Method based on computational intelligence techniques for localization of firearms projectiles inserted into the human body, by high sensitivity magnetic measurements

J D T Jimenez and E C Silva
Department of Electrical Engineering, Pontifical Catholic University of Rio de Janeiro, PUC-Rio, Rio de Janeiro, RJ, Brazil
E-mail: ing.juandario2@gmail.com, edusilva@ele.puc-rio.br

Abstract. In modern society, one of the most frequent clinical cases involves location and extraction of firearms projectiles, usually made of lead, a non-ferromagnetic material. The development of a technique that allows the precise location of these projectiles will aid their surgical removal, which has a great relevance because it contributes directly to the increase of the survival rate of wounded patients. This work presents and discusses a new approach, based on computational intelligence techniques, aiming at locating firearm projectiles inserted into the human body, by processing the information contained in magnetic field maps. The projectile is modelled by a sphere with radius $a$, located on a search space contained in a $xy$ plane, that is situated at a distance $h$ from the sensor, along the $z$ axis. The $x$ and $y$ positions of the projectile were estimated by a windowing algorithm. In turn, the distance $h$ between the sphere and the sensor is inferred by neural network, and the radius of the sphere $a$ is estimated by a genetic algorithm. The obtained results indicate that the developed technique was capable to estimate all parameters with high accuracy and precision.

1. Introduction
The penetration of metallic foreign bodies in human tissues is rather frequent, such objects might cause discomfort or be lodged close to organs at risk of perforation, often requiring surgical removal. Currently, the location of these foreign bodies is performed by conventional radiological techniques of imaging that have several drawbacks, such as the patients and staff exposure to ionizing radiation and the need for insertion of multiple radiopaque markers in different anatomical planes. Furthermore, the positioning information obtained by those methods is limited and imprecise [1]–[3]. These positioning parameters are essential for proper planning surgical procedures, impacting directly on the success rate levels and on the overall time required for surgical removal of the foreign body.

Previous works, highlighted in literature [1]–[3], developed methods for locating ferromagnetic foreign bodies inserted into the human body, by high sensitivity magnetic measurements. The results obtained by those methods have showed that they are considerably more precise than the conventional locating techniques. Moreover, the application of those methods led to the increasing of the success rates and the decreasing of the time spent on surgical removal procedures. However, one of the most frequent clinical cases in modern society involves locating and extracting firearms projectile fragments, which are usually made of lead, a non-ferromagnetic material. Despite the lead does not have remanent field ($\mu_r \approx 1.0$), it is a good conductor of electricity ($\sigma \approx 4.55 \times 10^6$ S / m). Thus, as proposed by an initial theoretical analysis discussed in [6], the location of metallic non-ferromagnetic...
bodies can be performed by applying an alternating primary magnetic field over the object, in order to induce eddy currents [4], [5]. This work focuses on the development of a new method, based on computational intelligence techniques, to process the information contained in magnetic field maps, aiming at locating firearm projectiles inserted into the human body.

2. Methodology
The proposed location technique models the projectile by a sphere with radius $a$, located on a search space contained in a $xy$ plane, that is situated at a distance $h$ from the sensor, along the $z$ axis. The primary alternating magnetic field, applied over the search space, is generated by a solenoid. If there is a firearm projectile in this region, parasitic currents will be induced in the projectile. As shown in figure 1, those currents will produce a secondary magnetic field that is measured by a gradiometric configuration of high-sensitivity magnetic sensors, in order to improve the signal-to-noise ratio.

![Figure 1.](image)

Figure 1. Measurement arrangement proposed in this work. The solenoid generates a time-varying primary magnetic flux density $B_0$ (blue dashed line), which is applied to the search space in order to induce also time-varying parasitic currents ($I_{\text{solv}}$) in the spherical foreign body (red dashed line). In turn, such currents produce a secondary magnetic flux density $B_s$ (green dash line). Thus, the result of the gradiometric (differential) reading by the sensor elements $S_i$ and $S_2$ is composed mainly by the gradient of the secondary magnetic flux density $B_s$ [8].

An algorithm of location (Position determination module) was developed to determine the position of the projectile ($x_0$ and $y_0$) in the $xy$ plane. This algorithm was based on a windowing technique, that calculates successive averages within windows of decreasing sizes. In turn, the determination of the distance $h$ between the geometrical centre of the sphere and the sensor $S_1$ is inferred by a neural network (Depth determination module), and the radius of the sphere $a$ is estimated by a genetic algorithm (Radius determination module).

2.1. Primary magnetic flux density
The solenoid was mathematically modelled, in a simplified way, as being composed by $n$ turns, parallel to each other, each of them with the same total length $l$. In this way, it is possible to use the Biot-Savart Law [7] to determine the components of the primary magnetic flux density $B_0(\vec{r})$, $B_0(\vec{r})$ and $B_0(\vec{r})$ generated by the solenoid at any point $\vec{r}$ of the space. Assuming that the solenoid is excited by a current $I$ and considering that the length $l$ of the $n$ turns can be discretized in an integer number of segments of size $\Delta l$, it is possible to define:

$$B_{\text{in}}(\vec{r}) = \sum_{i=1}^{n/\Delta l} \sum_{j=1}^{l/\Delta l} \frac{\mu_0 l_j y_j r_{ji}}{4\pi r_{ji}^3},$$

$$B_{\text{out}}(\vec{r}) = -\sum_{i=1}^{n/\Delta l} \sum_{j=1}^{l/\Delta l} \frac{\mu_0 l_j y_j r_{ji}}{4\pi r_{ji}^3},$$

$$B_{\text{in}}(\vec{r}) = \sum_{i=1}^{n/\Delta l} \sum_{j=1}^{l/\Delta l} \frac{\mu_0 l_j y_j r_{ji}}{4\pi \left( r_{ji}^3 - \frac{l_j y_j r_{ji}^3}{r_{ji}^3} \right)}.$$
In order to model the problem as realistically as possible, the real parameters of the excitation solenoid, implemented in [8], were considered: radius of 0.01 m, 40 turns, total length of 0.07 m and the thickness of the used wire of 0.00175 m. In addition, the solenoid was excited by a sinusoidal current with 2 mA amplitude and 8 kHz frequency.

2.2. Gradient of the secondary magnetic flux density
The system implemented in [8] used Giant Magnetoimpedance sensors to perform the readings of the gradient of the secondary magnetic flux density. Those sensors have only one axis of sensitivity, which was aligned to measure the z component of the secondary magnetic field. In turn, this component is affected by the three components of the primary magnetic flux density: \( B_{0x}(\vec{r}) \), \( B_{0y}(\vec{r}) \) and \( B_{0z}(\vec{r}) \). From the mathematical foundation explained in [4-8] and knowing that the proposed measurement structure is based on gradiometric (differential) readings between two magnetic sensors \( S_1 \) and \( S_2 \), separated by a distance \( l_s \), along the z axis, and assuming that both sensors are subjected to the same primary magnetic flux density, the gradient of the secondary magnetic flux density (\( \Delta B_z \)) between them can be expressed according to the equation (4).

\[
\Delta B_z = B_z(x, y, h) - B_z(x, y, h+l_s) = \frac{3}{2} \chi B_{0z}(a, f_o)(s_z - x) \left( \frac{h}{((s_z-x)^2+(y-y_s)^2+h^2)^{3/2}} \right) - \frac{h+l_s}{((s_z-x)^2+(y-y_s)^2+(h+l_s)^2)^{3/2}} \right) \]

\[
+ \frac{3}{2} \chi B_{0z}(a, f_o)(y_s-y) \left( \frac{h}{((s_z-x)^2+(y-y_s)^2+h^2)^{3/2}} \right) - \frac{h+l_s}{((s_z-x)^2+(y-y_s)^2+(h+l_s)^2)^{3/2}} \right) \]

\[
+ \frac{B_{0z}(a, f_o)}{2} \left( \frac{2y-s_z-x)^2 -(y-y_s)^2}{((s_z-x)^2+(y-y_s)^2+h^2)^{3/2}} \right) - \frac{2(h+l_s)^2 - (y-s_z-x)^2 -(y-y_s)^2}{((s_z-x)^2+(y-y_s)^2+(h+l_s)^2)^{3/2}} \right)
\]

The factor \( V(a, f_o) \) is defined by:

\[
V(a, f_o) = a^3 \left( \frac{(2\mu_r+1)\tanh \{v(a, f_o)\}}{v(a, f_o)} \right)
\]

\[
= \frac{\mu_r-1}{\mu_r+1-v(a, f_o)\tanh \{v(a, f_o)\}}
\]

in turn

\[
v = (1 + \frac{a}{\delta})
\]

\[
\delta = \frac{1}{f_0 \pi \mu \mu_0 \sigma}
\]

where: \( B_0 \) is expressed in teslas, \( x_0 \) and \( y_0 \) are the positions of the sphere and sensor respectively, with respect to the \( x \) axis, \( y_0 \) and \( y_s \) are the positions of the sphere and sensor respectively, with respect to the \( y \) axis, \( f_0 \) is the frequency of the primary magnetic flux density, \( \sigma \) is the electrical conductivity of the sphere and \( \mu_r \) is its relative magnetic permeability. In particular, assuming that the sphere is made of lead, the following average values can be used: \( \sigma = 4.55 \cdot 10^6 \text{ S/m} \), \( \mu_r = (1.7 \cdot 10^6) \) and \( \mu = \mu_r \mu_0 = 1.26 \cdot 10^6 \text{Tm/A} \).

Using the equation (4), the gradient of the secondary magnetic flux density \( \Delta B_z \) can be estimated at any position. Consequently, in order to make the model compatible with the system developed in [8], \( l_s \) was set to 0.07 m.

2.3. Position determination module \((x_0, y_0)\)
The matrix containing the measurements of the gradient of the secondary magnetic flux density is processed by this module, in order to estimate the position of the sphere \((x_0, y_0)\) in the \( xy \) plane. The
processing methodology adopted by the developed localization algorithm can be subdivided into the following steps: **First:** Define a mask of dimension \(n \times n\), and make a sweep with this mask by all possible positions of the measurement matrix. In each position evaluated, the average value of the measurements contained in the region delimited by the respective mask is calculated and stored. At the end of the scan, it is identified in which position of the measurement matrix the mask obtained the highest average value. **Second:** A new mask with dimension \((n-1) \times (n-1)\) is defined, which is used to make a scan inside the region delimited by submatrix \(M_1\), obtained in the first step. In an analogous way, the process performed in the previous step is repeated for submatrix \(M_1\), returning a submatrix \(M_2\) with the values and positions of the mask that returned the highest average value. **Third:** This process proceeds so that the mask size is reduced at each new step, until a scan mask of size 1 x 1 is reached. The position of the 1 x 1 mask correspondent to the highest magnetic flux gradient is considered as the best estimative for the position \((x_b, y_b)\) of the centre of the conducting sphere.

2.4. Depth determination module (h)
This module aims to infer the depth \(h\) of the conducting sphere in relation to the sensor \(S_r\), located at the bottom of the excitation solenoid. The module employs a Perceptron Multilayer Neural Network designed to infer \(h\), from a set of input parameters extracted from the measurement matrix of the gradient of the secondary magnetic flux, in the neighbourhood of the position \((x_b, y_b)\) of the sphere, estimated by the position determination module. In particular, three parameters of interest are extracted:

2.4.1 Area under the curve (A). Initially, the values contained in the measurement matrix are normalized with respect to the maximum value. Then, \(y\) is fixed at \(y_b\) and \(x\) is shifted around \(x_b\), in order to identify the left \((x_{left})\) and right \((x_{right})\) points of \(x\) corresponding to the normalized value of 0.8. Next, a polynomial fitting is adjusted to the data set and the area under the curve delimited by this polynomial is then calculated, between \(x_{left}\) and \(x_{right}\).

2.4.2 Average (md). This parameter is obtained by calculating the mean of the \(\Delta B\) values contained in a sub-matrix of the measurement matrix. The sub-matrix contains only the normalized values of \(\Delta B\) greater than 0.5.

2.4.3 Standard deviation (dp). This parameter is obtained by calculating the standard deviation of the values of \(\Delta B\) in relation to \(md\), taking into account the values contained in the same sub-matrix used to infer the attribute \(md\).

2.5. Radius determining module (a)
This module uses the parameters estimated by the previous modules – sphere position \((x_b, y_b)\) and depth \((h)\) – in order to estimate the value of the radius \(a\) of the sphere, using the mathematical approach presented in equation (4) and an optimization technique based on genetic algorithms (GA). The optimization process was implemented by a genetic algorithm that seeks to identify the value of the radius \((a)\) that minimizes the error between simulated matrices of the gradient of the secondary magnetic flux density, \(\Delta B_{z,Ga}\), and the measured matrix of the gradient of the secondary magnetic flux density, \(\Delta B_{z, B}\). The GA evolves through successive generations repeating this process, until a certain stopping criterion is reached. Equation (8) presents the mathematical definition of the evaluation function employed by the developed GA, assuming that both matrices have dimension \(n \times n\), and considering that \(i\) indicates the row and \(j\) the column of the matrix.

\[
e = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| \frac{B_{zt,Ga_{ij}} - B_{zt,ij}}{B_{zt,ij}} \right|
\]
3. Results
The performance of the modules for determination of position and radius were tested for 6860 different reference matrices. On the other hand, the depth module was tested for 2899 different reference matrices. These matrices were generated for different combinations of the variables of interest: position \((x_b, y_b)\), depth \(h\) and radius \(a\). Random magnetic noise matrices were added to each primary magnetic flux density matrix, associated with a combination of \(x_b, y_b, h\) and \(a\). The random magnetic noise matrices were generated with four different intensities \((e_r = 0\%, 1\%, 3\% \text{ and } 5\%)\) of the maximum value contained in the respective primary magnetic flux density matrix.

The table 1 indicates the lower and upper limits of the frequency distribution of the errors associated to the estimative of the variables \(x_b, y_b, h\) and \(a\); called \(E_{xb}, E_{yb}, E_h\) and \(E_a\), respectively. It is also presented their respective mean values, standard deviations and range of errors, for a confidence level of 99% [9-10].

| Parameters extracted from frequency distribution of the errors associated to the estimative of \(x_b, y_b, h\) and \(a\). |
|---------------------------------------------------------------|
| Minimum (mm) | Maximum (mm) | Mean (mm) | Standard Deviation (mm) | Range of error (mm) |
|---------------|--------------|-----------|-------------------------|---------------------|
| \(E_{xb}\)    | -5           | 5         | -0.06                   | 0.964               | -2.54 \leq E_{xb} \leq 2.42 |
| \(E_{yb}\)    | -5           | 5         | -0.06                   | 0.987               | -2.60 \leq E_{yb} \leq 2.48 |
| \(E_h\)       | -2.383       | 2.574     | 0.008                   | 0.267               | -0.68 \leq E_h \leq 0.69 |
| \(E_a\)       | 0.027        | 0.033     | 0.0003                  | 0.002               | -0.005 \leq E_a \leq 0.006 |

The 6860 cases, to which the errors \(E_{xb}, E_{yb}\) and \(E_a\) were calculated, were divided into 28 subsets corresponding to specific combinations of \(h\) and \(e_r\). On the other hand, the 2899 cases, to which \(E_h\) was calculated, were divided into 13 subsets according to \(h\). The average of the absolute error of each subset was calculated and the results are presented in figures 2 to 5.

Figure 2. \(|E_{xb}|\text{mean} \) vs depth, for \(e_r\) equals to: 0\%, 1\%, 3\%, 5\%.

Figure 3. \(|E_{yb}|\text{mean} \) vs depth, for \(e_r\) equals to: 0\%, 1\%, 3\%, 5\%.

Figure 4. \(|E_a|\text{mean} \) vs depth, for \(e_r\) equals to: 0\%, 1\%, 3\%, 5\%.

Figure 5. \(|E_h|\text{mean} \) vs depth, for 0\% < \(e_r\) < 5\%. 
According to the results shown in table 1, it is noticed that the developed method is an effective tool to estimate all of the desired parameters. By observing figures 2 and 3, it can be seen that the errors $|E_{ab}|_{\text{mean}}$ and $|E_{b}|_{\text{mean}}$ tend to increase with depth $h$. In turn, by comparing the cases with the same $h$, it is verified that the errors $|E_{ab}|_{\text{mean}}$ and $|E_{b}|_{\text{mean}}$ also tend to increase with the noise intensity $\varepsilon_r$. In figure 4, it can be seen that there is a certain tendency to increase the error $|E_{b}|_{\text{mean}}$ with the depth $h$ and the noise intensity $\varepsilon_r$, however this dependence is not as strong as that observed for the errors associated with the parameters $x_b$ and $y_b$. In turn, figure 5 allows to observe that the error $|E|_{\text{mean}}$ tends to increase with depth. Consequently, in general, as expected, the accuracy of the method worsens with increments of $h$ and $\varepsilon_r$.

4. Conclusions
The localization technique herein developed is based on the use of an alternating primary magnetic field source to induce parasitic currents in the fragments of firearm projectiles. In turn, these currents induce a secondary magnetic field, which can be measured by high resolution magnetic sensors. The measurements of these secondary magnetic fields can be processed in order to infer characteristics of its source. The present work focuses on the development of processing algorithms to determine the position $(x_b, y_b)$, depth $(h)$ and radius $(a)$ of fragments of firearm projectiles, inserted into the human body, from the information contained in gradient maps of the secondary magnetic flux density.

The localization technique proposed here aims to aid the surgical extraction processes of non-magnetic metallic foreign bodies, such as lead projectiles, inserted in the human body. The proposed method does not subject the patient and medical team to ionizing radiation. It is imperative that the developed technique presents high precision and high repeatability in the determination of the parameters associated with the foreign body to be detected, in order to minimize the risks inherent to its surgical removal. The obtained results have showed that the proposed method is suitable for the intended application. The range of errors associated to the estimative of all variables were always satisfactorily small. Furthermore, the proposed technique presented high accuracy and repeatability.

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