Aeromagnetic Search Using Genetic Algorithm

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Abstract

We propose the Genetic Algorithm (GA) approach for localization of an underwater magnetic dipole target by an airborne magnetometer. Airborne Magnetic Anomaly Detection (MAD) is used for decades to detect underwater targets, such as sunken ships. The target is assumed as a magnetic dipole, which produces an anomaly in the dominant Earth magnetic field. The aircraft follows a path, sampling the magnetic field and utilizing GA to estimate target location and magnetic moment. The method was simulated on a personal computer, obtaining promising results in the presence of noise. A scatter radius of about 60 m is achieved for SNR value of 0.2, which is acceptable for practical needs.

Introduction

The necessity to detect underwater wrecks and sunken ships has led to several detection techniques, one of which was the Magnetic Anomaly Detection (MAD). The MAD is based on the ability to sense the anomaly in Earth magnetic field produced by the target. In contrast to active detection methods, the MAD is a passive technique, with an advantage of not being discovered by the target. This work deals with an airborne 3-axis magnetometer. An aircraft seems to be the preferred platform to carry the magnetometer, because of its ability to rapidly cover large areas. Noise reduces MAD performance [1]. As a consequence measures should be taken in order to compensate for the noise before localization is executed. Several methods were proposed for estimating the noise parameters: The Least Squares method [6], Finite Impulse Response (FIR) filtering [5], and small signal analysis [2]. These methods offer platform maneuver noise estimation, while algorithms such as LMS [3] offer natural environmental noise prediction. After noise reduction, a localization algorithm is adopted, such as basis functions decomposition [4] or multichannel Levinson-Durbin algorithm [7]. Genetic algorithm was proposed for multi-source localization in magnetoencephalography (MEG) [8]. MEG applications have the advantage of static sensors over moving sensors, which are used for the presently proposed aeromagnetic search. The static sensors are placed around the target in order to achieve best sensitivity. On the other hand, aeromagnetic search path dictates the measurement position, which generally is not optimal. The static sensors are subject to a relatively constant Earth magnetic field, while the aircraft maneuvers through the position dependent Earth magnetic field. The aircraft maneuver through Earth magnetic field produces high noise level. Therefore, we have tested the proposed method for SNR≈0.2. In contrast, noise level in [8] is restricted to 2%, which results in SNR≈20. We implemented GA with integer encoded chromosomes rather than binary encoding [8].

Theory

The magnetized target produces a magnetic field, which is the physical phenomenon that enables the localization of a target by a magnetometer. A magnetic field of a target, when measured far enough can be approximated by a dipole field. The magnetic field measured by the magnetometer \( \vec{B}(\vec{m}, \vec{r}) \), is a sum of the target magnetic field and Earth magnetic field \( \vec{B}_{Earth} \) that is assumed as a known constant,

\[
\vec{B}(\vec{m}, \vec{r}) = \frac{\mu_0}{4\pi} \left[ \frac{3(\vec{m} \cdot \vec{r})\vec{r}}{r^5} - \frac{\vec{m}}{r^3} \right] + \vec{B}_{Earth}
\]

Consider that an aircraft carrying a magnetometer follows a search path as is illustrated in Figure 1. The airborne magnetometer measures the magnetic field along the search path.

By taking N samples of the measured magnetic field \( \vec{B}(1), \vec{B}(2), \ldots, \vec{B}(N) \), we get a nonlinear over-determined set of equations (for large enough N),
We aim to solve equation (2) for \( \vec{m} \) and \( \vec{r} \), which are the target magnetic moment, and the vector from the target to the first sample point respectively. The displacements \( \Delta \vec{r}_2, \Delta \vec{r}_3, \ldots, \Delta \vec{r}_N \) are the vectors from the position of the first sample to the position of samples 2, 3, ..., N respectively. The displacements can be measured precisely using advanced navigation systems, therefore \( \Delta \vec{r}_2, \Delta \vec{r}_3, \ldots, \Delta \vec{r}_N \) are considered as known. Solving equation (2) analytically is not trivial especially in the presence of noise. This has led us to propose a discrete approach. The problem domain is divided into cells of predetermined resolution. Each of the vectors \( \vec{m} \) and \( \vec{r} \), consists of three Cartesian components, Hence, one can define a single six element solution vector,

\[
\vec{X} = (\vec{m}, \vec{r}) = (m_x, m_y, m_z, r_x, r_y, r_z)^T \tag{3}
\]

For each component of \( \vec{m} \) and \( \vec{r} \) there should be set a range according to practical considerations concerning target possible location and magnetic dipole range. Then, for each component of \( \vec{m} \) and \( \vec{r} \) there should be defined a resolution according to the needed accuracy. A short example illustrates the process. Consider a search for a sunken ship, whose magnetic moment ranges from \(-100,000 \text{ A} \cdot \text{m}^2 \) to \(+100,000 \text{ A} \cdot \text{m}^2 \). The needed accuracy for estimating the target magnetic field is \(2,000 \text{ A} \cdot \text{m}^2 \). Assume that the search takes place in a cube with a side length of 200 m, and we would like to localize the sunken ship with accuracy of 2 m. For each element of the solution vector \( \vec{X} \), there are 100 possibilities, resulting in a finite solution space of a total of \(100^6\) possible solutions, from which we have to choose the actual one. Thus we have transferred a continuous equation set into a discrete form. As a consequence the problem becomes that of searching the (sub) optimal solution out of a finite solution space instead of solving equation (2) analytically. The bounded range of possible solutions and the restricted resolution result in sub optimal solutions rather than optimal solutions, but for many applications that is sufficient. Checking all possible solutions one by one would consume enormous time, which is not available in real time systems. For this reason we propose the Genetic Algorithm as a rapid search method.

The Genetic Algorithm

Genetic algorithms provide an effective way to solve problems such as traveling salesman (the shortest route to visit a list of cities). In this work we focus on GA as a search method to find the maximum of an object function, also called fitness function. The GA mimics the evolutionary principle by employing three main operators: selection, crossover, and mutation. As a first step we build a chromosome, which has the genotype of the desired solution. In the case of localization of a magnetic dipole the chromosome has the form of (3). Each element of the chromosome is called gene and may take only restricted values that were defined previously by range and resolution as is explained in the former example. Implementing the evolutionary principle obligates a collection of L chromosomes, which is entitled as population. At first, random values are set for each chromosome of the population. A fitness value is calculated for each chromosome by substituting for the chromosome into the

Figure 1: The aircraft follows the path (dotted arc), sampling the magnetic field (solid circles).
fitness function. The chromosomes can be arranged in a list from the fittest chromosome (with the largest fitness result) to the least fit one. Then the selection operator is applied, selecting only the K fittest chromosomes from the list. There are several ways to perform the selection, which would not be described here. After selection, the crossover operator is utilized resembling a natural breeding action. Only the K fittest chromosomes of the list are allowed to breed amongst themselves by the following mathematical operation,

$$\vec{X}_{\text{new}} = \lambda \vec{X}_i + (1 - \lambda) \vec{X}_j$$

(4)

Chromosomes $\vec{X}_i, \vec{X}_j$ are randomly chosen from the list of the K fittest chromosomes. $\lambda$ is a crossover parameter (usually 0.5), and $\vec{X}_{\text{new}}$ is a newborn chromosome. The process is repeated until a population of K newborn chromosomes is reached. Afterward mutation operator is implemented by randomly selecting a chromosome from the newborn population, and changing a random gene to a random permitted value. The randomness property enables the GA to overcome local minima. After mutation is applied, fitness evaluation is performed on the mutated newborn population. The process of fitness evaluation-selection-crossover-mutation is repeated for a predetermined number of generations or until the fittest chromosome reaches a predefined fitness value. The convergence of the GA is expressed by increase in the average fitness of the population from generation to generation. The chromosome with the largest fitness value is chosen as the solution, according to ‘survival of the fittest’ principle. Defining an appropriate fitness function is an important step in utilizing GA. The following fitness function is proposed for magnetic dipole localization by a 3-axis magnetometer, without considering noise characteristics:

$$\text{fitness} (\vec{X}_j) = -\sum_{n=1}^{N} \left[ \frac{B_x(n) - B_x(\vec{X}_j)}{B_x^2(n) + B_y^2(n) + B_z^2(n)} \right]_k^2 + \left[ \frac{B_y(n) - B_y(\vec{X}_j)}{B_x^2(n) + B_y^2(n) + B_z^2(n)} \right]_y^2 + \left[ \frac{B_z(n) - B_z(\vec{X}_j)}{B_x^2(n) + B_y^2(n) + B_z^2(n)} \right]_z^2$$

(5)

$B_k(n)$ represents the n-th sample of the magnetic field in the k direction, where k is one of the Cartesian axes x, y, or z. $B_k(\vec{X}_j)$ represents the calculated magnetic field in the k direction, at the position where the n-th sample was measured, due to a dipole with the properties of chromosome j. $B_k(\vec{X}_j)$ is the calculated projection of $B(\vec{X}_j)$ onto the k axis. The fitness function is expressed by the squared error sum relating the actual measured magnetic field and the calculated magnetic field. The denominator is used for normalization. The minus sign in front of the sum sets the upper bound of the fitness function to zero. It means that the fittest chromosome fitness value is closest to zero.

Simulation Results

The presently proposed approach has been tested by computer simulation. The simulation program permits the setting of aircraft flight track, target position, target magnetic moment, and GA parameters. We will introduce the reader with two concepts that served us in analyzing the results of the simulation. The first concept is the definition of the Signal to Noise Ratio (SNR). Generally SNR is defined as the ratio between signal power and noise power. We have, however, chosen a more severe criterion, the SNR is expressed here as the ratio between the noise amplitude and the amplitude of the calculated dipole signal. The latter criterion benefits from releasing SNR value from dependence on random noise raffle and search path shape. The second concept is the scatter radius, which is intended for evaluating the quality of the results obtained by the GA. The scatter radius is calculated as the average error in meters between simulated target position and GA result. Figure 2 represents the scatter radius obtained by the simulation for various values of SNR. Thousand simulations have been performed for each value of SNR. The simulated aircraft search path has been of 600 m length in the south-north direction at an altitude of 100 m. The airborne magnetometer has been sampled every 4 m. The simulated dipole target magnetic moment was chosen to be composed of three components: 80,000 $A \cdot m^2$ to the south-north, 20,000 $A \cdot m^2$ to the east-west, and 40,000 $A \cdot m^2$ downward. The simulated target was positioned at Closest Point of Approach (CPA) [3] of 300 m. Random uniform noise was added to the measured signal in order to simulate interference. The stop condition of the GA has been 2,500 generations and the population was set to 50 chromosomes. Selection of those parameters results in execution time of 25 sec on a PC, which indicates that the proposed method can be implemented in real time. Preliminary results show good localization characteristics in noisy environment. The scatter radius is about 60 m, for SNR=0.2, which is acceptable for practical needs.
Conclusion

A method for localization of an underwater target employing airborne MAD using GA has been proposed. The method has been tested by computer simulation, obtaining promising results. The present simulation is due to a 3-axis magnetometer. Other simulations of localization by gradiometric measurements are now being carried out. Further investigation is needed for optimization of fitness function according to noise characteristics.

REFERENCES