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Detection and localization of improvised explosive devices based on 3-axis magnetic sensor array system

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Abstract

The detection and localization of improvised explosive devices (IEDs) on the roadside is a new subject encountered in the struggle against terrorism. A novel detection and localization method was proposed for IEDs based on magnetic signals. Since most of the IEDs have the ferromagnetic properties, the magnetic field produced around the body by the IED can be detected by 3-axis fluxgate sensor array system. With these detected sensor data, the detection and localization of the IED can be computed by an appropriate method based on magnetic dipole model and nonlinear optimization algorithm. This paper studied respectively the properties of explosives and roads as target and environment to be detected. First, the gradient of total magnetic field was directly reconstructed from the magnetic field and the data of sensor array. In order to reduce the effects of the Earth’s magnetic field, the total gradient contraction was used to detect the IEDs. Second, the localization and magnetic moment parameters were searched in the rough by adopting the particle swarm optimization (PSO) algorithm and the precision ones were found by using steepest descent method. Simulation results show that the method mentioned achieves good effects, the maximum detection range of the sensor array can reach to 12m for a 15Am² target and the mean errors of localization and magnetic moment estimation are less than 0.16m and 1Am² respectively. Since the method need not know the IED’s magnetic moment in advance, it is adapt to battlefield environment. In addition, this detection method can be directly applied to solve the problem of detecting and localizing underwater IEDs.

Keywords: Explosive device detection; Magnetic detection; Magnetic localization; Magnetic dipole model; Nonlinear optimization algorithm.

1. Introduction

Since 2003’s, several anti-terrorism war such as the Iraq war and the Afghanistan war had happened and indicated that attacks from improvised explosive devices (IEDs) are one of the major causes of death and injury to civilians and soldiers. IEDs (e.g., bombs, artillery shells, mines, etc.) are often constructed by using materials at hand. They are usually placed on the roadside or buried in the ground and are detonated by pressure exerted by an unsuspecting individual or vehicle [1].

Nowadays, the IED detection method includes chemical sniffers sensors, thermal infrared imagery sensors, ground penetrating radar, and the microwave radar. Nevertheless, these methods not only require large devices and complex operation, but also are costly and time consuming. To address this problem, in this paper , we propose a passive magnetic anomaly sensing system(PMAS), that is made of twenty-one 3-axis fluxgate sensors. Since most of the IEDs have the ferromagnetic properties and the magnetic field produced by a distant ferromagnetic target is not significantly affected by intervening media such as soil, foliage and water, the PMAS that measure the static magnetic anomaly field of IEDs can be used to detect, locate the targets and achieve high accuracy. In addition, the magnetic technique is of higher speed, less cost and can be more easily realized comparing with other possible techniques, e.g., ground penetrating radar, and microwave radar techniques.

The initial application of the PMAS concept was the scalar total field magnetometry for vehicle detection. Some researchers use a dipole model for a magnetic object and provide many techniques to detect the position of a magnetic target [2]. However, direct measurements of the small IED’s magnetic induction fields are complicated by the relatively very large Earth field. Recently, determination of the target’s location and magnetic moment requires the use of tensor gradiometer sensors, because the Earth field has a small gradient. Roy Wiegert [3] uses the tensor gradiometer sensors to locate and classify the unexploded ordnance from highly mobile platforms.

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Since the magnetic field created by a IED is a high order nonlinear function of the 6-D target’s location and magnetic moment, the nonlinear least square optimization algorithm is a common method [4]. However, the nonlinear optimization method has its limitations. This algorithm not only must have an initial estimation of the location and magnetic moment parameters, but also takes a long time to compute those parameters. If the initial parameters have a large error, the algorithm might fail to give a correct global solution. To solve such a problem, we propose the particle swarm optimization (PSO) algorithm. The PSO algorithm is a multi-agent parallel search technique developed by Kenney and Eberhart in 1995[5]. PSO is a stochastic optimization algorithm based on Swarm Intelligence Algorithm (SIA). It doesn’t require too much prior knowledge of the initial parameter values but to provide a wide search range [6]. Unfortunately, when objective function reaches to neighbourhood of local optimal solutions, convergence rates would be likely to become slow and fall into local optimal solutions. To avoid these drawbacks, a improved PSO (IPSO) that utilizes the steepest descent method to accelerate the computing speed of classical PSO is presented, in which the classical PSO algorithm is first used to find the localization parameters. Then, the steepest descent algorithm is applied for further computation by using the initial parameters obtained from the classical PSO algorithm. This approach can provide not only the good accuracy, but also the satisfactory execution speed.

In this paper, a novel PMAS technique based on the proposed IPSO algorithm will be provided to detect and locate a IED by using 3-axis fluxgate sensor array system. The algorithm has been applied in our computer simulation of PMAS, and has been observed to have a good performance with high accuracy, rapid execution, and high robustness.

The organization of the paper is as follows. Section 2 introduces the mathematical model of the PMAS, including the basic principle, explanation of magnetic gradient tensor equation, and the proposed IPSO algorithm. Then section 3 explains the computer simulation of the PMAS and the discussion of the results. Finally, the conclusive remarks are provided in section 4.

2. Mathematical model of the PMAS

2.1 Basic principle

The PMAS is shown in Fig.1, including a magnetic sensor array, a computer, and a patrol car. The IED is placed on the roadside. Since most of the IEDs have the ferromagnetic properties, the ferromagnetic IED can generates a magnetic field around the road. A magnetic sensor array is supported by a patrol car and detects the magnetic field. Fig.2 shows the 3-axis fluxgate sensor array. In this figure, magnetic sensors are represented in number. There are twenty-one 3-axis fluxgate sensors totally.

Consider a static IED which produces a distant magnetic field, the field can be modeled as a dipole field [7]. As shown in Fig.2, let $A(x, y, z)$ be the 3-D position where a 3-axis fluxgate sensor is placed. The magnetic induction field $B_4(T)$ at distances “$r$” more than about 3 times the physical dimensions of the IED, which is generated by the IED with magnetic moment $M[\text{Am}^2]$ can be calculated as:

$$B_4(M, r) = \frac{\mu}{4\pi} \left[ \frac{3(M \cdot r)r}{|r|^5} - \frac{M}{|r|^3} \right].$$

Wherein $\mu$ is the magnetic permeability of the surrounding media. For non-magnetic media, the magnetic permeability $\mu \approx 4\pi \times 10^{-7} \text{Tm/A}$.
Fig. 2 Coordinate system for IED’s localization. \( A(x, y, z) \) is the position of magnetic sensor, \( M \) is the magnetic moment of a IED.

Fig. 3 Sketch of a five 3-axies magnetic sensors(sensors 4, 10, 11, 12, and 18).

Since the Earth’s magnetic field \( B_E (50,000 \text{nT}) \) is orders of magnitude larger than \( B_A (\approx 1 \text{nT}) \), direct measurements of magnetic anomaly fields \( B_A \) from a total field \( B_T = B_E + B_A \) is complicated. Recently, some researchers use the gradiometer sensor system to reduce the effects of \( B_E \). Moreover, the gradient of \( B_E, \nabla B_E \approx 0.02 \text{nT/m} \), is more less than that of \( B_A \). So that \( \nabla B_T = \nabla (B_T + B_A) \approx \nabla B_A \), and the gradient \( \nabla B_A \) is a tensor whose matrix elements is given by[7]:

\[
G_{ij} = \hat{\delta}_i \left( \frac{1}{\mu_0} \frac{\partial}{\partial r_j} \right) [-3(\mu_0/4\pi)[M \cdot r(5r_i r_j - r^2 \delta_{ij}) - r^2 (r_i M_j + r_j M_i)]r^{-7} \quad (2)
\]

\[
\hat{\delta}_i = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad (3)
\]

Wherein the \( r_i \) terms refer to the \( x, y, z \) coordinates at the measuring point, and the gradient tensor can be represented by:

\[
G = \begin{bmatrix} \frac{\partial B_x}{\partial x} & \frac{\partial B_x}{\partial y} & \frac{\partial B_x}{\partial z} \\ \frac{\partial B_y}{\partial x} & \frac{\partial B_y}{\partial y} & \frac{\partial B_y}{\partial z} \\ \frac{\partial B_z}{\partial x} & \frac{\partial B_z}{\partial y} & \frac{\partial B_z}{\partial z} \end{bmatrix} \quad (4)
\]

2.2 Detection model

As shown in Fig. 3, the five 3-axis magnetic sensors are used to get the gradients of total field along \( x, y \) and \( z \) direction respectively. All the sensors are 3-axis fluxgate sensor, the baseline \( d = 0.3 \text{m} \) is the length of between sensor 11 and other sensors. Each sensor measures \( x, y \) and \( z \) components of magnetic field. The geometrical symmetry axis (S) is aligned with the \( x \)-direction of forward motion of the sensor array. As a result of Maxwell’s Equations \( \nabla \cdot \mathbf{B} = 0 \) and \( \nabla \times \mathbf{B} = 0 \):
The gradient tensor matrix $G$ is traceless and symmetric, and the gradient tensor can be obtained by:

\[
\begin{align*}
\frac{\partial B_x}{\partial y} - \frac{\partial B_y}{\partial x} &= 0 \\
\frac{\partial B_z}{\partial y} - \frac{\partial B_y}{\partial z} &= 0 \\
\frac{\partial B_y}{\partial z} - \frac{\partial B_z}{\partial y} &= 0 \\
\frac{\partial B_z}{\partial x} + \frac{\partial B_x}{\partial y} + \frac{\partial B_y}{\partial z} &= 0 \\
\end{align*}
\]

The scalar magnitude of the magnetic gradient tensor $G$ is given by the square root of the trace of the product $G \cdot G^T$, and the total gradient contraction is given by:

\[
C_T^2 = (\frac{\partial B_x}{\partial x})^2 + (\frac{\partial B_y}{\partial y})^2 + (\frac{\partial B_z}{\partial z})^2 + (\frac{\partial B_y}{\partial x})^2 + (\frac{\partial B_z}{\partial y})^2 + (\frac{\partial B_z}{\partial x})^2 + (\frac{\partial B_y}{\partial z})^2
\]

The quantity $C_T^2$ is a rotationally invariant and robust scalar that is not affected by changes in sensing platform orientation. Specifically, $C_T$ is a function of the distance "r" and magnetic moment $M$ [7], that is:

\[
C_T = k(\mu / 4\pi)M / r^4
\]

Recent results from Roy Wiegert [3] indicate that $k$ is a number that varies from about 7.3 for "polar" points aligned with the dipole axis to 4.2 for points on the "equator" transverse to the dipole axis. Therefore, $C_T$ can provide an appropriate way for magnetic target detection.

2.3 Localization and magnetic moment estimation model

The method of PMAS is depicted in Fig.1. The total field magnetic sensor array configuration is depicted in Fig.2. As shown in Fig.4, the twenty-one sensors are divided into five groups: group 1(sensors 2,12,13,14 and 16), group 2(sensors 3,11,12,13 and 17), group 3(sensors 4,10,11,12 and 18), group 4(sensors 5,9,10,11 and 19), group 5(sensors 6,8,9,10 and 20). The purpose of these sensor groups is to get the gradients of total field respectively. The five groups sensors array supported by a patrol can be used to get the gradients of total field at five different locations. Since the sensor 11 is embedded in the geometrical center of the sensor array, the IED’s location can be represented by $r$, $r = -r_f(x, y, z)$ . Without loss of generality, assuming that the patrol car drives along a line that parallels $x$ axis of the IED, at the time $f$, the sensor 11 is located at $A_f(x, y, z)$.

Fig.4 Sketch of localization and magnetic moment estimation model based on twenty-one 3-axis fluxgate sensors.
By using (2),(6) and the coordinate system shown in Fig.3 and Fig.4, the IED’s location \( r(-x,-y,-z) \) and magnetic moment \( \mathbf{M}(m_x,m_y,m_z) \) can be represented by the following nonlinear formula:

\[
\begin{bmatrix}
\frac{\partial B_h}{\partial x} \\
\frac{\partial B_h}{\partial y} \\
\frac{\partial B_h}{\partial z}
\end{bmatrix} = \begin{bmatrix}
3x(r_i^2-5x^2) & 3y_i(r_i^2-5y^2) & 3z(r_i^2-5z^2) \\
3x(r_i^2-5y^2) & 3y_i(r_i^2-5y^2) & 3z(r_i^2-5y^2) \\
3x(r_i^2-5z^2) & 3y_i(r_i^2-5z^2) & 3z(r_i^2-5z^2)
\end{bmatrix} \begin{bmatrix}
m_x \\
m_y \\
m_z
\end{bmatrix} .
\]

(9)

Where \( r_i^2 = x^2 + y_i^2 + z^2 \), \( y_i = y + (3 - l)d, l = (1,2,3,4,5) \). With the sampled signals of these sensor groups, the IED’s location \( r \) and magnetic moment \( \mathbf{M} \) can be calculated through an appropriate nonlinear algorithm based on the proposed mathematical model, and the magnetic moment \( \mathbf{M} \) can be used to perform classification of the IEDs.

2.3 Localization and magnetic moment estimation algorithms

In practice, the target signal is contaminated by noise. Therefore, only an approximate solution can be found. It can be found from (9) that one group sensors are the minimum to solve the 6 unknown localization and magnetic moment parameters. When \( l > 1 \), the solution is not unique. Here, we define objective error as:

\[
E_{xx} = \sum_{i=1}^{5} \left( \frac{\partial B_h}{\partial x} - \frac{\partial B_{h_i}}{\partial x} \right)^2 ;
E_{xy} = \sum_{i=1}^{5} \left( \frac{\partial B_h}{\partial y} - \frac{\partial B_{h_i}}{\partial y} \right)^2 ;
E_{xz} = \sum_{i=1}^{5} \left( \frac{\partial B_h}{\partial z} - \frac{\partial B_{h_i}}{\partial z} \right)^2 ;
E_{yy} = \sum_{i=1}^{5} \left( \frac{\partial B_{h_i}}{\partial y} - \frac{\partial B_{h_i}}{\partial y} \right)^2 ;
E_{yz} = \sum_{i=1}^{5} \left( \frac{\partial B_{h_i}}{\partial z} - \frac{\partial B_{h_i}}{\partial z} \right)^2 ;
\]

The total error is the summation of the above six errors, then the total error \( E \) can be obtained by:

\[
E = E_{xx} + E_{xy} + E_{xz} + E_{yy} + E_{yz} + E_{zz}.
\]

(10)

where \( \frac{\partial B_h}{\partial x}, \frac{\partial B_h}{\partial y}, \frac{\partial B_h}{\partial z} \) and \( \frac{\partial B_{h_i}}{\partial x}, \frac{\partial B_{h_i}}{\partial y}, \frac{\partial B_{h_i}}{\partial z} \) are defined by (9), and \( \frac{\partial B_{h_i}}{\partial y}, \frac{\partial B_{h_i}}{\partial y}, \frac{\partial B_{h_i}}{\partial z} \) are the six measured data of the \( l \)-th sensor group. We must try to obtain a solution of parameters \( p(x,y,z,m_x,m_y,m_z) \) that minimize the total error. Substitute parameters \( p \) into (10), the objective function of this optimization problem can be defined as follows:

\[
F(p) = \min_p(E).
\]

(11)

These unknown parameters \( p \) can be eventually estimated by numerically solving objective function (11). Since the Equation (10) is a high order nonlinear function of the 6-D target’s location and magnetic moment, the nonlinear least square optimization algorithm is a common method. However, as mentioned in Section 1, the nonlinear optimization method has its limitations. In this paper, we propose the particle swarm optimization (PSO) algorithm.

The PSO algorithm can be used for searching the solution within some given range for the variables. Considering the case of PMAS, we limit the parameters \( x, y \) and \( z \) within \([-20,20]\) and \( m_x,m_y,m_z \) within \([-10,10]\). Assume that \( n \) is the population size and then the \( i \)-th particle is \( X_i = [x_i,\ldots,x_{6i}] = [x,y,z,m_x,m_y,m_z] (1 \leq i \leq n) \). Each particle is updated by following two best values in every iteration. The first one is the best solution achieved so far. This value is called \( P_{i} \). Another best value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. It is called \( P_{g} \), which is a global best. For each computation, all the particles update their position by the following equations:
\[ V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \]

\[ X_i^{k+1} = X_i^k + V_i^{k+1} \]  
for \( i = 1,2,3,...n \)  
\[ (12) \]

\( V_i \) represents the velocity of the particle \( i \), \( V_i \in (-1,1) \); \( \omega \) is called inertia weight; \( c_1 \) and \( c_2 \) are accelerant constant; \( r_1 \) and \( r_2 \) are random real numbers in the range of \([0,1]\). In order to achieve the stable convergence of the algorithm, the inertia weight and the accelerant constant are set to the following equation [8]:

\[ \omega = 0.9 - \frac{k}{2k_{\text{max}}} \]

\[ 2\omega + 2 > c_1r_1 + c_2r_2 \]  
\[ (13) \]

\( k_{\text{max}} \) is the maximum number of iterations; \( k \) is the current iteration or generation number.

Although the classical PSO is a stochastic optimization algorithm based SIA, the convergence speed would become slow and fall into local optimal solutions in the anaphase. To avoid these drawbacks, we propose a improved PSO (IPSO) that utilizes the steepest descent method to accelerate the computing speed of classical PSO. The classical PSO algorithm is first used to find the unknown parameters. Then, the steepest descent algorithm is applied for further computation by using the initial parameters obtained from the classical PSO algorithm. The solution is iteratively updated as:

\[ X^{t+1} = X^t - \lambda \cdot J(X^t) \]

\[ (14) \]

Where \( J(X') \) is the Jacobian vector of the objective function \( F(p) \), define as follows:

\[ J(X') = \left[ \frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \ldots, \frac{\partial F}{\partial x_n} \right] \]

\[ (15) \]

Where \( \lambda \) is a parameter smaller than 1 and is obtained at each iteration by means of a line search procedure [9]. Iterations are stopped when the following convergence criterion is satisfied:

\[ \| J(X') \| \leq \varepsilon \]  
\[ (16) \]

Where \( \varepsilon = 10^{-12} \) is an empirical threshold.

Based on the conclusion above, we can introduce the steepest descent method to PSO to achieve high performance optimization. The concrete steps of this improved PSO are as follows:

Step1: Generate \( n \) particles with random selected positions \( X_1, X_2, \ldots, X_n \) and velocities \( V_1, V_2, \ldots, V_n \).

Step2: Evaluate the fitness of each particle based on (11).

Step3: Update individual and global best positions as below:

- The word “data” is plural, not singular. Compare each particle’s fitness with its previous best fitness (\( P_i^k \)) obtained. If the current value is less than \( P_i^k \), then set \( P_i^k \) equal to the current value and the \( P_i^k \) location equal to the current location.

- Compare \( P_i^k \) with each other and set \( P_g^k \) equal to the greatest fitness.

Step4: Update the velocity and position of the particle according to (12).

Step5: Repeat step 2 to 5, until current iteration iterative \( k \geq k_{\text{max}} \). \( k_{\text{max}} = 200 \) is an empirical threshold.

Step6: The steepest descent method uses \( P_g^k \) as initial parameter to find precision parameters according to (14), (15) and (16).

The calculation result is \( X^{t+1} \).

This approach can provide not only the good accuracy, but also the satisfactory execution speed.

3. Computer simulations of the PMAS

A dipole was used for a magnetic object to produce a series of sampled data for numerical simulation, and the ability of PMAS to detect a IED and estimate its Localization and magnetic moment was tested in MATLAB programs. To test the anti-interference ability of the algorithm, white-noise was added to the sensor signals and the noise power was adjusted according to the examined signal-to-noise ratio.

As shown in Fig.5, a IED was placed at the origin of the coordinate frame. The IED’s magnetic moment was set to be \( M = 15\text{Am}^2 (m_x = 6.5\text{Am}^2, m_y = 8.5\text{Am}^2, m_z = 10.5\text{Am}^2 \) represent projections onto the East, North and upward directions, respectively) which is approximately equivalent to that of a medium size ferrous IED. The magnetic sensors array was
moved along a South-North track, starting at $S(10m, -20m, 0m)$ and ending at $E(10m, 20m, 0m)$ sampling the magnetic field every 0.1m. The starting point distances from the IED were chosen to be twelve meters in order to correspond to the detection range (for a 15 Am$^{-2}$ target) that should be obtainable from a good fluxgate sensor system with a resolution of $10^{-11}$ T [10].

![Fig.5 Sketch of simulation for PMAS.](image)

#### 3.1 Detection range via the baseline length

As mentioned in Section 2.2, the $C_f$ can be used to indicated the IED presence. This curve peaks when the sensor array is directly inline with the IED. Threshold levels can be established to eliminate false sensing from other ferromagnetic objects. In order to investigate the length of baseline on the detection performance of PMAS, simulations of group 3 (Fig. 3) and group 6 (Fig. 6(a)) with different baseline length was performed. As shown in Fig.6(b), the results reveal group 6 has the better performance than that of group 3 for short-range detection, and increasing the length of baseline is beneficial to increase the detection range. When the measured threshold is set at $2 \times 10^{-10}$ T/m, the maximum detection range of group 6 can reach to 12 m for a 15 Am$^{-2}$ target.

#### 3.2 Localization and magnetic moment estimation errors

Several simulation tests were carried out in order to evaluate the performance of the PMAS and the proposed IPSO algorithm to localize a IED and estimate its magnetic moment within the detection range (12 m). we define two parameters, localization error ($E_l$) and magnetic moment estimation error ($E_m$) as follows:

$$E_l = \sqrt{(x_l - x_t)^2 + (y_l - y_t)^2 + (z_l - z_t)^2}$$

$$E_m = \sqrt{(m_{lx} - m_{tx})^2 + (m_{ly} - m_{ty})^2 + (m_{lz} - m_{tz})^2}$$

where $(x_l, y_l, z_l, m_{lx}, m_{ly}, m_{lz})$ represent the calculated location and magnetic moment parameters, and $(x_t, y_t, z_t, m_{tx}, m_{ty}, m_{tz})$ represent the true location and magnetic moment parameters of the IED.

Although one group sensors is the minimum to solve the 6 unknown localization and magnetic moment parameters, the noise response of one group sensors implementation might often be unacceptable. Fig. 7 shows the localization and magnetic moment estimation errors using one group (only group 3), three groups (groups 2,3,4) and five groups (groups 1, 2,3,4,5) via random noises with level 0 to 10 (10 is about 3 % full output range of the fluxgate sensors).
Fig. 7 (a) Localization error with 1 group, 3 groups and 5 groups sensors. (b) Magnetic moment error with 1 group, 3 groups and 5 groups sensors.

Fig. 8 Execution time under localization and magnetic moment estimation errors (0.3 m/1.5 Am²).

Table 1 Statistic results of the localization and magnetic moment estimation errors with the cases of one, three, and five groups 3-axis fluxgate sensors

| Number of sensor group | Localization error mean ($E_l$) (m) | Localization error standard deviation ($\sigma_{E_l}$) (m) | Magnetic moment estimation error mean ($E_m$) (Am²) | Magnetic moment estimation error standard deviation ($\sigma_{E_m}$) (Am²) |
|------------------------|------------------------------------|--------------------------------------------------------|-----------------------------------------------|---------------------------------------------------------------------|
| 1 group                 | 0.6318                             | 0.4537                                                 | 1.9094                                        | 2.0186                                                              |
| 3 groups                | 0.2645                             | 0.1895                                                 | 1.5237                                        | 1.1100                                                              |
| 5 groups                | 0.1512                             | 0.1223                                                 | 0.9018                                        | 0.6363                                                              |

Table 1 shows the mean ($E_l$, $E_m$) and standard deviation ($\sigma_{E_l}$, $\sigma_{E_m}$) of the localization and magnetic moment estimation errors with the cases of one, three, and five groups 3-axis fluxgate sensors. It can be seen that the errors are too large in the one group sensors case and the accuracy is much improved when more sensors are used. The result with five groups sensors is very satisfying.

We also test the execution time for five groups sensors. The iterative results, as shown in Fig. 8, show that the average execution time is 1.9s under condition that localization error is 0.3 m and magnetic moment estimation error is 1.5 Am². The execution time reaches about 2 second, which enable it possible for the PMAS to give a warning in real time.

4. Conclusions

The purpose of this study is to give a method of localization and magnetic moment estimation of a static ferromagnetic IED by a PMAS. The PMAS is composed of a magnetic sensor array of twenty-one, or more number of, 3-axis fluxgate sensors. In order to reduce the effects of the Earth’s magnetic field, the total gradient contraction ($C_{T}$) was used to detect the IEDs. As shown in section 3.1, the numerical simulation result shows that the long baseline is beneficial to increase the detection range, and the maximum detection range of group 6 fluxgate sensors can reach to 12 m for a 15 Am² target.

Assuming a magnetic dipole model of the IED, the problem was formulated as a nonlinear equation set. We used the IPSO algorithm to solve the equation set, and estimated the localization and magnetic moment parameters. Since the method need not know the IED’s magnetic moment in advance, it is adapt to the battlefield environment. Compared to the classical PSO algorithms, this algorithm has faster speed. The numerical simulation results show that the proposed PMAS is not only real-time, but also high-precision. For a five groups sensors array, the mean errors of localization and magnetic moment estimation are...
smaller than 0.16 m and 1.2 A m$^2$ respectively. The short execution time together with its high accuracy make the PMAS appropriate for real-time detection IEDs.

This work will facilitate the development of magnetic sensor for IED detection. In the near future, we will use the IPSO algorithm to build a real PMAS composed of the fluxgate sensor array and provide the localization and magnetic moment estimation parameters for IEDs in real time.

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