographical location given the magnetic field properties. Deriving an exact inverse map for IGRF is not tractable because of the highly non-linear relationships between the location and the field properties as can be seen in equations Eq.1.

We propose to develop a feed-forward neural network model to approximate the above-discussed inverse mapping; details are discussed in the next subsection. To train the neural network, we generate data by sampling the IGRF model across the globe over a grid with resolution of 1 degree latitude and 1 degree longitude. This inverse method idea relies on the unique variations of the magnetic field properties across the globe as can be see in the contour plots of the field properties in Figures 1, 2, and 3.

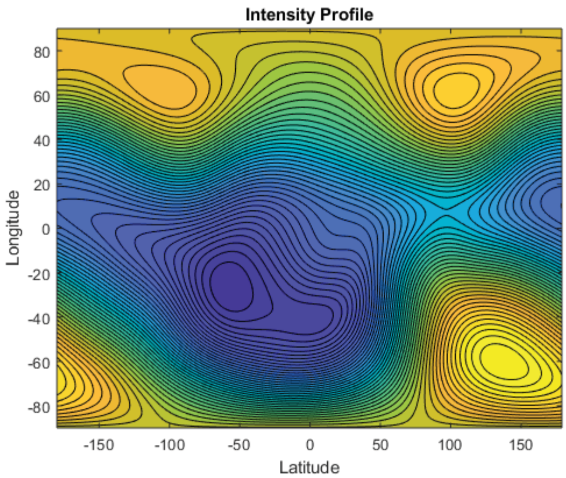

Fig. 1. Contour plot for field intensity across the global map.

A. Feed-forward Neural Network Model

A feed-forward neural network is different from a recurrent neural network in that there is only a single flow direction for the information. This means the feed-forward neural network doesn't have any loops, and the information is transferred in a uni-directional manner that is from the input nodes to the hidden nodes to the output nodes [9].

The feed-forward network is a classification algorithm which is biologically inspired in that it acts as the nervous system in an animal as shown in Figure 4. The figure shows the neural network is designed with multiple organized layers which consist of various neuron-like processing units where each unit in the layer is connected with the units in the previous layer, these are also known as nodes each node may have symmetrical or different strengths or weights. The data

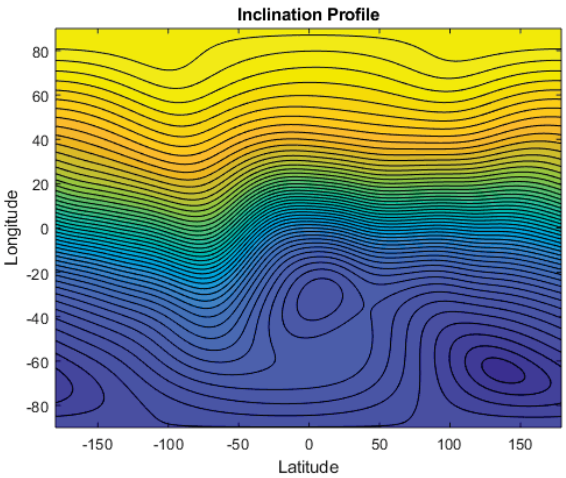

Fig. 2. Contour plot for inclination profile across the global map.

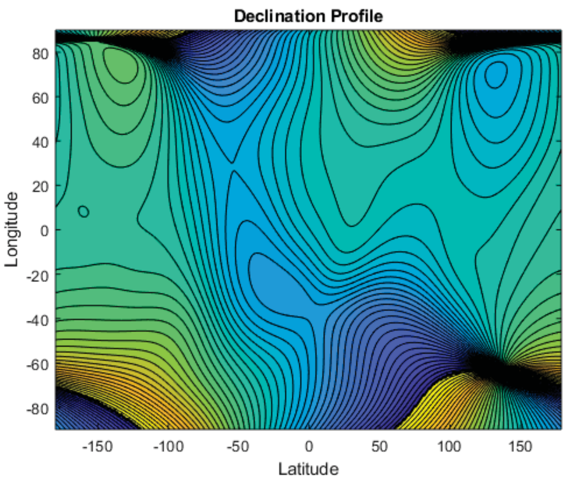

Fig. 3. Contour plot for declination profile across the global map.

in the network enters with the input layer and gradually runs through each layer to reach the output layer. The figure 4 displays a basic working model of a five-layer hidden network having different weights with two output nodes and three input nodes, the figure also displays the directional flow of the information between the different layers in the network.

B. Location Estimation

We assume that the underwater vehicle is equipped with magnetometers (e.g., triaxial fluxgate magnetometer to measure the change in field variation, proton precision or Overhauser magnetometer is used to record the absolute values of declination and inclination) that provide the readings of the magnetic field properties at uniform time intervals along the path of the vehicle [8]. We estimate the position of the vehicle by feeding the sensor readings for field intensity, inclination, and declination to the trained neural network, which outputs the location estimate. The error between the position of the

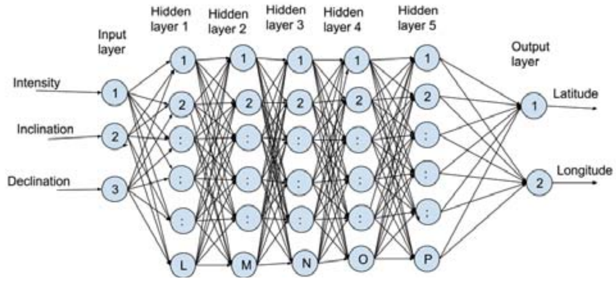

Fig. 4. Feed-forward neural network structure, where L,M,N,O,P represents the number of nodes in each layer.

exact samples and the estimated samples is used to determine the performance of our method.

$$e_p(I) = \left\| l(I) - \hat{l}(I) \right\|_2 \tag{4}$$

where

$$l(I) = \begin{bmatrix} lat(I) \\ long(I) \end{bmatrix}; \hat{l}(I) = \begin{bmatrix} \hat{lat}(I) \\ \hat{long}(I) \end{bmatrix} \tag{5}$$

$lat(I)$ and $long(I)$ represents the actual location (longitude and latitude);
$\hat{l}(I)$ and $\hat{lat}(I)$ represents estimated location (longitude and latitude);
$e_p(I)$ represent the position error between the actual location (longitude and latitude) and the estimated location;
I is the position index in the path;
and the norm represents the Euclidean distance.

III. Results and Discussion

In this section, we present the simulation results and our observations. We discuss multiple cases where we vary the number of layers and the neurons and study their impact on the performance in terms of the location error. We consider several case studies with varying parameter sets in the neural network as discussed below. To assess the impact of the neural network parameters on the error performance, we consider a scenario where we evaluate the magnetic field properties at certain known locations. Figure 6 shows the actual locations given by the green colored crosses and the green colored curve represents the fitted curve for these locations. The neural network's performance plot is given in Figure 5. The performance of the neural network is determined by the mean squared error between the actual and the estimated locations. Generally the mean squared error reduces for each epochs as seen in Figure 5. The Figure 5 represents the training performance for one of the scenario(case 5) discussed below.

A. Case 1

- In Case 1, we study the performance of neural network with three hidden layers and 25 neurons per layer.

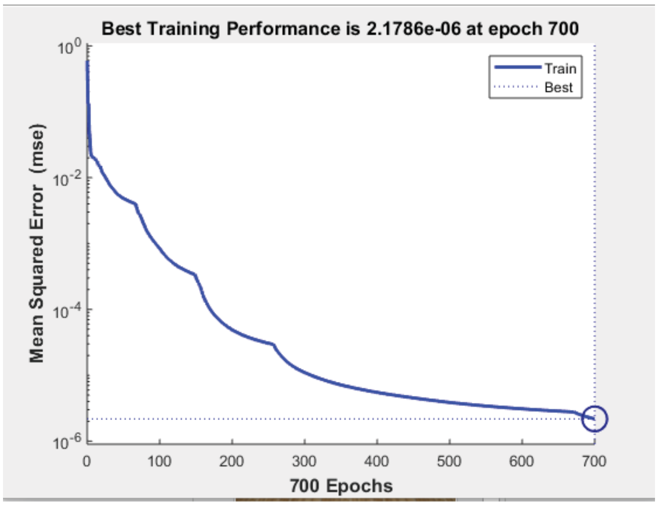

Fig. 5. Neural network performance plot.

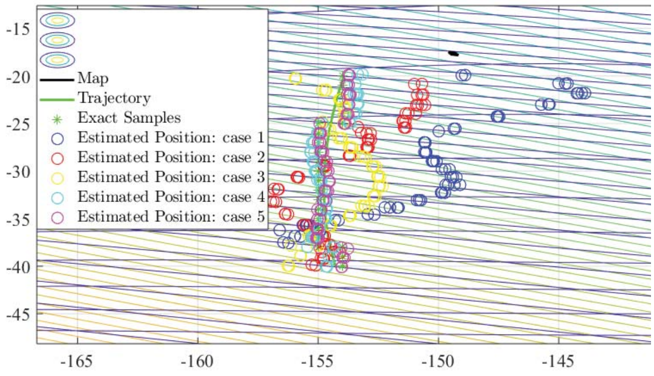

Fig. 6. Mapping results from all the cases at the same location.

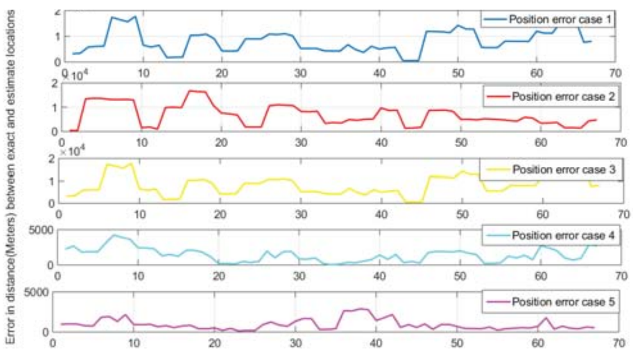

Fig. 7. Error plot between the exact and estimated location for different neural networks at same location.

- In Figure 6 the blue circles represent the location estimates generated from the neural network.
- In this case, as can be seen in Figure 7, we notice that the error in the estimated location is significantly high, which gets improved in the below case studies.

B. Case 2

- Here, we study the impact of increased neurons per layer on the location error. Specifically, we consider three hidden layers with 35 neurons per layer.
- As expected, we observe the improvement in error performance in Figure 6. Figure 7 shows the quantitative improvement in the error.

C. Case 3

- Case 3 addresses the performance of another neural network with a five hidden-layer configuration. The hidden layer, in this case, is represented with set of 25 neurons for each layer.
- We observe from Figure6 that the location estimates are closer to the actual locations compared to the previous scenarios. However, this improvement in performance comes at a cost - increased computations in the training phase.

D. Case 4

- Case 4 studies the impact of increased number of neurons on location error in a five hidden layer configuration. Specifically, we consider five hidden layers with 35 neurons per layer.
- We observe from Figure 6 improvement in the performance with location estimates mapped closer to the actual locations.
- Now Figure 7 displays the error in distance (meters) between the exact location and the estimated location, demonstrating the performance improvement in this case.

E. Case 5

- In Case 5, we observe the performance of the best optimized neural network that we trained with five hidden layers with 40, 34, 60, 80, 15 neurons in each layer respectively.
- We observe from Figure 6 significant improvement in the estimation performance.
- We also observe from Figure 7 that the error in mapping the estimate location is lowest among all the scenarios.
- Error between mapping of the actual samples and the estimated samples at multiple regions on the global map is displayed in Figure 9, where as Figure 8 displays the mapping between the actual and estimated samples highlighted with different colours at different location.
- We are also able to conclude from Figure 8 that the performance of our algorithm depends on the level of crisscrossing between the earth's magnetic field contour lines.

- The regions with higher crisscrossing between the field profiles provide more accurate results. Figure 10 represents some of the high error regions where there is minimal crisscrossing between the field properties.
- Error between mapping of the actual samples and the estimated samples in high error regions on the global map is displayed in Figure 11
- Figure 12 represents a heat map generated which displays the regional efficiency of estimate location mapping along the globe with varying geomagnetic field properties.

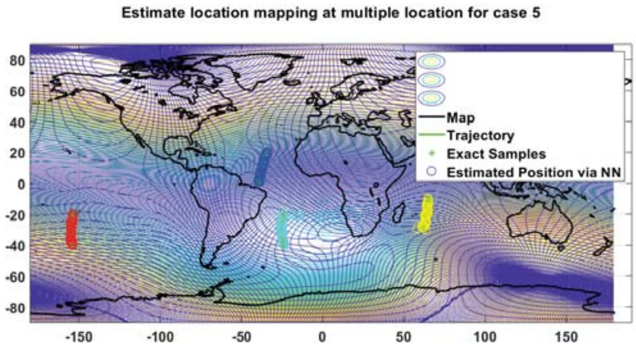

Fig. 8. Estimated locations for Case 5 at multiple regions.

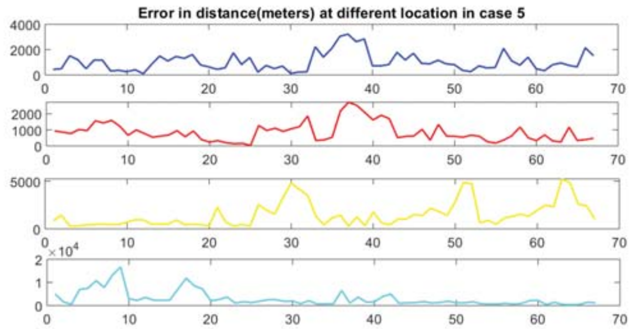

Fig. 9. Error plot between exact and estimated samples for Case 5 in multiple regions.

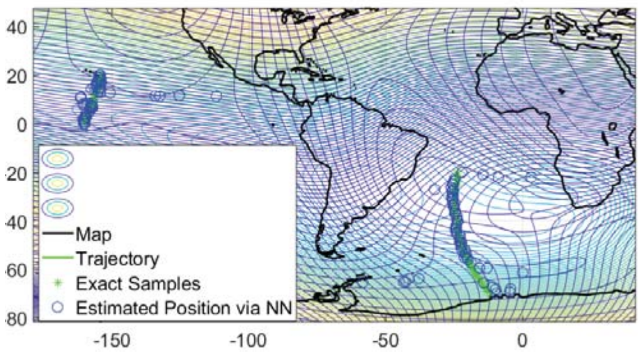

Fig. 10. Estimated locations for Case 5 at multiple high error regions.

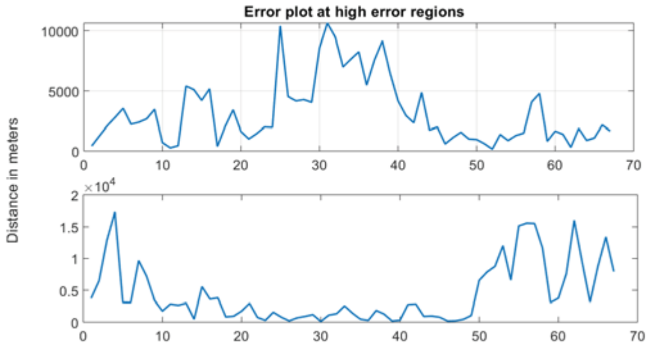

Fig. 11. Error plot between exact and estimate locations for Case 5 in high error regions.

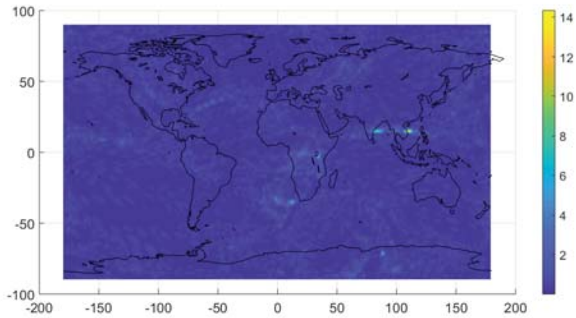

Fig. 12. Heat map for regional accuracy around the globe for Case 5.

IV. Conclusions

We developed a novel underwater navigation method, which uses variations in geomagnetic field properties to find absolute location on the globe. Our algorithm uses the geomagnetic field properties such as the field intensity, inclination, and declination to uniquely identify the location on the globe where the above magnetic field properties are measured (via magnetometers). We trained a feed-forward neural network to identify the mapping from the field properties to the absolute global location. We tested the performance of our algorithm under various scenarios with varying number of hidden layers and neurons in the neural network. We validated our algorithm in simulated environments (MATLAB); hardware implementation and field testing to be considered in our future studies.

V. Acknowledgment

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