Electrical Impedance Tomographic Imaging of Buried Landmines

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Abstract—A prototype confirmation landmine detector, based on electrical impedance tomography (EIT), that can operate under realistic environmental conditions, has been developed. Laboratory and field experiments demonstrated that it is possible to reliably reconstruct, on the scale of the electrode spacing (in width and depth), conductivity perturbations due to a shallow, buried antitank mine or similar object, in a variety of soils (black earth, clay, sand) down to depths equal to the dimensions of the object (1 to 1.5 electrode spacings, equivalent to 14 to 21 cm for a 64 electrode, 1 m × 1 m array). These represent the first EIT images of real landmines computed from measured data. Occasional problems were encountered with electrical contact in very dry soils, with excessive insertion pressure being required for reliable electrode contact. However, poor contacts could be detected and the offending probe was either reinserted or compensation was applied. A matched filter detection algorithm based on a replica of the object of interest was developed and shown to effectively reduce the false alarm rate of the detector. EIT is especially suited for wet lands and underwater, where other mine detectors perform poorly. Experiments in a water and sediment filled tank have demonstrated that detection of mine-like objects in such an environment with a submerged array is feasible. These experiments represent the first EIT measurements of targets using an electrode array submerged underwater. EIT may also have an application in locating intact mines in the berms formed by mine clearing equipment. The EIT sensor head could be made cheaply enough to be disposable and remotely inserted to improve safety.

Index Terms—Conductivity measurement, impedance imaging, impedance tomography, object detection, soil, underwater object detection.

I. INTRODUCTION

THE detection of landmines is a difficult problem that has been researched extensively since the Second World War. Virtually every technology imaginable has been studied [1]–[4] by researchers in dozens of countries. If we restrict ourselves to sensors that operate in close proximity to the landmine (“close-in sensors”), fast scanning sensors generally have high false alarm rates (FARs). For example, humanitarian demining teams using hand-held electromagnetic induction (EMI) sensors (so called “metal detectors”) typically uncover 100 to 1000 inert metal objects for every mine [5]. Some ground probing radars (GPR) have a probability of detection ($P_d$) of 0.8 with a probability of false alarm (PFA) of roughly 0.1 [1], which can correspond to a huge total of false alarms $^1$. The number of false alarms is very important in demining, since each false alarm must be treated as though it were a live mine and carefully uncovered. This is a tedious, stressful and time consuming operation.

High FARs from single sensors can be somewhat reduced by combining information from such sensors using data fusion. However, often the reduction is not sufficient to be operationally practical and sometimes detection rates also suffer. At the 1998 US GSTAMIDS (Ground STandoff Mine Detection System) trials of five prototype multisensor, vehicle-mounted mine detector systems, FARs after fusion of data from EMI and GPR arrays and infrared imagers were between 0.03 and 0.08 m$^{-2}$, for a $P_d$ greater than 0.9 [6]. For a 3 m sensor width, this corresponded to 90 to 240 false alarms per kilometer. The HSTAMIDS (Handheld STandoff Mine Detection System) multisensor hand-held mine detector, consisting of an EMI and a GPR sensor, has achieved a $P_d$ of 0.95 but with a FAR of 0.23 m$^{-2}$ [1].

Another approach to reduce FARs is to use “confirmation sensors”. These are sensors that are slow compared to the scanning sensors but reduce FARs either by detecting a property that is unique to the landmine, such as explosives, or by imaging the object. Confirmation sensors require a fast scanning detector to first find suspicious regions that require further investigation. Examples are thermal neutron activation sensors [7] which detect bulk nitrogen, nuclear quadrupole resonance detectors which detect bulk explosives [8], neutron imagers [9] and X-ray backscatter imagers [10]. All have advantages and disadvantages [1].

In this paper, we describe an instrument that when placed on the ground, uses electrical impedance tomography (EIT) to reconstruct the subsurface electrical conductivity. The subsequent conductivity image can be used to identify anomalies, such as landmines. Electrical impedance tomography is essentially an extension of the well known geoeXploration technique of resistivity surveying [11]. Conventional geoeXploration methods, such as Wenner arrays, are of little use for mine detection, since interpretation of results requires the assumption of a model which is too simple or inappropriate, such as a multilayered half-space. In EIT, electrical potentials are measured at grid points on the ground surface, for a number of current injection (excitation) sites. This ensemble

$^1$In Cambodia between 1992 and 1998, roughly 200 million items were found by demining teams [1], which would have translated into 20 million false alarms for such a GPR.
of surface potential measurements is then used to solve the associated quasi-static inverse problem to estimate the sub-surface conductivity distribution which could have caused the measured potentials.

For landmine detection, the chief advantage of the method is that it works best in wet environments, where many other electromagnetic technologies, such as electromagnetic induction (conventional metal detectors) and radars perform poorly. In special cases such as landmines buried in marshy soil or in the seabed underwater in the surf zone, or verification of berms formed in landmine clearance operations, the method may become the technique of choice. Because of the simple hardware requirements, EIT can potentially provide a low cost confirmation detector. The chief drawback to the method is the logistics of inserting probes in the ground in proximity to a mine. This may be made more acceptable by using low insertion pressure probes and by mounting on a teleoperated platform. Further, in some roles, such as surf zone landmine detection, the probes may not have to contact the soil in which the mine is buried.

EIT is not new. The feasibility of imaging the electrical conductivity of a region employing DC or very low frequency AC was demonstrated in 1978 by Lytle and Dines who used an array of electrodes surrounding the region of interest [12]. There has been a substantial amount of research aimed at biomedical imaging, with much less effort directed toward geophysical applications. Much of the research has been aimed at algorithm development and simulation. Recently, Kotre [13] has reported work on the application of EIT for underground probing and Tolmasky has done theoretical work related to the detection of landmines [14]. Both studies were based on simulations only.

Very little research has been done on the use of EIT for ground probing, particularly from the top surface. Between 1979 and 1989, DRDC Suffield directed Quantic Electrosan to investigate EIT for the detection of buried unexploded ordnance (UXO) and landmines [15], [16]. This work, which was mostly based on simulation of measurements, showed some potential for imaging buried objects whose conductivity contrasted with the surrounding medium. A number of serious theoretical and practical problems were not overcome. The research effort failed to reliably reconstruct accurate three dimensional volume conductivity images of ordnance from single sided (top surface) voltage measurements. Images were poor or convergence failed due to the ill-conditioned nature of the problem. Even when convergence did occur, computation times were very long and reconstructed images were of poor quality. The chief problem with the images was low spatial resolution, which was of the order of 10% of the diameter of the electrode array. This was somewhat problematic, since EIT relies on imaging contrasts in conductivity to distinguish mines from rocks, soil inhomogeneities and other natural anomalies. Increased spatial resolution increases the FAR. The geometry used in these studies was one that is more common to the UXO problem (depth dimension similar to horizontal dimensions). Reconstruction of the 2D case (2D conductivity distribution, measurements on 1 edge) was more successful, mostly because it was mathematically a better conditioned inverse problem.

The previous work was aimed at detecting both buried mines and UXO. Because the latter can be buried at a priori unknown depths of up to 2 m, volumes were interrogated that had roughly equal dimensions. However, UXO are really not of primary interest for EIT, since they are metallic and can be detected by more conventional means. It was observed [3] that when one restricts the problem to buried landmines, it is possible to exploit the properties of the problem, particularly the relatively shallow burial depth and low conductivity casing of plastic mines. A shallow depth makes the problem "quasi-two dimensional", which was seen in the earlier studies to be better conditioned than the three dimensional problem. The low conductivity may reduce aliasing problems found earlier with metallic ordnance caused by the high conductivity step between the soil and the metallic ordnance. Finally, depending on the number of electrodes and type of reconstruction algorithm, reconstruction times range from sub-second to several seconds, which fits the requirements for confirmation detection and possibly scanning detection of landmines.

With this in mind, DRDC Suffield and General Dynamics Canada (GDC) carried out a joint project between 1998 and 2002 to develop a prototype EIT confirmatory landmine detector that was rugged enough to ensure that the detector performance could be evaluated under realistic environmental conditions. Tests were first conducted on mine surrogates in a laboratory soil box to determine limits of sensitivity, detection depths, optimum electrode spacings (ES) and effects of different soils. Experiments on detection of real landmines and minelike objects were then conducted at DRDC Suffield. Preliminary results of this work have been reported in [17], [18]. These represent the first EIT images of real landmines computed from measured data.

One environment that may give EIT a competitive edge is the surf zone, where the electrodes may be fully submerged. However to the authors’ knowledge, EIT has not been previously used with an electrode array submerged underwater. To answer a number of questions regarding the feasibility of EIT in this role, Neptec and DRDC Suffield collaborated in 2003 and 2004 to investigate the ability of scaled electrode arrays to detect minelike objects buried in sediment in a water tank. Preliminary results of these experiments have been reported in [19].

II. The EIT Instrument

Electrical Impedance Tomography uses low-level electrical currents to probe a conductive medium and produce an image of its electrical conductivity distribution. While a pair of electrodes is stimulated, the electrical voltage is measured on the remaining pairs of electrodes. After all the independent combinations of interest have been stimulated, an algorithm using the measured data reconstructs an image of the electrical conductivity distribution within the volume. In the case of ground probing, an array of electrodes is placed on the ground surface to provide an image of the conductivity distribution below the surface. The EIT technology will detect mines buried in the ground by detecting ground conductivity anomalies. The presence of a metal or plastic mine will disturb the
conductivity distribution in the soil. The signal characteristics are based on the size, shape, conductivity and depth of the buried mine.

Fig. 1 shows the instrument. There are three major components of the EIT detector: the electrode array, the data acquisition system and the data processing application. They are described in more detail in the following subsections.

The electrode array assembly is made of two Plexiglas plates, each 12.7 mm thick, held together by 8 stainless steel support rods (9.52 mm diameter). The assembly is used to hold the individual electrode assemblies in place and to support the metal enclosure containing the data acquisition electronics. The plates are square, with dimensions of \(1\times1\) m and are held 0.15 m apart. The spacing between the electrodes is set at 0.14 m and the array is arranged in 8 rows of 8 columns. The individual electrode assemblies are spring-loaded and can move vertically between the two plates in order to comply with the terrain variations. Each electrode is made of a threaded stainless steel rod, 6.35 mm in diameter and 0.31 m in length. Most of the electrode surface is covered with a PVC tube to keep the electrode shaft electrically insulated. A stainless steel electrode tip is installed at the end of the electrode shaft. The shape of the electrode tip was designed to reach the soil top layer for commonly found soil surface covers, such as grass, weeds and hard crust. It was determined experimentally that when a force of about 6.7 N (1.5 lb) is applied over that type of electrode, a reliable electrical contact is usually established with the soil.

The data acquisition system incorporates the electronics and firmware required for the electrical stimulation of the electrodes and the recording of the resulting potentials. The electronics is housed in a sealed anodized aluminum enclosure, mounted on the electrode array structure. The EIT instrument is a high precision impedance meter. It uses four electrodes to perform a transfer impedance measurement. Two electrodes are used to inject a current \(I\) in the medium and two others to measure the potential difference \(V\) developed on the medium surface. The transfer impedance is given by \(V/I\).

A high level diagram of the data acquisition electronic circuit is given in Fig. 2. The EIT data acquisition electronics is physically partitioned into three main subsystems, namely: 1) switching logic which selects the stimulating and recording electrode configurations (active electrodes); 2) signal preprocessing circuitry, which applies gain and filters the incoming signals (interface board); and finally 3) control and measurement subsystem that generates all necessary signals for the system to work (data acquisition board). Data acquisition is performed by a DT7102 12-bit PCMCIA card\(^2\) that fits in a laptop computer. The active electrode boards and the interface board are located in the waterproof enclosure on top of the array. Each active electrode board controls up to 16 electrodes and these boards can be daisy-chained. The electronic enclosure contains 4 boards for a total of 64 electrodes. The interface board powers the active electrode boards and relays the control signals coming from the computer. It also filters the analog signals before they are sent to the data acquisition board. A battery and dc/dc converters are located inside the enclosure to provide the power. The dc/dc converter is used to provide \(\pm 12\) V for the analog circuitry. An external cable is used to recharge the battery.

The medium is stimulated with a square wave of low frequency (~1 kHz). The stimulation sequence is shown in Fig. 3. For each configuration (a set of four electrodes, stimulating and recording), a square wave is generated to excite the medium. Then \(N\) samples are collected to measure the voltage difference between both recording electrodes and \(N\) samples are collected to measure the current injected. The default number of samples \(N\) is set to 100, (50 during the stimulation on the positive polarity and 50 during the stimulation on the negative polarity). The data acquisition card is capable of a 200 kHz sampling rate.

For each configuration, transfer impedance estimates, \(Z\), are formed according to

\[
Z = \frac{V_+ - V_-}{I_+ - I_-}
\]

\(^2\)Data Translation, Marlboro, MA, USA
where $I_+$ and $I_-$ are the positive and negative stimulation currents and $V_+$ and $V_-$ are the resultant potentials. Stimulation currents are generated with respect to a common reference electrode and voltage measurements are made with respect to another common reference electrode, allowing measurements corresponding to specific electrode configurations to be reconstructed from the raw measurements. The impedance estimates are then averaged over the total number of samples. This measurement method eliminates the electrode polarization voltage that usually appears as a bias voltage on the recording electrodes. The success of the method is based on the assumption of a slow variation of polarization effects compared to the acquisition speed. When constructing the configuration sequence, care has to be taken not to obtain voltage measurements on electrodes that have been recently stimulated. This breaks the above assumption because the polarization voltage on a stimulated electrode drops off quite rapidly just after the voltage is removed and then decreases very slowly thereafter. Avoiding making a measurement with an electrode which has just been stimulated prevents the measurement from being done in the time interval where the polarization voltage varies rapidly.

The set of configurations of stimulating and recording electrodes used for the measurements are a variant of the widely used method initially proposed by Barber and Brown for EIT instruments [20]. The approach uses adjacent electrodes (both for the stimulation and recording) that provide linearly rapidly just after the voltage is removed and then decreases very slowly thereafter. Avoiding making a measurement with an electrode which has just been stimulated prevents the measurement from being done in the time interval where the polarization voltage varies rapidly.

The data processing application comprises the software required for the data acquisition, conductivity reconstruction algorithm and the target detection algorithm. Because poor electrode contact is inevitable from time to time, the data acquisition software includes a module to detect electrodes with bad electrical contact. Once identified, new reconstruction and detection matrices can be calculated. Alternatively, a faster approach is to replace the measured values at the electrodes with nominal or interpolated values. The data acquisition, conductivity reconstruction and target detection modules are hosted on a laptop computer. The conductivity reconstruction and target detection algorithms are described in the next section.

III. SIGNAL PROCESSING

A. Reconstruction Algorithm

The algorithm developed for the estimation of the electrical conductivity distribution is a linearized reconstruction based on the sensitivity matrix approach. It starts with the basic electromagnetic equations governing flow of current in an isotropic region $V$, which are derived from a quasi-static approximation to Maxwell’s equations, assuming zero volume current density, and the continuity equation for electrical current,

$$\nabla \cdot (\sigma \nabla \phi) = 0 \text{ in } V$$

$$\sigma \partial_{\nu} \phi = i \text{ on } \partial V$$  \hspace{1cm} (2)

where $\sigma$ is the electrical conductivity (a scalar, due to isotropy), $\phi$ is the potential, and $i$ is a surface current density on the boundary $\partial V$ of $V$. We wish to solve (2) for $\sigma$, given knowledge of the current source $i$ and a partial knowledge of $\phi$ (upper surface only). By reformulating the above differential equations in an integral form and then linearizing and discretizing, one obtains [21]

$$\delta Z = S \delta \sigma$$  \hspace{1cm} (3)

The $n$ elements of the vector $\delta Z$ represent the difference between the transfer impedance measurement for a given configuration of pairs of stimulators and recorders and the transfer impedance predicted by an homogeneous, semi-infinite model for the same configuration. The size of the vector is determined by the number of independent measurements used by the system. $S$ is the sensitivity matrix. Its form arises from the linear approximation and its elements are evaluated by averaging over a grid cell, the scalar product of the electric field caused by the stimulating electrodes with the electric field that would result if the recording pair were stimulated [22], [23]. The $m$ elements of the vector $\delta \sigma$ represent the conductivity perturbations (with respect to the uniform conductivity semi-infinite model) over a regular grid covering the region of interest. In practice, the vector $\delta Z$ is measured and the vector $\delta \sigma$ is desired. The latter is the solution that is referred to as the “conductivity distribution reconstruction”.

The solution to (3) requires the inverse of $S$. Since $S$ is generally not square and is very ill-conditioned, various regularization methods have been used by different groups to produce a pseudo-inverse. This includes regularization by truncation of singular values [24], by truncation of singular values along with a weighting scheme [22], and by using a probabilistic maximum a posteriori (MAP) method [25]. MAP was used as an initial approach. First $S$ is represented as a product of three matrices using singular value decomposition (SVD) [26]

$$S = U \Lambda V^T$$  \hspace{1cm} (4)

where $U$ and $V$ are square orthogonal matrices of dimensions $n \times n$ and $m \times m$, respectively. $A$ is a (generally) nonsquare...
\( m \times n \) diagonal matrix (only \( \Lambda_{ii} = \lambda_i \) elements are nonzero). The superscript \( T \) denotes the transpose of the matrix. The pseudo-inverse of \( S \) can be written as

\[
S^{-1} = VA^{-1}U^T
\]

MAP regularization consists of replacing \( \Lambda^{-1} \), given by

\[
\Lambda^{-1} = \begin{pmatrix}
\frac{1}{\lambda_1} & \frac{1}{\lambda_2} & \frac{1}{\lambda_3} & \cdots \\
\frac{1}{\lambda_1 + \mu^2} & \frac{1}{\lambda_2 + \mu^2} & \frac{1}{\lambda_3 + \mu^2} & \cdots \\
\end{pmatrix}
\]

with \( \Lambda^\# \) given as

\[
\Lambda^\# = \begin{pmatrix}
\frac{1}{\lambda_1} & \frac{1}{\lambda_2} & \frac{1}{\lambda_3} & \cdots \\
\frac{1}{\lambda_1 + \mu^2} & \frac{1}{\lambda_2 + \mu^2} & \frac{1}{\lambda_3 + \mu^2} & \cdots \\
\end{pmatrix}
\]

where \( \mu \) is defined as \( \mu = \sigma_n / \sigma_\delta \), the ratio of the standard deviation of the measurement noise to the root mean square (RMS) conductivity perturbation signal. This approach aids an intuitive understanding of the EIT reconstruction problem when it is recognised that the unit vectors from the columns of \( V \) provide a basis for the space spanned by all possible \( \delta \sigma \) vectors. The SVD decomposition of \( S \) then reveals which of these basis vectors (each of which can of course be mapped onto a 3-D grid to give basis conductivity distributions) produce the largest measurements. The strength of this coupling between perturbation and measurement is given by the corresponding singular value. The smaller the coupling between the basis vector and measurement, the worse will be the signal-to-noise problem, and the harder it will be to reconstruct a conductivity perturbation resembling that basis vector. The maximum \( a \) priori regularisation limits the effect of the poorly coupled bases while leaving the strongly coupled ones largely unaffected. The most difficult aspect of applying this reconstruction scheme is the determination of the appropriate value of \( \mu \). It is effectively the average of the perturbation signal-to-noise ratio, but this may be difficult to determine \( a \) priori.

In practice, it was found that this method could not properly determine the value of \( \mu \). We reverted to the simpler singular value truncation method, where only the \( k \) largest singular values in (6) are kept. The determination of the number of singular values to be kept was done through trial and error. A large number of singular values would produce a pseudo-inverse with potentially large noise amplification. This could be seen in the presence of spikes in the reconstructed images. A low number of singular values may result in a loss of definition of the reconstructed conductivity perturbation.

The conductivity reconstruction is now approximated by

\[
\delta \sigma \approx S^\# \delta Z
\]

where \( S^\# \) is the Moore-Penrose pseudo-inverse [22] given by

\[
S^\# = VA^\#U^T
\]

and

\[
\Lambda^\# = \begin{pmatrix}
\frac{1}{\lambda_1} & & & \\
& \frac{1}{\lambda_2} & & \\
& & \ddots & \\
& & & \frac{1}{\lambda_k}
\end{pmatrix}
\]

B. Target Detection Algorithm

Equation (8) is used as the basis of a detection algorithm that can be tuned to a specific type of mine, based on its shape and size. This is important for an EIT mine detector because the detection algorithm can reduce the number of false alarms. The mine detection algorithm is based on a matched filter (MF) approach. It consists of calculating the detector response for a replica of the size and shape of the object of interest, for a number of grid locations underneath the detector. The detector response, for a given replica, is calculated by assigning a zero conductivity to the nodes of the calculation grid that represent the size and shape of the replica. A correlation is then performed between the detector response for the replica and the actual detector response obtained from the measurements, for all the replica positions considered. The position that yields the largest correlation value is identified as the most likely position for the mine.

In what follows, we will choose the horizontal axes to be \( x \) and \( y \) and the vertical or depth axis to be \( z \). For the full scale 16 x 16 array, a grid with a resolution of 15 x 15 x 3 nodes is used for the calculations, making \( m = 675 \). This resolution is equivalent to 0.5 ES (0.07 m), in \( x \), \( y \) and \( z \). For every node \( i \) of that grid, a correlation operator is defined by the scalar product

\[
\delta \sigma_i^T \delta \sigma
\]

where \( \delta \sigma_i \) is the detector response for a replica, at position \( i \), and \( \delta \sigma \) is the detector response for the present set of measurements. Using (8), the first term of the expression 11 can be written as an approximate function of the measurement vector as

\[
\delta \sigma_i^T \approx S^\# \delta Z_i^T
\]

where \( \delta Z_i \) is the vector whose elements are the difference between the transfer impedance values calculated with the replica at position \( i \) and the transfer impedance values calculated with the homogenous model. The vectors \( \delta Z_i \) are calculated using (3) and using one unit of conductivity for the conductivity perturbation at the positions occupied by the replica on the calculation grid. Using (12) and (8) in (11), the correlation operator becomes

\[
\delta \sigma_i^T \delta \sigma = \left( S^\# \delta Z_i^T \right)^T S^\# \delta Z
\]

A detection operator \( D_i \) can now be defined using (13) for a replica at position \( i \), i.e.,
\[ D' = (S^T \delta Z_i)^T S^# \] (14)

An \( m \times n \) matrix \( D \) is then generated for every node \( i \) of the calculation grid. An \( m \times 1 \) correlation vector \( C' \) is defined by multiplying the MF \( D \) by the measurement vector \( \delta Z \), i.e.,
\[ C' = D \delta Z \] (15)

Because the MF response decreases with increasing target depth, it is necessary to provide some sort of normalization. One way is to divide \( D \) by the detector response obtained from a uniform conductivity perturbation, i.e., the response obtained after assigning a conductivity perturbation of one unit at each node of the calculation grid. The normalized correlation vector \( C \) is defined as
\[ C = (D \delta Z) / (D \delta Z') \] (16)

where / denotes element by element division of two vectors. The detector response, \( D \delta Z' \), is calculated using (3) for a uniform conductivity perturbation \( \delta \sigma' \) of one unit at each point on the calculation grid.

As previously stated, the detection calculations were done using a grid comprising 675 node points and 1698 independent measurements. For that application, \( \delta Z \) is a column vector with a size of 1698 elements, \( D \) is a matrix with a size of 675 \( \times \) 1698 and \( C \) is a column vector with 675 elements. \( D \) is pre-calculated and if there are more than one target of interest, additional operators \( D \) can be made available for each type of target. In the context of this work, the replicas were representative of the size and shape of the minelike objects used for the tests.

In the submerged electrode experiments done in the water tank (Subsection IV-C), two variants of a normalized MF detector were compared. The first used a detection operator matrix \( A \) obtained from the normalized sensor signatures in the “measurement space” \( \delta Z / \| \delta Z \| \), for a minelike object positioned at various coordinate locations under the footprint of the electrode array, i.e.,
\[ C^m = A (\delta Z / \| \delta Z \|) \] (17)

where the correlation vector \( C^m \) is an \( l \times 1 \) column vector, \( A \) has dimensions \( l \times n \), \( l \) is the number of coordinate locations and \( n \) is the number of configurations of stimulator/recorders used (256 for the underwater application). The second MF used a detection operator matrix \( B \) obtained from the normalized sensor signatures in the “conductivity reconstruction space” \( S^# \delta Z / \| S^# \delta Z \| \) for a minelike object positioned at various coordinate locations under the footprint of the electrode array, i.e.,
\[ C^e = B (S^# \delta Z / \| S^# \delta Z \|) \] (18)

where the correlation vector \( C^e \) is an \( l \times 1 \) column vector, \( B \) has dimensions \( l \times p \), \( l \) is the number of coordinate locations and \( p \) is the number of coordinate locations for which \( \delta \sigma \) was calculated (162 in this particular application). Designing a detector based on operator \( A \) has the advantage of being based on the raw independent measurements of electrical potentials and no modeling of the environment is required. A detector based on operator \( B \) requires a model of the electric field distribution in the conductive medium. One goal of the water tank experiments was to compare the performance of the two detector operators.

More sophisticated algorithms are required to handle layered and more complex media. This is a subject of on-going research.

IV. MINE DETECTION EXPERIMENTS

A. Sandbox Experiments with Subscale Electrode Array

Evaluation of the influence of various parameters on the reconstruction of the conductivity distribution was carried out in a laboratory sandbox using a subscale electrode array. The box measured 1 m \( \times \) 1 m \( \times \) 0.5 m \((x, y, z)\) and was filled with black earth or sand to a level of 0.4 m. A 5 \( \times \) 5 array was used with an ES of 8 cm. Five minelike target objects were used, namely: 1) large cylindrical plastic container (14.5-cm diameter, 7 cm thick); 2) small cylindrical plastic container (11.5-cm diameter, 5.7 cm thick); 3) aluminum cylindrical camping pot (16-cm diameter, 6 cm thick); 4) nonmetallic foam square (12.5 cm on a side, 5.3 cm thick); and 5) nonmetallic foam equilateral triangle (19 cm on a side, 5.3 cm thick). The electrode array was seated horizontally at \( z = 0 \).

Reconstruction was carried out using a 22 \( \times \) 22 \( \times \) 6 node grid \((x, y, z)\) with a grid resolution of ES/3 (2.667 cm).

Figs. 4, 5, 6 are contour maps of the estimated conductivity distribution \([-\delta \sigma \text{ from (8)}]\) obtained using the reconstruction algorithm for the nonmetallic cylinder in black earth (conductivity 15-20 mS/m) at three different depths of burial (top of mine to soil surface). Contours of constant reconstructed conductivity perturbation are plotted on an arbitrary scale. The center of the cylinder is situated at a horizontal position (0,0). The reconstruction algorithm uses a grid with 6 depth increments (2.667 cm thick). Reconstructions of the conductivity distribution can be obtained for a grid layer corresponding to any of the depth increments. The depths chosen for Figs. 4, 5, 6 were those that had the maximum detection algorithm response for each case.

Reasonable reconstructions of the conductivity distribution were obtained to a depth of 1.75 ES for a nonmetallic object of diameter roughly 2 ES and thickness slightly less than 1 ES. A small horizontal displacement of the conductivity anomaly was observed. The center of the reconstructed anomaly was seen to be displaced equally in the \( x \) and \( y \) directions from the true center, with a total displacement approximately equal to 1/4 of the depth. Similar shifts have also been noted in soil and underwater experiments using different arrays (described later), but the shifts are not consistent. The exact nature of their cause is not yet known. At shallow depths the radius of the object was slightly underestimated, while at larger depths it was slightly overestimated. This, as we shall see, is caused by an decrease (worsening) in the horizontal spatial resolution with increasing depth.

The horizontal spatial resolution is actually a function of both the reconstruction depth and the density of the electrode
array used to make the measurements. To evaluate the resolution, a simulation was performed to calculate the point spread function (PSF) by reconstructing a narrow perturbation using a pseudoinverse calculated assuming no noise and one corresponding to the typical noise levels seen in practice. The horizontal resolution was defined as the full width at half maximum (FWHM) for the response over a horizontal plane located at the same depth as the source perturbation. The depth of the perturbation was varied and the density of electrodes over a common area was varied from $3 \times 3$ to $7 \times 7$. Results of these simulations are presented in detail in [17]. In the noise-free case, there was a linear improvement in the horizontal resolution as the electrode density increased. However in the typical noisy case, the FWHM changed by only about 25% over the entire range of electrode densities and there was very little improvement in the performance beyond a $4 \times 4$ array.

For the typical noise and depths of our experiments, horizontal resolution was found to follow the approximation

$$FWHM \approx d$$

(19)

where $z = -d$ is the depth of the target object.

Similar images were obtained for the metallic cylinder in black earth, except that the reconstructed conductivity was positive instead of negative and the burial depth limit for reliable conductivity reconstruction was 1.5 ES. Reliable reconstruction of the conductivity distribution was obtained down to depths of between 1 and 1.5 ES. These results were consistent in different soil types (sand and clay) and in soils with a wide range of conductivities (1.3 - 24 mS/m). For the above depth range, reliable reconstructed images of minelike objects buried at a fixed depth have been obtained for different horizontal positions across the array ($x$, $y$ displacements up to at least $\pm 1/4$ of the array width).

Experiments carried out with the square and triangular nonmetallic targets at different orientations indicated that the shape of the objects could not be resolved, even when the object was at a very shallow depth (i.e., 0.5 ES). Although the detection algorithm response depended strongly on the size and position of the object, neither the conductivity reconstruction nor the detection algorithm exhibited a significant shape dependence.

Although good conductivity reconstructions were obtained, the reconstruction image by itself could not discriminate as well as the MF detection algorithm. The detection algorithm (16) was shown to be an effective means of reducing the number of false alarms by tuning the detector to a given object size, and possibly to a limited degree, to a given shape. The detection algorithm was shown to be capable of differentiating between the large and small plastic cylinders (separated by roughly 23 cm center to center) regardless of their relative

Fig. 4. Contour map of conductivity distribution reconstruction for a non-metallic minelike cylindrical object buried in black earth. The object is buried at 4-cm depth (0.5 ES). Reconstruction depth is 5.33 cm. Axes units are distance from the horizontal center of the object (0,0) in meters.

Fig. 5. Contour map of conductivity distribution reconstruction for a non-metallic minelike cylindrical object buried in black earth. The object is buried at 8-cm depth (1 ES). Reconstruction depth is 5.33 cm. Axes units are distance from the horizontal center of the object (0,0) in meters.

Fig. 6. Contour map of conductivity distribution reconstruction for a non-metallic minelike cylindrical object buried in black earth. The object is buried at 14-cm depth (1.75 ES). Reconstruction depth is 16 cm. Axes units are distance from the horizontal center of the object (0,0) in meters.
TABLE I
TARGETS USED IN GDC OUTDOOR EXPERIMENTS.

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Case Material</th>
<th>Diameter (cm)</th>
<th>Thickness (cm)</th>
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<tr>
<td>PM60 mine replica</td>
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<td>12.5</td>
</tr>
<tr>
<td>TM46 mine replica</td>
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<td>30.5</td>
<td>8.5</td>
</tr>
<tr>
<td>AT mine surrogate</td>
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<td>25.5</td>
<td>9.0</td>
</tr>
<tr>
<td>AT-like container</td>
<td>plastic</td>
<td>28.0</td>
<td>12.5</td>
</tr>
<tr>
<td>AP-like container</td>
<td>plastic</td>
<td>11.0</td>
<td>6.0</td>
</tr>
</tbody>
</table>

depth of burial (4 and 8 cm). Since these experiments consistently demonstrated that the detection algorithm was more robust and reliable than the conductivity reconstruction results, for the remainder of this paper only the results obtained with the detection algorithm will be presented.

B. Outdoor Tests With Full Scale Array

Preliminary performance evaluation of the $8 \times 8$ EIT detector was done in a field near GDC’s Ottawa headquarters using buried replicas of antitank (AT) landmines, an AT mine surrogate and some minelike objects, similar in size to AT and anti-personnel (AP) mines. Table I lists the dimensions of the targets. The evaluation was done over a grassy terrain with sandy soil having an electrical conductivity of the order of 2 mS/m. The electrode array was seated horizontally at $z = 0$. Reconstruction was carried out using a $15 \times 15 \times 3$ node grid ($x, y, z$) with a grid resolution of ES/2 (7 cm).

First, the performance versus depth of object burial was investigated. Figs. 7, 8 and 9 illustrate the detector performance obtained for an AT mine surrogate buried at depths of 7, 14 and 21 cm (top of mine to soil surface). The object was a circular plastic container with a diameter of 28 cm and a thickness of 12 cm. Each figure represents the intensity of the MF detection as a function of the position (m) in the $x - y$ plane. For all cases, the detector response is calculated at a grid layer located 14 cm below the electrode array.

Using minelike objects with a size of the order of two electrode-spacings (ES), reliable detections were obtained down to a range of 1.0-1.5 ES. For a 28-cm diameter AT mine, this results in a detection range of about 15-20 cm in depth, which is a practical range for AT mines. The detection of targets down to a depth of 17 cm has been successful in all cases, while the strength of the detection varies for targets buried at a depth of 21 cm and separated by 14 cm. As can be seen, the detector could readily resolve two minelike objects of diameter 2 ES buried at 1 ES and separated by 0.5 ES. The resolution of two minelike objects buried at 1.5 ES and separated by 1 ES was not successful, confirming that the resolving power of the detector decreases significantly with the depth of burial.

Measurements on buried real de-fuzed AT landmines were made at the DRDC Suffield Mine Pen facility. The first set of experiments were performed on a hard packed gravel road containing various buried landmines. The EIT detector was used to image several inert AT mines and mine surrogates close proximity. Fig. 10 illustrates the detector response for two AT minelike objects, identical to those used in the depth study above, buried at a depth of 14 cm and separated by 7 cm. (The separation distance is defined as the shortest distance between the edges of the two objects.) Fig. 11 illustrates the detector response for the same minelike objects buried at a depth of 21 cm and separated by 14 cm. As can be seen, the detector could readily resolve two minelike objects buried at a depth of 21 cm and separated by 14 cm.
Fig. 9. EIT detector response for a minelike target buried in sandy soil at a depth of 21 cm. Horizontal axes units are horizontal distance from the center of the object (0,0) in meters. Vertical axis is the detector response in arbitrary units.

Fig. 10. Contour map of the EIT detector response for two minelike targets buried in sandy soil at a depth of 14 cm and separated by 7 cm. Axes units are the distance from the horizontal center (0,0) in meters.

Fig. 11. Contour map of the EIT detector response for two minelike targets buried in sandy soil at a depth of 21 cm and separated by 14 cm. Axes units are the distance from the horizontal center (0,0) in meters.

TABLE II

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Case Material</th>
<th>Diameter (cm)</th>
<th>Thickness (cm)</th>
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<td>TMA3 AT mine</td>
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<tr>
<td>M15 AT mine</td>
<td>painted metal</td>
<td>33.7</td>
<td>15.0</td>
</tr>
<tr>
<td>PtMiBaIII AT mine</td>
<td>plastic</td>
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<td>10.7</td>
</tr>
<tr>
<td>TMA4 AT mine</td>
<td>plastic</td>
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<td>6.5</td>
</tr>
<tr>
<td>AT mine surrogate</td>
<td>plastic</td>
<td>25.5</td>
<td>9.0</td>
</tr>
</tbody>
</table>

Fig. 12. EIT detector response for a TMA3 non-metallic antitank landmine buried in natural prairie soil at a depth of 6.4 cm. Horizontal axes units are the horizontal distance from the center of the object (0,0) in meters. Vertical axis is the detector response in arbitrary units.

buried at different depths. Table II lists the dimensions of the AT mines and surrogates used for the tests. Fig. 12 shows the detector response for a TMA3 nonmetallic AT mine buried at a depth of 6.4 cm. Fig. 13 shows the detector response for a M15 metallic AT mine buried at a depth of 16.5 cm. Fig. 14 shows the detector response for a PtMiBaIII nonmetallic AT mine buried at a depth of 6.4 cm. Fig. 15 shows the detector response for a TMA4 non-metallic AT mine buried at a depth of 19.1 cm. The grass covered terrain was composed of loam with an electrical conductivity of the order of ~15 mS/m over a layer of clay. The electrode array was seated horizontally at $z = 0$. Reconstruction was carried out using a $15 \times 15 \times 3$ node grid ($x$, $y$, $z$) with a grid resolution of ES/2 (7 cm).

The EIT detector performed well on the gravel road in the DRDC Suffield Mine Pen facility, in spite of the hard soil crust, covered with small pebbles, which was thought would...
prevent a good electrode-soil contact. Most of the AT mines (TMA3, M15, PTMiBAIII) were clearly detected, down to depth of 16 cm. The response for the TMA4 buried at 19 cm was not as clear as for the other mines, the detector being at the limit of its capability for that depth. The metal M15 mine was detected (plot not shown) as a nonconductive object presumably because of its coat of paint. The same behaviour had been observed for the metal TM46 mine during the trials at GDC.

Another series of experiments was carried out along a 31-site grass-covered alley of surrogate nonmetallic AT mines and undisturbed controls, in the DRDC Suffield Mine Pen. It was found that when the measured conductivities (from the reconstruction) were below approximately 8 mS/m, the reconstructions were good. However, when the conductivity was higher than that value, there appeared to be a strong, broad return from the lower layers and the AT target responses were weaker than expected and were not well detected. These observations may actually be related, since it is possible that the broad signal was masking portions of the response of the targets. At first, it was thought that a two layer subsurface environment might be responsible for the problems encountered. The reconstruction results themselves suggest the presence of two layers of soil, having significantly different electrical conductivities. This was confirmed on retrieving some of the mine surrogates after the experiment, when visual inspection revealed two soil layers, the second starting at a depth of roughly 20-30 cm. However, measurements along the alley using an EM38 electromagnetic induction-based conductivity meter, showed constant conductivity estimates for horizontal readings of roughly 15 mS/m, while conductivity estimates for vertical readings varied from 15 mS/m to 26 mS/m along the alley. The horizontal estimates are very roughly equal to the conductivity of the top layer in a two-layer model and the vertical estimates are very roughly equal to the bottom layer conductivity. The presence of an apparently strong return at the bottom of the volume of interrogation would normally indicate a very low conductivity layer, contradicting the EM38 data. A second possibility was that the strong return was an artifact, brought about by the type of normalization used (16). However, re-analysis using a standard norm did not significantly change the results. At the time of writing, the explanation for the anomalous behaviour at this location for conductivities above 8 mS/m is unknown.

The present linear conductivity reconstruction algorithm assumes a conductivity perturbation in a semi-infinite homogeneous medium. The algorithm requires a revision in order to work properly in environments that present multiple layers of soils having significantly different conductivities. An alternative approach would be to use an nonlinear algorithm which makes no a priori assumptions about the underlying conductivity distribution. One such method is that due to

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Wexler which iteratively solves the Poisson equation while trying to simultaneously satisfy the Dirichlet and Neumann boundary conditions [15].

C. Water Tank Experiments

The objective of these experiments was to assess the capability of detecting a minelike object buried at shallow depth in underwater sediments. The shallow underwater environment is inhospitable for many sensors and also presents challenges for an EIT sensor. One aspect has to do with the presence of a double-layer environment where the sediment layer will usually be less electrically conductive than the water layer. Another aspect has to do with the volumetric reconstruction of the local conductivity distribution.

The data acquisition system was similar to that described in Section II, except that the stimulating square wave had a frequency of approximately 100 Hz. Fig. 16 shows a picture of the electrode array used for these experiments. The electrode array consisted of 16 stimulating electrodes with one reference electrode and 16 recording electrodes with another independent reference electrode, providing a total of 256 independent configurations. The electrodes were made of stainless steel and were embedded in a Plexiglas plate. The inter-electrode separation was 3.5 cm. Since the minelike objects of interest were located in the sediment layer, the design of the electrode array was critical in order to optimize the electric current density going in the sediment layer. It was particularly important to ensure that the electrodes were electrically insulated on the upper face of the plate, such that the electric current would primarily flow to and from the bottom face of the plate.

The experiments were conducted in a 50 cm × 36 cm × 30 cm (length, width, height) water tank. Fig. 17 shows the water tank filled with a layer of sand and a layer of water, with the electrode array positioned over the layer of sand. Experiments were conducted with water only and with water and sediments.

Two non-conductive minelike objects were used for this study to evaluate the discrimination capability of the detector. The first one was a 7.5 cm diameter hockey puck, while the second, smaller object was a slice from a 5 cm diameter wax candle. Both objects had a thickness of 2.54 cm, giving the candle slice an area and volume roughly half that of the hockey puck.

Three sets of experiments were done. The first set compared the performance of the MFs defined in the measurement space versus the ones defined in the conductivity reconstruction space. The second set of experiments evaluated the validity of the semi-infinite model approximation when the electrode array is submerged in water. The third set assessed the discrimination capability of the sensor. Each of these experiments will now be discussed.

The first set of experiments was done with the electrode array positioned at the surface of the water tank. The hockey puck target was used to generate detection operators A (17) and B (18) at several relative positions between the electrode array and the target, along the main axis of the tank (x-axis), at depths (water surface to top of target) of 3 and 6 cm. Once the operators were defined, an independent set of measurements was repeated with the target positioned at $x = 0$ and $z = 3$ and 6 cm. The sensitivity matrix $S$ (3) was computed using a semi-infinite model for the electric field distribution, complemented with electric images to compensate for the boundaries of the tank.

Fig. 18 summarizes the results of the MF output versus x position, for the target located underneath the center of the electrode array ($x = 0$). The vertical axis is the correlation amplitude, the dotted curve corresponding to $C^m$, obtained with operator A, and the solid curve to $C^n$, obtained with operator B. The first two graphs on the top row give the correlation amplitude for the MF at $z = -3$ cm, with the target located at $z = -3$ and $-6$ cm respectively. As expected the correlation amplitude is larger when the target is also at a depth of 3 cm. However the operator B appears better at rejecting the response of the system, when the target is buried at a depth of $-6$ cm. This performance is even more dramatic
for the MF at $z = -6$ cm, as shown by the first two graphs on the bottom row. In this case the correlation obtained from operator $\mathbf{B}$ is clearly strong for the target buried at 6 cm and weak for the target buried at 3 cm, whereas the correlation obtained from operator $\mathbf{A}$ is of similar amplitude in both cases. Since the detection of deeper targets will be more susceptible to noise, it is clear that operator $\mathbf{B}$ has a noise filtering effect when compared to operator $\mathbf{A}$. The graphs in the third column show the response obtained from both operators in the absence of a target. Operator $\mathbf{B}$ provides a very low correlation amplitude as would be expected. Overall, these results clearly show that the $\mathbf{B}$ detection operator defined in the conductivity reconstruction space is much better at filtering out the noise.

As explained in Subsection III-A, reconstruction of the subsurface conductivity distribution, whether to image it directly or to design the $\mathbf{B}$ detection operator, requires the calculation of the sensitivity matrix $\mathbf{S}$. The elements of $\mathbf{S}$ are determined by the scalar product of the electric field caused by the stimulating electrodes with the electric field that would result if the recording pair was stimulated. The computation of these electric fields requires a model. When the electrode array is positioned at the surface of a conductive medium, a semi-infinite model is usually a good initial approximation. When the electrode array is submerged, the complete model will depend on the array geometry and construction, including the presence of the cables, which could be complicated (Fig. 17).

The second set of experiments was performed to assess the deviation of the semi-infinite model from the actual measurements. The electrode array was positioned at the surface of the water and the water level was set at 16 cm. The 256 element vector of potential measurements, was compared to the vector of predicted potentials using a semi-infinite model, with images included to take the tank boundaries into account. The correlation amplitude between measured and predicted data was 0.9997. The tank water level was then increased by small increments and the potentials were measured at each new level. Fig. 19 shows the correlation amplitude between the measured and predicted potential vectors versus the water level above the electrode array.

The data show a correlation amplitude of about 0.998 with 12 cm of water above the array, the maximum that the tank could hold. This means that the semi-infinite model is still a very good approximation. Fig. 19 suggests that the correlation amplitude is approaching an asymptotic value, indicating that the semi-infinite model approximation would eventually become depth-independent. This is not unexpected because the electrode array is made of a Plexiglas plate that acts as an electrically insulating plate. Low intensity electric currents going around the plate cause the small departure from the semi-infinite model. Extending the insulating plate further away from the electrodes could minimize this effect even further.

A third set of experiments was done using a 6-cm water layer on top of a 22-cm sediment (sand) layer as shown in Fig. 17. The hockey puck and candle slice were used to assess the ability of the sensor to detect and discriminate minelike objects buried at shallow depths in the underwater sediments.

An operator $\mathbf{B}$ was defined for each one of the objects. The electrode array was positioned underwater, just on the surface of the sediment layer. The hockey puck was buried at depths of 3 and 6 cm in the sediment and the sensor response in the conductivity reconstruction space was acquired for several positions along the $z$ axis, the main axis of the tank. Equation (8) was used to compute the $\delta \sigma$ vector and construct the operator $\mathbf{B}$. A semi-infinite model for the electric field distribution was used to compute $\mathbf{S}^{\infty}$. The same process was then repeated for the candle slice.

Using data collected with the electrode array positioned over the sediment layer, in the absence of a buried target, a correlation amplitude of 0.994 was obtained between the measured potentials vector and the predicted potentials vector, using a semi-infinite model. This relatively high correlation...
the soil and the electrodes is immediate, reliable and can be achieved with minimal pressure. The electrode shape is not critical. It was found that using a force of about 6.7 N (1.5 lb) over a pointed electrode is sufficient in most cases to achieve a good electrical contact for more difficult soil surfaces, such as ones with a hard crust and vegetation cover.

Reconstruction of the underlying conductivity anomalies was generally successful in a number of different soil types at target burial depths of between 0.5 and 1.75 electrode spacings (ES) for targets of 2 ES diameter and 1 ES thickness, although some problems were experienced in the two layer soil site at DRDC Suffield. A nonlinear reconstruction algorithm could solve this latter problem. The spatial resolution was found to be roughly equal to the target burial depth for the range of depths and geometry of these experiments. Increasing the electrode density would offer a slight improvement, particularly in a low noise environment. The reconstruction of the conductivity distribution of metallic mines behaved the same as for nonmetallic mines, except for a sign reversal of the conductivity.

The MF detection algorithm provided better detection results than examination of the reconstructed conductivity reconstruction, due to the a priori knowledge provided by the filter. Detection of objects with diameters of 1 ES was problematic. For the present geometry, objects of diameter 2 ES correspond to size to AT mines, whereas those of diameter 1 ES correspond to AP mines.

The detection and discrimination of minelike targets buried in a sediment layer underwater using a submerged electrode array was found to be feasible. Three main concerns turned out not to be problems: 1) operating a submerged electrode array; 2) being able to inject sufficient current into the normally less conductive sediment layer; and 3) possible lack of validity of the uniform half space model for the unperturbed conductivity distribution. An MF detector operator derived in conductivity reconstruction space performed better than an MF detector operator derived in measurement space. The disadvantage of the former operator is that a model for the unperturbed conductivity distribution is required.

VI. CONCLUSIONS

A prototype confirmatory landmine detector, based on EIT, that is capable of operating under realistic environmental conditions has been developed. Laboratory and field experiments demonstrated that it is possible to reliably reconstruct, on the scale of the ES (in width and depth), conductivity perturbations due to a shallow, buried antitank mine or similar object, in a variety of soils down to depths equal to the dimensions of the object (1 - 1.5 ES or ~14 - 21 cm for a 64 electrode, 1 m × 1 m array in black earth, clay and sand). These represent the first EIT images of real landmines computed from measured data. An MF detection algorithm based on a replica of the object of interest was developed and shown to effectively reduce the FAR of the detector. Occasional problems were encountered with electrical contact in very dry soils, with excessive insertion pressure being required for reliable electrode contact.

EIT requires an electrode-soil contact in the proximity of the target object. Electrical contact cannot be assured in all type
of environments. However, poor contacts can be detected, as is done for the present instrument, and one can either reinsert or compensate for the offending probe. For explosive objects, such as landmines, the proximity of probe to target may be an operational concern. Teleoperation can alleviate this concern and certain specialized roles may eliminate the requirement. One such special niche is mine detection in environments such as beaches, ocean littorals and other wet areas, where EIT works at its best, soil contact may not be required and other detectors perform poorly. Experiments described in a water and sediment filled tank have demonstrated that detection of minelike objects in such an environment with a submerged array is feasible. These experiments represent the first EIT measurements of targets using an electrode array submerged underwater. EIT may also have an application in locating intact mines in the berms formed when mine clearing equipment neutralizes and removes mines. Most mines in such berms are already inert, reducing the likelihood of an initiation when inserting the sensor head. Further, the EIT sensor head could be made cheaply enough to be disposable and remotely inserted to improve safety.

Ongoing research is investigating the use of nonlinear iterative reconstruction algorithms to improve imaging and detection performance and improvements to the hardware and software to enhance signal to noise ratios.

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REFERENCES


