Approach to geomagnetic matching for navigation based on a convolutional neural network and normalised cross-correlation

Donghun Kim\(^1\), Hyochoong Bang\(^1\),*, Jae Cheul Lee\(^2\)

\(^1\)Department of Aerospace Engineering, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Eoeun-dong, Yuseong-gu, Daejeon, Republic of Korea
\(^2\)Hanwha Corporation, 10, Yuseong-daero 1366 beon-gil, Yousung-gu, Daejeon, Republic of Korea
E-mail: hcbang@ascl.kaist.ac.kr

Abstract: Geomagnetic information is available over much of the Earth. Geomagnetic navigation based on neural networks (NNs) is challenging because all measurement vectors mapping to the positions on the reference map should be classified in advance, and the measurements for mapping are highly non-linear. This approach fails to map positions when measurements that have not been pre-classified in the new area are input. It limits the navigation area because it is hard to assign all positions on the reference map to classes. In this study, the authors present a new approach combining two symmetric convolutional NNs (CNNs) and normalised cross-correlation (NCC). Two symmetric CNNs trained to find similarity are used to find candidate regions in a search area. Then NCC is applied to find a matching position. This approach enlarges the geomagnetic navigation area regardless of training, and it enables processing even if geomagnetic measurements are acquired in a new area. The results of the numerical simulation indicate that the mean matching rate is over 98.6% for the best and worst geomagnetic profile. Furthermore, they show that the algorithm can be applied for initial position estimation in a search area by showing improvement of convergence time and position estimation error.

1 Introduction

The definition of ‘navigation’ is moving from one place to another or looking for the route required for such a move [1]. For navigation, knowing the current position before a move is key. An inertial navigation system (INS) is a typical dead-reckoning system that can provide accurate position information. The INS estimates the current position by integrating the measurements from inertial sensors such as a gyroscope and accelerometers without external help. However, position errors accumulate over time due to the uncertainty of the sensors. Over a prolonged period, the cumulative errors cause the INS to diverge. The cumulative errors of the INS can be compensated by a complementary system. A typical complementary system is a global positioning system (GPS). A GPS can estimate a position based on received precise time information from multiple satellites through radio signals. Errors, therefore, do not accumulate. However, the system is vulnerable to external interference such as jamming.

There are alternative navigation systems based on geophysical information such as terrain [2], geomagnetic [3, 4] and gravity gradiometry [5]. These navigation systems estimate position by comparing the acquired geophysical measurements from the sensor with a previously stored reference database. A typical example is a terrain referenced navigation (TRN) [2]. This measures the terrain elevation in the downward direction using a radio altimeter and barometer while a vehicle is in motion. Then, the estimated position is determined by comparing the measured elevation with the pre-stored digital terrain elevation data and finding a position corresponding to the measured elevation. However, TRN has the disadvantage that performance degrades when the terrain is flat or when the same terrain is repeated [6]. Therefore, it cannot apply to sea or desert where flat terrain is repeated as well as terrain information is available only on land.

Geomagnetic aided navigation (GAN) is another navigation system that uses the Earth's magnetic fields. Unlike terrain profiles for TRN, geomagnetic information is available in most regions of the Earth [4]. Therefore, GAN has the advantage of expanding the operational scope to the whole world, while TRN is only available on land. Position estimation using geomagnetic involves comparing geomagnetic measurements from a magnetometer with geomagnetic values on a previously stored reference geomagnetic map to find a position that matches the measurements. For GAN, many matching method studies have recently been conducted. Algorithms for geomagnetic matching for navigation can be classified into three types, namely filter-based, correlation-based and neural network (NN)-based algorithms. An extended Kalman filter (EKF) and a particle filter (PF) are typical filter-based algorithms. An EKF exhibits linearisation error and risk of divergence depending on the initial position error [7]. Nonetheless, an EKF is widely used as the most traditional approach. Unlike an EKF, a PF is a non-parametric/non-Gaussian filter that is used for navigation with highly non-linear measurements. Recently, a marginalised PF combined with a Kalman filter and a PF was combined with geomagnetic correction methods and applied to an aerial application, effectively reducing the degree of navigation error [4].

The iterative closest contour point (ICCP) is an example of a correlation-based geomagnetic matching algorithm [8]. This uses the geomagnetic intensity measurement. The ICCP estimates position iteratively by matching measurements and geomagnetic intensity sampled from a geomagnetic intensity map by calculating the mean absolute difference. With the development of vector measurement, algorithms based on geomagnetic vector information are evolving. The vector ICCP (VICCP) is another example for a correlation-based approach based on vector measurement. These estimates position iteratively based on ICCP using geomagnetic vector measurements. In this case, using vector measurements achieves a much higher matching rate than ICCP [9].

Geomagnetic matching for navigation can be considered as a problem of classifying measured geomagnetic measurements into corresponding positional classes on a reference map. It has very non-linear properties for classification from geomagnetic measurements to specific positions. This non-linear classification problem can be solved by using NNs. The geomagnetic matching based on probabilistic NN (PNN) is an example of an NN-based algorithm using a classification approach [10]. A PNN is an NN for classification by modelling the conditional probability function [11]. The parameters of each probability function for specific
positions related to measurement vectors are trained in advance. When the geomagnetic measurement vector is acquired, the input vector is classified to a specific position by PNN selecting the maximum value of the likelihood function. An NN-based approach has the strong advantage of modelling the relationship between non-linear measurements and positions. However, major problems arise for GAN using NNs approach. In the case of a classification-based approach such as with a PNN, the positions on the geomagnetic reference map corresponding to the measurements must be classified as positional classes in advance. There are infinite positions on the geomagnetic reference map, and it is impossible for all of the positions to be defined as positional classes in advance. If the classification-based approach is applied to geomagnetic navigation, it can only be used in a limited area previously classified, and thus cannot process acquired measurements in a new search area. Therefore, the geomagnetic navigation area is restricted by using the classification-based NN approach.

Our motivation is to expand the scope of GAN by solving the problem of limitation of the navigation area that occurs in the classification-based NN approach. Based on our motivation, the objective of this paper is to propose a new approach combined with NNs and a correlation method that can estimate positions for GAN even when previously untrained measurements are input in a new search area. To achieve our objective, there are three challenging issues to overcome. The first is to propose a new architecture based on NNs combined with a correlation method that can perform geomagnetic matching for navigation on previously unclassified areas and be trained with a small number of samples. The second is generating datasets based on the simulated dynamics of a vessel for training and validation. Defining the loss function for training to make the two symmetric CNNs find candidate regions by measuring the distance between geomagnetic measurement patterns and candidate regions is also a challenging issue. Thus, in this paper, we show a new approach to geometric matching for navigation that enables position estimation in a wide search area by incorporating CNNs and NCC. The viability of the proposed algorithm can be confirmed from continuous position estimation results for GAN using numerical simulation on a large search area.

Our innovation is to propose a distance-based approach based on two symmetric CNNs combined with NCC to GAN. By proposing the new approach, we show the possibility of enlarging a navigational area for GAN to where geomagnetic information is available. The proposed approach has the advantage in that no matter where measurements are acquired, the position can be estimated by adjusting the size of the search area and setting its origin position. Based on our innovation, our contributions to GAN can thus be summarised as follows. We have expanded the navigational area by defining the structure of two symmetric CNNs for GAN. This algorithm overcomes the disadvantage that the classification-based approach for GAN is used in a pre-classified area. By defining the NN structure, position estimation can be made possible by retrieving a candidate region from an acquired measurement pattern with no positional information in advance from the new search area. Also, we have combined two symmetric CNNs and NCC for geomagnetic navigation. Therefore, the matching rate of GAN can be dramatically increased. It is also our contribution.

In the following section, we illustrate the proposed approach scheme before presenting details of the two symmetric CNNs and the NCC used in the algorithm. Numerical simulations are conducted to show the validity of our algorithm in different geomagnetic measurement profiles. In particular, we demonstrate that using the results of the proposed algorithm as the initial position estimation for a PF used for geomagnetic navigation, convergence time and position estimation error are improved.

2 Geometric matching using CNNs and NCC

In this section, we present the scheme of the proposed geometric matching for navigation, which is based on CNNs and NCC. We begin with an illustration and a discussion of the entire configuration of the proposed scheme in the following subsection. After this, we discuss how to retrieve a candidate region using two symmetric CNNs and find a matching position using NCC.

2.1 Proposed scheme for geometric matching

The proposed geometric matching for navigation consists of an abstraction step and a refinement step. Two symmetric CNNs are used in the abstraction step to retrieve small search maps that are most similar to the measurement pattern, and the boundary of the candidate small search map retrieved from the abstraction step is expanded into an augmented map. Finally, the matching position is obtained from the measurement map and the augmented map by NCC. By using this two-step approach, a gradual matching from a wide area to a matching position is done from the given information. A block diagram of the proposed algorithm is illustrated in Fig. 1.

In Fig. 1, the geomagnetic grid map is a kind of map having geomagnetic intensity values corresponding to positions on the two-dimensional plane with unit grid intervals. The abstraction step consists of an operation to retrieve a candidate small search map from a broad search area using two symmetric CNNs that share a common NN parameters vector, \( \mathbf{W} \), and a metric function that determines the difference between two different information inputs. If the two inputs are similar, the difference between the similarity metrics is reduced. Conversely, if the inputs are different, then the difference between the similarity metric is increased [12].

The search area, \( A_i \), is defined as an \( m \times m \) sub-area of the geomagnetic grid map, with an origin position at \( a_i = [x_i, y_i] \). \( a_k \) can be updated at each discrete time, \( k \), with position estimates, \( \hat{x}_k \), such that \( a_{k+1} = \hat{x}_k - m/2.m/2 \). Here, \( b_i \) is the input to the two symmetric CNNs, \( S_i \), and the measurement map, \( M_i \), the sizes of both being equal to \( n \times n \).

The small search maps are geomagnetic grid maps that form a finite division of the search area, described as \( S_i \in A_i \). The small search maps, \( S_i \), are defined as geomagnetic information at all positions in the search area, given by \( b_i = [x_i, y_i] \), that satisfy the boundary condition. This boundary condition is defined as \( a_{i+1} = [m+n, m-n] \) for all \( i \), where \( i \) is the index of \( S_i \), \( i = 1, \ldots, (m-n)^2 \), and \( n < m \).

The other input, \( M_i^k \), refers to the measurement map at a discrete time \( k \). This measurement map represents a measurement pattern and is created with a collection of geomagnetic measurements and corresponding position information. The collection of geomagnetic measurements, \( M_i \), is defined as a set of geomagnetic measurements obtained at a discrete time \( k \), i.e.

\[
M_i = \{ [x_j, y_j] \}_{j=1}^N, \quad \text{where } z_k \text{ denotes a geomagnetic measurement obtained from a magnetometer, and } j \text{ is the index representing the discrete time offset of the geomagnetic measurements to be included in } M_i. \text{ For each discrete time } k, \text{ an INS provides position information in the form of } x_k = [x, y]^T, \text{ such that a set of positions corresponding to } m_i \text{ can be defined as } p_i = \{ [x_{i-j}, y_{i-j}] \}_{j=0}^{N}. \text{ The upper limit of } j, \text{ is calculated at each discrete time such that the boundary condition, } x_{i-j} - x_i \leq n, \text{ is satisfied. Then, the components of } m_i \text{ and } p_i \text{ are selected. To generate } M_i^k, \text{ the components of } m_i \text{ are mapped to an } n \times n \text{ space, with } x_k \text{ defined as the first position of } M_i, \text{ and } x_{i-j} \text{ defined relative to } x_k. \text{ In the absence of a measurement in } M_i, \text{ it has a value of 0 and finally } M_i^k \text{ forms a pattern for geometric matching.}

The outputs of the two symmetric CNNs are \( G_W(S_i) \) and \( G_W(M_i) \), both with a size of \( \text{R}^{m\times m} \). Here, \( G_W(\cdot) \) is a mapping function such that \( G_W(\cdot): \text{R}^{m\times m} \rightarrow \text{R}^{m\times m} \) with the NN parameter.
vector, \( W \), is used to calculate the similarity metric in the target space. The retrieved small search map, \( S_i = S_{i-1}^{\text{aug}} \), can be found by retrieving the result of \( G_w(S_i) \) which is closest to \( G_w(M_i) \). This is calculated by finding the index, \( r \), using (1), as the origin of \( S_i \) is \( b_i = b_i^{c-r} \). The size of the retrieved small map \( S_i \) is also \( n \times n \).

\[
r = \arg\min_i \| G_w(S_i) - G_w(M_i) \|_2, \quad i = 1, \ldots, (m-n)^2 \tag{1}
\]

A boundary check is performed at the end of the abstraction step, as shown in Fig. 1, to determine whether the change in position obtained with \( b_i \) is equal to or greater than the actual variation in the vehicle’s position. This variation in position is obtained by measuring the difference between \( b_i \) and \( b_{i-1} \), the origin of the previous retrieved small map, \( S_{i-1} \). If the change in position is larger than the movement variation in position, the next most similar \( S_i \) is selected as \( S_i \), and the checks are repeated until \( b_i \) is within the acceptable boundary. This process is necessary with geomagnetic matching for continuous position estimation during navigation.

The second step for successive geomagnetic matching is the refinement step. In the refinement step, NCC is applied to determine the position that matches the measurement map, \( M_k \), in the augmented map, \( F_k \), expanded from the retrieved small map, \( S_i \). NCC refers to a high-level machine vision technique that identifies parts of a source image that match a predefined template [13–15]. In this step, \( S_i \) must be expanded through augmentation to reduce the possible boundary errors when utilising NCC. This map augmentation thus expands the boundary of \( S_i \) such that the final size of the augmented map, \( F_k \), is \( p \times p \) (\( p > n \)), and the new map includes \( b_k \). The origin of \( F_i \) is defined as \( x_i = [x, y]^T \). Once augmentation has been conducted, NCC can be performed as

\[
\gamma_k(x,y) = \sum_{u=x}^{x+p-1} \sum_{v=y}^{y+p-1} \frac{(F(x+u,y+v) - \bar{F}) \times (M(u,v) - \bar{M})}{\sqrt{\sum_{u=x}^{x+p-1} \sum_{v=y}^{y+p-1} (F(x+u,y+v))^2} \sqrt{\sum_{u=x}^{x+p-1} \sum_{v=y}^{y+p-1} (M(u,v))^2}}
\]

0 \leq x \leq p-1, \quad 0 \leq y \leq p-1, \tag{2}

where the functions \( F(\cdot) \) and \( M(\cdot) \) return the geomagnetic values at the corresponding positions of \( F_i \) and \( M_i \), respectively. During the NCC, \( x \) and \( y \) are the relative coordinates, starting with the first component at \( e_s \) of the augmented map. In the equation, \( u \) and \( v \) are also relative coordinates in the measurement map \( M_k \). \( F \) and \( M \) are the mean geomagnetic values of \( F_i \) and \( M_i \), respectively. NCC operates all values of \( x \) and \( y \) on \( F_i \), moving in a sequence resembling a sliding window. The size of \( \gamma_k(x,y) \) after NCC is \( p \times p \).

The relative matching position, \( n_k = [x, y]^T \), is selected as the coordinate with the maximum value from the results of the NCC step, as shown in (3). The final matching position, \( x_k = [x, y]^T \), is subsequently defined as \( x_k = e_s + n_k \). Pseudocode for each process step of the proposed matching algorithm is presented in Figs. 2 and 3.

\[
n_k = \arg\max_{x,y} \gamma_k(x,y), \quad 0 \leq x \leq p-1, \quad 0 \leq y \leq p-1 \tag{3}
\]

In Fig. 2, the function of map\((x, y)^T, n \times n)\) is to return an \( n \times n \) map of geomagnetic intensities, defined by the origin of the geomagnetic grid map, \( [x, y]^T \). Also, sort index (\( \cdot \)) returns the indexes of \( \mathcal{D}_k \), the Euclidean distance between the small search maps and the measurement map in the target space \((\mathcal{D}_k = \| W(S_i) - G_w(M_i) \|_2)\), in increasing order of distance. This function is executed by a multi-core processor such as a general-purpose graphical processing unit, for speedy batch processing.

2.2 Calculating similarity using two symmetric CNNs

As discussed above, classification-based geomagnetic matching approaches are hindered by training complexity, as several positions need to be matched to ensure the success of the algorithm. To apply a NN to the matching problem, a method which obtains information to solve the problem from the given data without requiring specific information about the category required by the classification should be used [12]. The conventional approach for solving these types of problems is to employ a distance-based method that computes a similarity metric between an input pattern to be classified and a pre-stored prototype. In this paper, the measurement map is analogous to the input pattern, and the small search maps are assumed to be the pre-stored prototype.

This similarity metric can be trained using paired data to be matched. NNs to calculate the similarity metric can be used to retrieve the most similar candidate region for the small search maps in the search area, even if the measurement map is obtained from previously unclassified categories. The key is to find a
mapping function to map from the input space to the target space. This mapping function calculates the similarity between the measurement map and the small search maps in the search area based on the distance in the target space, meaning that a semantic distance that cannot be measured in the input space can still be measured as a simple Euclidean distance from the target space. In order to perform this operation, the same function, \( G \), sharing the same learnable parameter vector, \( W \), is used to process the two inputs. This NN structure is called a Siamese architecture [16].

In this paper, we constructed two symmetric CNNs sharing the same parameter vector as the Siamese architecture to calculate distance in the target space. At the pixel level, CNNs work well and can learn using a range of simple to complex expressions in an integrated manner [17]. Therefore, CNNs can be used to process non-linear geomagnetic information because they are suitable for modelling non-linear systems using a multilayer structure. Also, they can extract input features without being affected by the geometric distortion of the input data [18, 19]. The configuration of the two symmetric CNNs used in this study is shown in Fig. 4. As shown in Fig. 4, \( S \) and \( M \) are the inputs of the two symmetric CNNs with the size of \( n \times n \). \( W \) is the learnable parameter vector shared by two symmetric CNNs trained to calculate distance, and \( G_W(S) \) and \( G_W(M) \) are the results of mapping \( S \) and \( M \) to a low-dimensional space using the two symmetric CNNs. The two symmetric CNNs should be trained so that the distance is shorter if \( S \) and \( M \) are obtained from the matched pairs, whereas the distance must be longer if \( S \) and \( M \) are obtained from the mismatched pairs in the following equation:

\[
D_W(S, M) = \| G_W(S) - G_W(M) \| (4)
\]

In this study, training is achieved using supervised learning, to minimise the loss function given in (5) [12]

\[
l(W) = \sum_{i=1}^{p} L(W, (Y_i, S_i, M_i)). (5)
\]

where the training sample, \( (Y_i, S_i, M_i) \), consists of a binary label, \( Y \), and the two input samples \( S \) and \( M \). \( i \) is the index of the samples, and \( p \) denotes the number of training samples used in batch processing. Here, \( Y = 0 \) if \( S \) and \( M \) come from matched pairs, and \( Y = 1 \) otherwise. The loss function for training two symmetric CNNs is defined in (6), where \( L_0 \) and \( L_1 \) denote the partial loss function for matched data pairs and mismatched data pairs, respectively.
by the distance between the input samples when they have been
and results. We begin by discussing the details of the training
functions used in this paper are expressed in (7)
and (8). In (7), for \( L_M \), \( m \) denotes the margin, and the \( \max(\cdot) \) function is used to select the larger of \( (m - D_0(S,M)) \) and 0. In contrast, \( L_s \), the loss function for the mismatched pairs, is defined by the distance between the input samples when they have been mapped to the target region.

\[
L(W,(Y,S,M)) = (1 - Y) \times L_M(D_0(S,M)) + Y \times L_S(D_0(S,M))
\]

(6)

The partial loss functions used in this paper are expressed in (7) and (8). In (7), for \( L_M \), \( m \) denotes the margin, and the \( \max(\cdot) \) function is used to select the larger of \( (m - D_0(S,M)) \) and 0. In contrast, \( L_s \), the loss function for the mismatched pairs, is defined by the distance between the input samples when they have been mapped to the target region.

\[
L_M(D_0(S,M)) = \max((m - D_0(S,M)), 0)
\]

(7)

\[
L_S(D_0(S,M)) = \| G_0(S) - G_0(M) \|
\]

(8)

### 2.3 Specifications of two symmetric CNNs

The specifications of the CNNs used to construct the two symmetric CNNs are summarised in Table 1. We used five two-dimensional CNNs to create the two symmetric CNNs, as detailed below. In this table, \( C \) represents a CNNs layer. Each CNNs layer has a max pooling layer, denoted as \( P \), which halves the size of its output. Finally, the CNNs has a fully connected layer, \( F11 \), at its output, for the transformation of the results of the calculation to a low-dimensional space, i.e. \( \mathfrak{R}^{28 \times 28} \rightarrow \mathfrak{R}^{1 \times 1} \).

### 3 Numerical simulations

In this section, we present details of the conditions for the numerical simulations used to verify the viability of our algorithm and results. We begin by discussing the details of the training conditions for two symmetric CNNs, after which we present the results of Monte Carlo simulation of geomagnetic matching using the proposed algorithm and geomagnetic anomaly grids. Finally, we demonstrate that using the geomagnetic matching results as input data for a PF is an effective method for reducing the convergence time of the filter and the initial position estimation errors at the beginning of the navigation.

#### 3.1 Geomagnetic anomaly grids

Geomagnetic anomalies are generated as a result of geologic features enhancing or depressing a local magnetic field [20]. Hence, geomagnetic anomaly grids are used in the simulations. In this paper, we have used the geomagnetic map information from geomagnetic grids to conduct simulations and to create the training datasets for the geomagnetic matching algorithm. Specifically, we adopted the Earth magnetic anomaly grid 2 (EMAG2), provided by the National Oceanic and Atmospheric Administration (NOAA), for model training. As presented, this dataset has a resolution of two arc minutes per grid and contains information from ranges where measurement is impossible. As such, it must be processed before it can be used for simulation. Fig. 5 shows a plot of EMAG2 following processing, for use in simulation.

### 3.2 Training two symmetric CNNs

To train two symmetric CNNs, we sampled geomagnetic intensity values from the geomagnetic anomaly grid and processed these sampled values into separate training and validation datasets. A training dataset, defined as \( \{(Y,S,M)\}_{i=1}^{V} \), is composed of matched data samples, \( (Y,S,M) \), and mismatched data samples, \( (Y,S,M) \), where \( i \) is the index of the data samples contained in the dataset, and \( Y \) is a binary label, as defined above. \( S \) represents an \( n \times n \) sample extracted from the geomagnetic anomaly grid that is matched to the measurement map, \( M \), while \( S \) corresponds to a sample that does not match another \( M \). In this study, we assume that the geomagnetic matching algorithm uses batch processing at the initial navigation stage to search an initial position from a wide area. From this assumption, it follows that a vessel only engages in linear movements. Hence, \( M \) only contains measurement data corresponding to linear motion.

Three different datasets are generated for training to satisfy the diversity of training and to reflect uncertainty for the magnetometer. The three datasets are distinguished by the measurement noise components to be added: Dataset 0, where there is no measurement noise added to the dataset, Dataset 1, where the maximum 1.5 nT of zero-mean white Gaussian noise components are added to the dataset, and Dataset 3, where the maximum 3 nT of zero-mean white Gaussian noise components are added to the dataset.

Each training dataset contains 150,000 data sample pairs, as illustrated in Fig. 6. We also generated three different types of validation datasets corresponding to the different training datasets, to verify the results of the model trained. Each of these validation datasets consists of 50,000 data sample pairs.

For the training of the two symmetric CNNs, each of the three training datasets is selected randomly and used to train the
3.3 Geomagnetic matching for GAN

As previously stated, the proposed geomagnetic matching approach consists of an abstraction step and a refinement step. To verify its operation, we conducted numerical simulations assuming geomagnetic matching was being conducted using a vessel engaging in a linear motion in an ocean environment on a two-dimensional plane. The simulation parameters about the abstraction step are as follows. \( A_k \), the search area is 56 × 56 in size. Each \( S_k \) matrix was set to cover a 28 × 28 region in the search area, and the number of \( S_k \) is 784. Based on previous consideration, \( M_l \) is also 28 × 28. The boundary check range, \( r_b \), was defined as 16 times the change in the vessel's position at each discrete time, \( k \). The simulation parameters for the refinement step are defined as follows. The augmented map, \( F_k \), extended from the boundaries of \( S_k \), was defined as being 31 × 31 in size. In \( M_l \), some are valid geomagnetic measurements concerning the actual linear motion that are extracted for the NCC. The size of the extracted measurement map is 1 × 28, as indicated by a parameter, which indicates the size of the NCC measurement, denoted by \( r_{\text{NCC}} \). The simulation parameters used in each process step are summarised in Tables 3 and 4.

Simulation conditions for the vessel movement, sampling period and measurement noise components are summarised in Table 5 of the simulation conditions for measurement acquisition. In Table 5, the measurement noise is zero-mean white Gaussian noise added to the geomagnetic measurement to reflect real-world uncertainty for the magnetometer. The level of the measurement noise is up to 3 nT. We completed five iterations of Monte Carlo simulations for two different scenarios to validate our algorithm. Fig. 7 illustrates how both cases are defined graphically. In Simulation Case 1, the geomagnetic anomaly profile varies evenly from approximately −400 to 600 nT. In contrast, Simulation Case 2 includes a region where the value of the geomagnetic anomaly changes sharply between approximately −400 and 600 nT.

The results of geomagnetic matching obtained from Simulation Cases 1 and 2 are shown in Figs. 8 and 9, respectively. The results of only three iterations of Monte Carlo simulation are shown here for the convenience of illustration. For both cases, \( b_0 \), the origin of \( S_k \), is illustrated in the image labelled ‘(b)’ in the relevant figure. The dot-dashed rectangle indicates the search area, \( A_k \), at the onset of the simulation. The dashed rectangle indicates \( S_k \). The final matching positions for the appropriate simulation case, obtained via the NCC following the refinement step, are shown in Figs. 8c and 9c. Here, the dashed rectangle indicates \( F_k \).

A comparison of Figs. 8b and 9b highlights the effect of geomagnetic information on the performance of our algorithm. We note large deviations in the origin positions of the retrieved small search maps obtained in Simulation Case 2, in contrast to those observed with Simulation Case 1. These large deviations arise because the corresponding data points are associated with greatly varying geomagnetic anomaly information which, however, maintains patterns similar to that of its surrounding anomaly information. To be more precise, the presence of these considerable deviations is ascribed to the fact that small search maps processed via the two symmetric CNNs come in the end similar values.

The accuracy of the geomagnetic matching simulations can be assessed by considering the amount of deviation between the results, which depends on the differing characteristics of the
Fig. 8 Results of geomagnetic matching with Simulation Case 1
(a) True positions, (b) Origin positions of the retrieved small search maps after the abstraction step, (c) Estimated positions after the refinement step, (d) RMS error for the longitudinal and latitudinal directions.

This finding implies that our algorithm is capable of matching in the given search area even when geomagnetic measurements are corrupted by unexpected variation of noise not used in the training process.

To compare the geomagnetic matching algorithms, we show the mean matching rates from three different algorithms in terms of geomagnetic matching for navigation such as the VICCP [8], geomagnetic matching based on PNN, and MSD [10], respectively in Table 7.

As mentioned at the beginning of the paper for application of the proposed algorithm, the simulation results obtained by a combination of the proposed geomagnetic matching algorithm and the PF are presented here. Considering that the geomagnetic measurements are strongly non-linear and that the position estimation results tend to have multimodal, non-Gaussian characteristics [21, 22], a PF can serve as an effective filter for this...
form of geomagnetic navigation. We only considered the geomagnetic information from Simulation Case 1 for this experiment. First, we simulated the matching performance of the sequential importance sampling with resampling (SISR) [21], as a baseline. The results of this experiment are shown in Fig. 12, on the next page from which it can be observed that significantly large positional errors are only present at the initial stage of navigation, due to uncertainties resulting from the wide search area. These large initial errors also lead to an increase in the convergence time.

In an attempt to overcome this limit, matching positions from the proposed geomagnetic matching algorithm are used as the input information for the SISR to initialise starting position. The corresponding simulation results are shown in Fig. 13. As shown in Fig. 13, the use of the proposed geomagnetic matching results as the initialisation positions for the SISR can effectively reduce the convergence time required when the SISR is exclusively applied while also reducing the estimation errors associated with the initial position. When attempting to reduce the convergence time, it should be noted that the application of the SISR combined with the proposed geomagnetic algorithm also requires time to execute the algorithm before the SISR proceeds. This initialisation time is equivalent to the 28 discrete time periods required to create a measurement map. In spite of this, the overall convergence time of the combined scheme constitutes a 2.6-fold reduction over that obtained using only the SISR. Also, we observe a close to 9.4-fold improvement in DRMS with the combined scheme, compared to when the SISR is used exclusively, as summarised in Table 8.

4 Conclusion
In this paper, a new approach for geomagnetic matching for navigation, based on CNNs combined with NCC, was presented. It should be noted that the navigational area for GAN is limited when using a classification-based NN. In our approach, two symmetric CNNs were employed and trained to find the similarity in target space to retrieve a candidate region from small search maps.
Subsequently, NCC was applied to determine the final matching position. By applying this architecture to GAN, we can confirm that the navigational area is expanded to where geomagnetic information is available without any pre-classification. This is confirmed from the results of numerical simulation for the performance relationships. The results of numerical simulation for Simulation Cases 1 and 2 confirmed that the average geomagnetic matching rate for different geomagnetic profiles is 98.6%. It was also confirmed that the proposed matching algorithm could achieve a matching rate of 96.4% on average, even when the geomagnetic measurements are corrupted by a noise level four times higher than when training. Hence, we demonstrated the viability that the

![Fig. 10 Performance relationships](image)

(a) Measurement noise versus matching rates, and (b) Measurement noise versus DRMS

![Fig. 11 Performance relationships](image)

(a) Search area versus matching rates, and (b) Search area versus execution time

| Matching algorithm | Matching rate | Unit |
|--------------------|--------------|------|
| proposed algorithm | 98.6         | %    |
| VICCP              | 98           |      |
| PNN                | 95.65        |      |
| MSD                | 28.8         |      |

![Fig. 12 RMS error of the SISR for the Simulation Case 1 profile in](image)

(a) Longitudinal direction, and (b) Latitudinal direction

Subsequently, NCC was applied to determine the final matching position. By applying this architecture to GAN, we can confirm that the navigational area is expanded to where geomagnetic information is available without any pre-classification. This is confirmed from the results of numerical simulation for the performance relationships. The results of numerical simulation for Simulation Cases 1 and 2 confirmed that the average geomagnetic matching rate for different geomagnetic profiles is 98.6%. It was also confirmed that the proposed matching algorithm could achieve a matching rate of 96.4% on average, even when the geomagnetic measurements are corrupted by a noise level four times higher than when training. Hence, we demonstrated the viability that the
The proposed approach to GAN could effectively perform geomagnetic matching even using geomagnetic measurements from a new area. It was also confirmed that the initial convergence time and DRMS error were effectively reduced if SISR PF was initialised with the proposed algorithm before the navigation start.

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Table 8 Simulation results of SISR and SISR initialised using the proposed geomagnetic matching

| Sim. case | DRMS, m | Convergence time, min | Long. direction | Lat. direction |
|-----------|---------|-----------------------|----------------|---------------|
| SISR      | 329     | 295                   | −313           | −1163         |
|           | 2318    |                       | M                 |                |
|           | 3123    |                       |                 |               |
| SISR initialised by the proposed algorithm | 329 | 0 | −46 | −482 |
|           | 229     |                       |                | 236           |
|           | 329     |                       |                 |               |