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Enhanced Interpretation of Magnetic Survey Data using Artificial Neural Networks: a Case Study from Butrint, Southern Albania

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ABSTRACT The classical city of Butrint in southern Albania embodies over three millennia of settlement history. A Roman colony was established sometime after 31 BC, which led to the expansion of the city southwards onto a low-lying floodplain where settlement continued well into the late antique period.

In this paper we describe the results of a detailed magnetometry survey undertaken to investigate Roman settlement upon the floodplain. The study included the use of multilayer perceptron neural networks to further process the magnetic data and derive estimates of feature burial depths, allowing a three-dimensional reconstruction of buried subsurface remains to be made. The neural network approach potentially offers several advantages in terms of efficiency and flexibility over more conventional data inversion techniques. The paper demonstrates how this can lead to an enhanced interpretation of magnetic survey data, which when combined with other geoarchaeological data can provide a clearer picture of settlement evolution within the context of landscape change. The value of this processing technique is also evident within the context of cultural resource management strategies, which potentially restrict more intrusive methods of investigation. Copyright © 2004 John Wiley & Sons, Ltd.

Key words: Butrint; Albania; artificial neural network; multilayer perceptron; magnetic prospection; three-dimensional modelling; depth estimation

Introduction

The classical city of Butrint, Southern Albania, occupies a coastal location upon the eastern shore of the Straits of Corfu. Settlement dates back to the Archaic period (ca. eighth century BC) and Butrint had become a fortified trading post by the sixth century BC (Ugolini, 1937). By the first century BC the city had grown into an important urban centre and soon after the defeat of Mark Antony at Actium, ca. 31 BC, Emperor Augustus succeeded in establishing a colony at Butrint. The archaeological record shows extensive construction in and around the existing city at this time and the settlement of the adjacent floodplain, which is the focus of the current geophysical investigation.

Butrint is located upon a small limestone promontory (Figure 1) jutting out into a lagoonal lake; the remnants of a former coastal embayment. Like many coastal sites in the Mediterranean, valley infilling in the late Holocene has led to the formation of a large deltaic floodplain surrounding the southern and western flanks of the settlement, which is today over 2 km inland.

A number of topographical and geophysical surveys conducted over the past few years have shown that the reorganization of the settlement

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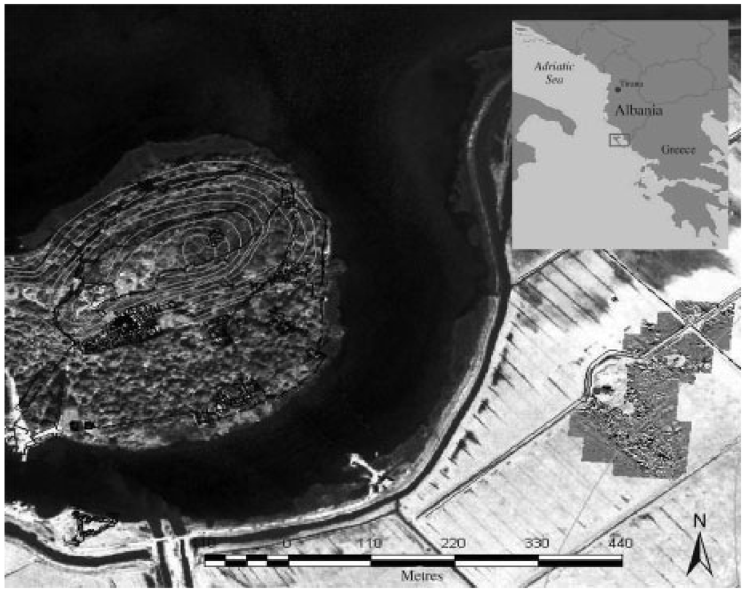

Figure 1. Aerial view of the classical city of Butrint showing the location of the current geophysical survey. Satellite image ©DigitalGlobe.

during the establishment of the colony led to the expansion of the city southeastwards on to the floodplain, adding over 2.5 ha to its overall size (Stevens, 2001; Hounslow and Chroston, 2002; Chroston and Hounslow, forthcoming). This phase of settlement was later abandoned sometime after the sixth century AD and continued accretion of the floodplain has led to the burial of surviving remains by over 1 m of alluvial deposits.

The current study presents a detailed investigation of the main concentration of settlement upon the floodplain. Data processing techniques utilizing artificial neural networks are used to further process the magnetic data in order to derive estimates of burial depth and target geometry of detected features. The archaeological site at Butrint was inscribed as a World Heritage site in 1992, and the area of protection enlarged in 2000 to encompass much of the alluvial plain upon which the current study is focused. The protected nature of the site and limited potential for excavation as a result of hydrological conditions has highlighted the importance of geophysical remote sensing techniques. One of the motivations for numerically extracting a higher level of information from geophysical data is, therefore, to maximize the amount of knowledge relating to the site as a cultural resource within the landscape. This information not only has intrinsic archaeological value, but is also vitally important to the ongoing management strategy of the cultural landscape in terms of current and future land-use.

The geophysical survey

The current geophysical survey covers an area of ca. 3.7 ha encompassing a dense concentration of magnetic anomalies located by previous surveys upon the plain (e.g. Stevens, 2001; Hounslow and Chroston, 2002; Chroston and Hounslow, forthcoming). The location of the survey in relation to the wider cityscape is shown in Figure 1. The survey was conducted using a Geometrics G-858 magnetometer measuring vertical gradient, with a sensor separation of 1 m. The magnetometer was mounted upon a wheeled cart, which provided added positional accuracy of the sensors and proved ideal for the terrain. The survey was undertaken within the constraints of a grid of 20 by 20 m squares, with measurements being taken at an average of 0.25 m intervals along lines spaced 0.5 m apart. The survey grid was orientated north–south. Access to the western portion of the study area was restricted by vegetation and the presence of extant building remains. Elements of a network of modern drainage ditches also dissect the study area.

The results of the survey are shown in Figure 2 and the corresponding archaeological interpretation in Plate 1. It can be seen that the survey results reveal a fairly clear map of surviving subsurface elements, showing the overall plan of the settlement and the layout of a number of individual buildings and possible streets.

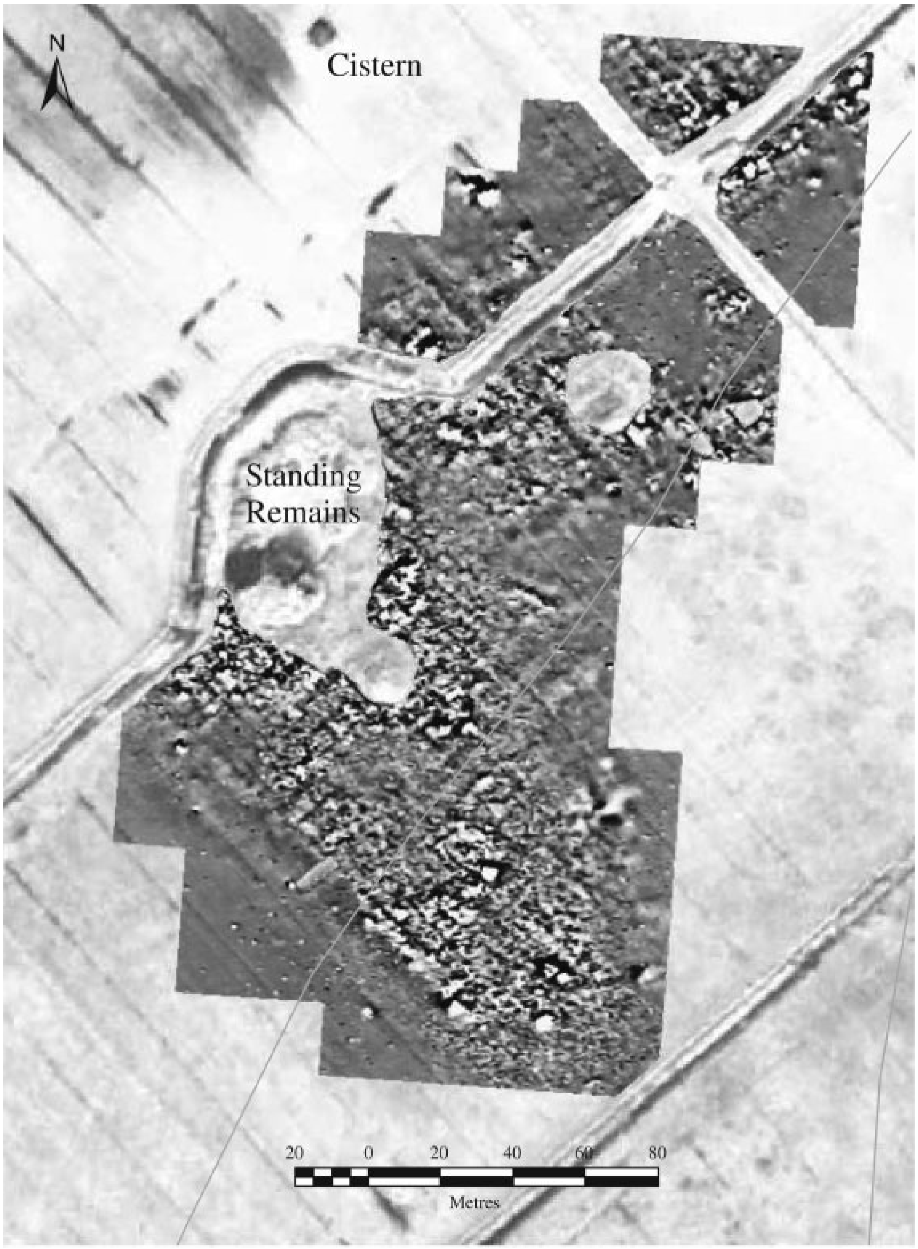

Figure 2. Magnetic survey results.

Building outlines are generally recorded as linear negative anomalies (shown black in the greyscale plot), often strongly contrasted by larger, more diffuse positive anomalous responses. The negative linear responses result from surviving wall elements of predominantly limestone construction (i.e. non-magnetic structures), and the associated positive anomalies are due to magnetic material such as fired clay brick and tiles filling adjoining spaces (see below). Similar magnetic responses from Roman building remains have been recorded at Wroxeter (Gaffney *et al.*, 2000) and at Falerii Novi in the Tiber Valley (Keay *et al.*, 2000).

The detected settlement remains appear to follow a northwest–southeast alignment, respecting that of the aqueduct remains, which cross the plain from a source ca. 10 km higher up the valley, running through the main area of settlement as indicated in Plate 1. This orientation is likely to reflect the original alignment of the colony, although the earlier settlement layout of gridded *insulae* is likely to become increasingly obscured by later phases of construction. The southwestern edge of the settlement was apparently bounded by a channel, no longer visible upon the surface, but which possibly provided the opportunity for some form of quayside. The broad linear feature running northwest–southeast, parallel to the line of the aqueduct is thought to have been a canal, the remains of which were examined within the section of the modern drainage ditch which cuts though the site.

A number of fairly coherent building plans can be seen in the southwest portion of the settlement, one of which is dominated by a large square open-space or peristyle measuring ca. 27 by 27 m. Immediately northeast of the peristyle, there appears to be a centrally located rectangular building, defined by a strong set of negative magnetic anomalies, which could be interpreted as a *triclinium*. The extensive range of buildings to the southeast are also well defined within the survey. Together, the overall plan of these buildings might well be interpreted as a large late-Roman town house or *domus*, of which there are numerous examples, such as the 'Governor's Palace' at Aphrodisias and the 'Palace of the Dux' at Apollonia (Ellis, 1994), that follow a similar layout.

Figure 3. Excavated test trench showing surviving limestone wall section.

Ground-truth data

In order to understand the results from the magnetic survey, a number of small test trenches targeted over specific magnetic anomalies were excavated (see Figure 3). Wall elements of predominantly limestone construction were found to be the dominant surviving archaeological feature and to be responsible for the linear negative magnetic anomalies recorded in the survey. The Roman ground level was found to be ca. 1 m below the current surface, and wall sections survive to a height of up to 0.6 m. The 'visibility' of these wall features is often enhanced by an infilling layer of brick and tile, providing a strong magnetic contrast. Columns of soil samples were taken from exposed sections and magnetic susceptibility and remanence measurements undertaken. The magnetic susceptibility of the alluvial soils was found to range between 20 and 40 $\mathrm{SI} \times 10^{-8}$, which is fairly typical for alluvial soils (cf. Graham and Scollar, 1976). Soils were also found to exhibit a low remanent magnetic intensity, with values of ca. 36×10^{-8} Am^2; unlikely to have any adverse effect upon the magnetic survey measurements. Similar measurements were also performed on a range of building materials. Although the ubiquitous limestone blocks exhibited no significant magnetic properties, fragments of *hypocausis* tile showed a large remanent magnetic effect, with magnetic intensities reaching 715×10^{-8} Am^2.

Data processing using artificial neural networks

Previous analysis of the magnetic survey data at Butrint has been based on attempts to recognize

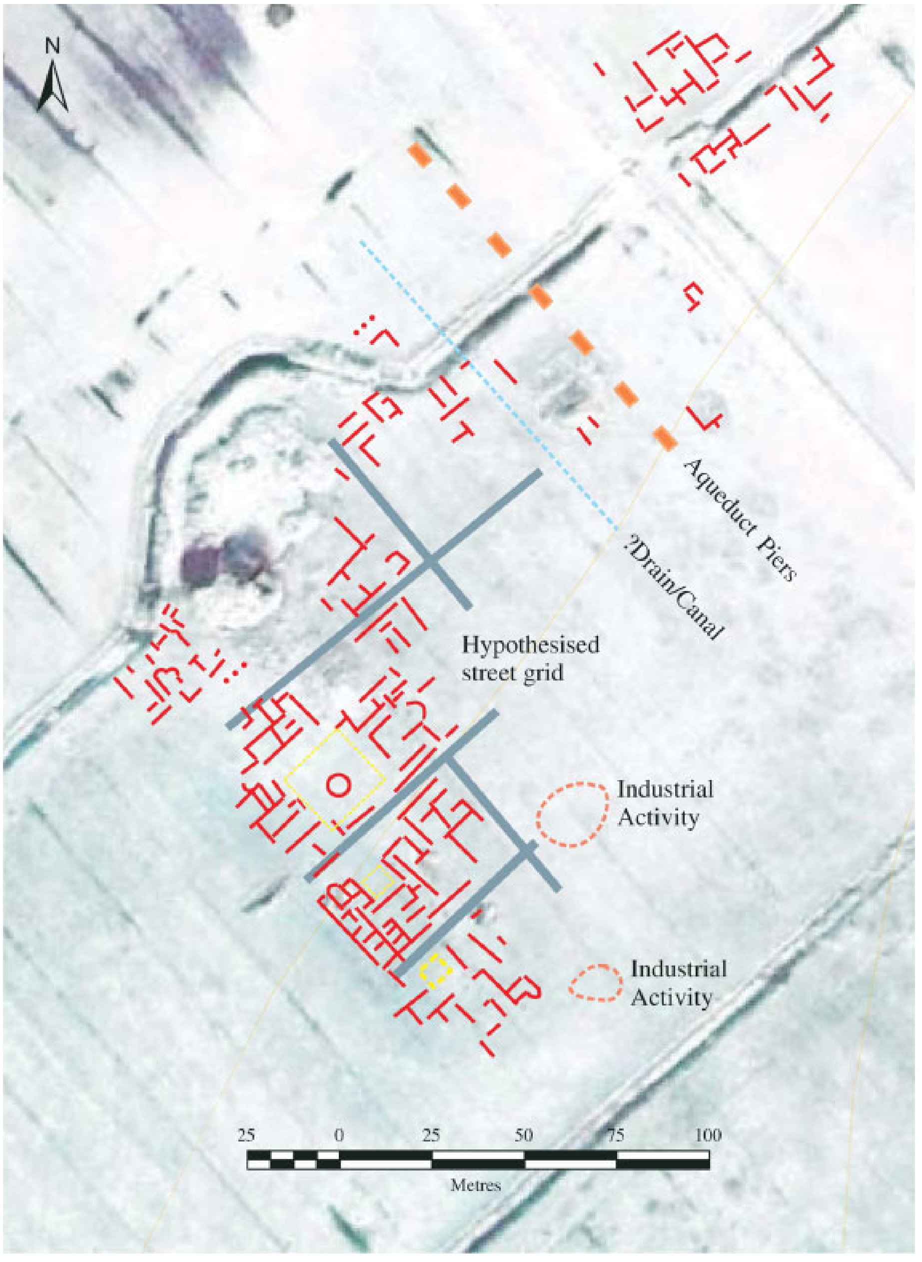

Plate 1. Basic interpretation of geophysical results, showing principal wall alignments.

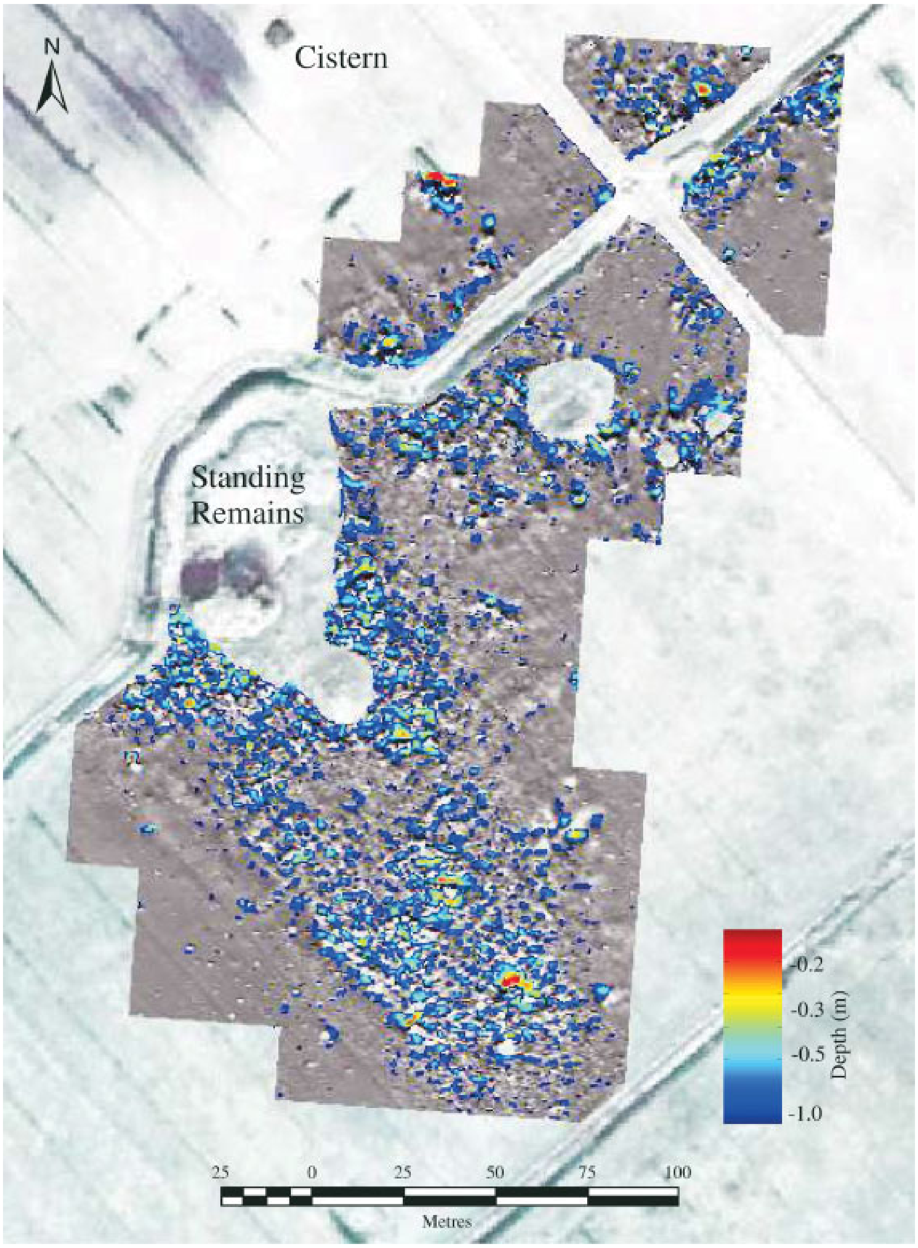

Plate 2. Predicted burial depths of wall remains, overlain onto the magnetic survey data.

and interpret anomaly alignments (see Hounslow and Chroston, 2002). The aim of the current study is to provide an enhanced interpretation of the magnetic survey data by creating an easily interpretable subsurface representation of detected archaeological remains of interest. The problem is, therefore, one of inversion, which traditionally is achieved by calculating a magnetic model of causal source structures. This usually consists of a regular array of homogeneous dipole sources or blocks having specified values of magnetization, simulating archaeological features (e.g. Scollar, 1969; Li and Oldenburg, 1996). The determination of a final subsurface model for a given set of magnetic survey measurements is then achieved by adjusting the magnetization and/or distribution of the dipole sources until a satisfactory approximation of the measured data is achieved (Doneus *et al*., 2001). The reconstruction problem is therefore one of optimization, which can be solved by a wide variety of iterative optimization algorithms and global search methods (Eder-Hinterleitner *et al*., 1996; Herwanger *et al*., 2000). Plausible models are achieved by imposing a number of *a priori* constraints, often derived from ground-truth data, thus getting around the problem of non-uniqueness. In practice, achieving a suitably realistic model can be extremely dificult, especially where a number closely spaced, magnetic sources give rise to complex anomalous responses. Significant levels of noise within the data caused by smaller magnetic bodies within the overlying layers, such as scatters of building material debris within the plough-zone, further complicate the modelling procedure. Additionally, when the survey area to be modelled is large, the computational costs of the inversion become extremely high and impractical in the majority of cases.

The work presented within the current study takes a fundamentally different approach to the modelling problem by utilizing artificial neural networks to learn the non-linear mapping between the measured survey data and the required subsurface parameters. Artificial neural networks have been successfully applied to a number of geophysical problems in this way, including parameter estimation, classification, filtering and optimization (Poulton *et al*., 1992; Sheen, 1997; Van der Baan and Jutten, 2000; Calderón-Macías *et al*., 2000; El-Qady and Ushijima, 2001). The adoption of the neural network approach holds several advantages over more conventional modelling techniques, allowing the effective solution of non-linear problems from complex, incomplete and noisy data. The computational expense of the inversion using neural networks, being dependent upon the dimension of the space of unknown parameters rather than the physical dimensions of the model space, is also comparatively low (Spichak and Popova, 2000).

The multilayer-perception (MLP) network

For this study, we adopt the multi-layer perception network architecture, which has become a popular choice for solving many non-linear problems (Bishop, 1995). Data processing using this type of network can be viewed as mapping from a set of input variables $x_1, \ldots, x_d$, which in this case represents a vector of magnetic field strengths $\boldsymbol{x}$, to a number of output variables, y_k, where k is the number of required source parameters. This is achieved through adopting a massively parallel connectionist architecture (Jang *et al*., 1997) of simple processing units; the basic functioning of which was originally inspired by the biological neuron. The strength or *weight* of the interconnections between processing units within the network determines the overall flow of data and these can be adjusted to optimize the mapping. The problem of determining optimal connection weights is solved by using a data set of *training data* (Bishop, 1995).

The mapping performed by the neural network can be illustrated in terms of a mathematical function that contains a number of adjustable parameters, with values that are determined through the use of the training data (Bishop, 1995). Such representative functions could be written in the form

$$\boldsymbol{y} = \boldsymbol{y}_k(\boldsymbol{x};\, \boldsymbol{w})$$

where $\boldsymbol{x}$ is the vector of input variables and $\boldsymbol{w}$ denotes the vector of adjustable parameters, or *weights* within the network. A training process is then applied to determine the values of the weight parameters on the basis of the training data set (Bishop, 1995). For a training set with n elements, each data pair consists of a vector of inputs $\boldsymbol{x}$, denoted by $\boldsymbol{x}^n$ and the corresponding desired value for the output y, which can be denoted by t^n, where n is the number of patterns in the training set. These desired outputs are known as *target* values in the neural network context (Bishop, 1995). The training procedure can be seen as a process of minimizing the error, E, between the desired output t^n for a particular input x^n and the corresponding value predicted by the network, through choosing suitable values of $\boldsymbol{w}$. This process is often referred to as *supervized learning* (Bishop, 1995). The error, E, is based upon a sum-of-squares error function with a minima that is determined by a form of gradient descent optimization. The process of adjustment is repeated until the network output and the training data targets are similar for all the training pairs in the training data. The network is then said to be trained and can be used to map or invert magnetic data for which the corresponding source parameters are not known.

Choice of parameters

The distinctive negative magnetic responses caused by buried limestone wall features makes them an obvious choice for further data processing or inversion. In terms of deriving source parameters, from an archaeological perspective depth of burial below the surface is potentially one of the most useful, giving information that can be linked to settlement phases, depositional environments and soil erosion. It was therefore decided to focus upon using the neural network routines to predict the burial depths of wall features detected within the magnetic survey.

To be able to accurately resolve wall positions and depths from the survey data, it is necessary to consider a number of magnetic field strength values simultaneously. This can be achieved by sequentially parsing an input grid or 'window' over the input data, where the magnetic field strength values derived from the input window form a matrix of values input into the neural network as a vector. The corresponding network output represents a depth value below the centre of the input window. A sequence or grid of depth predictions, made as the input window is parsed over the input data, allows a three-dimensional subsurface representation of detected wall elements to be made.

Network training and data processing

Suitable training data for the neural network were generated through the three-dimensional forward modelling of magnetic responses for a number of models representing buried wall sections of a variety of types and burial depths. These training models were based upon known archaeological examples recorded within the test trenches and included wall elements with gaps, abutting sections and stepped sections. Model parameters were based upon the magnetic susceptibility measurements of samples taken during the test excavations, allowing a realistic layered earth model to be produced within which the wall elements were modelled. The resulting anomalous magnetic field was calculated over a grid at 0.5 m intervals over the model surface, and at observation heights of 0.3 and 1.3 m, allowing the vertical gradient to be calculated. Noise sampled from the magnetic survey data was also added to the training data to create a more realistic response, following the method outlined by Scollar (1970). In addition, a range of training data representing unwanted magnetic responses, such as those caused by modern land drains, were added to the training data set, with corresponding null target data. This effectively encourages a filtering function by the network, in which only magnetic responses represented in the training data are considered.

Data were input into the network as a vector of 25 magnetic field values, representing measurements over a 2 by 2 m horizontal area, i.e. at a resolution of 0.5 m. This was found to be an optimal trade-off between input window size, the number of input values (which dictates the complexity of the network) and the horizontal resolution of the input data. The input window was then parsed sequentially over the area of input data at 0.5 m steps to generate a sequence of input vectors $\boldsymbol{x}^n$. For network training, the corresponding target data consisted of a single value representing the depth below the surface to the modelled wall features. The network architecture therefore consisted of 25 inputs, an initial hidden layer of 16 neurons (capable of being pruned during training to reduce network complexity) and one output. A second auxiliary output was added to the network giving the variance of the predicted output, providing error bars to indicate the uncertainty of network predictions (Nix and Weigend, 1994).

Pre-processing of the network input data was also undertaken to make it invariant under rotation. This was necessary to avoid an excessively large training data set, which would be required to represent all possible wall orientations. By transforming the magnetic input data into a rotationally invariant form, only one orientation of wall essentially needs to be modelled. A reduction-to-pole operator was first applied to the data, adding overall symmetry to the magnetic anomalies represented, following Gunn (1975). Rotational invariance was then achieved by calculating the corresponding ninth-order Zernike moments of each input window of data, following Prismall *et al.* (2002). Zernike moments are constructed using a set of complex polynomials, which form a complete orthogonal basis set and possess very little information redundancy but having a high robustness to noise (Teh and Chin, 1988; Kim and Kim, 2000).

Results

The trained neural networks were initially evaluated and optimised using forward modelled synthetic test data, based upon the plan of buried wall elements from an excavated Roman town house recorded at Butrint, shown in Figure 4(a).

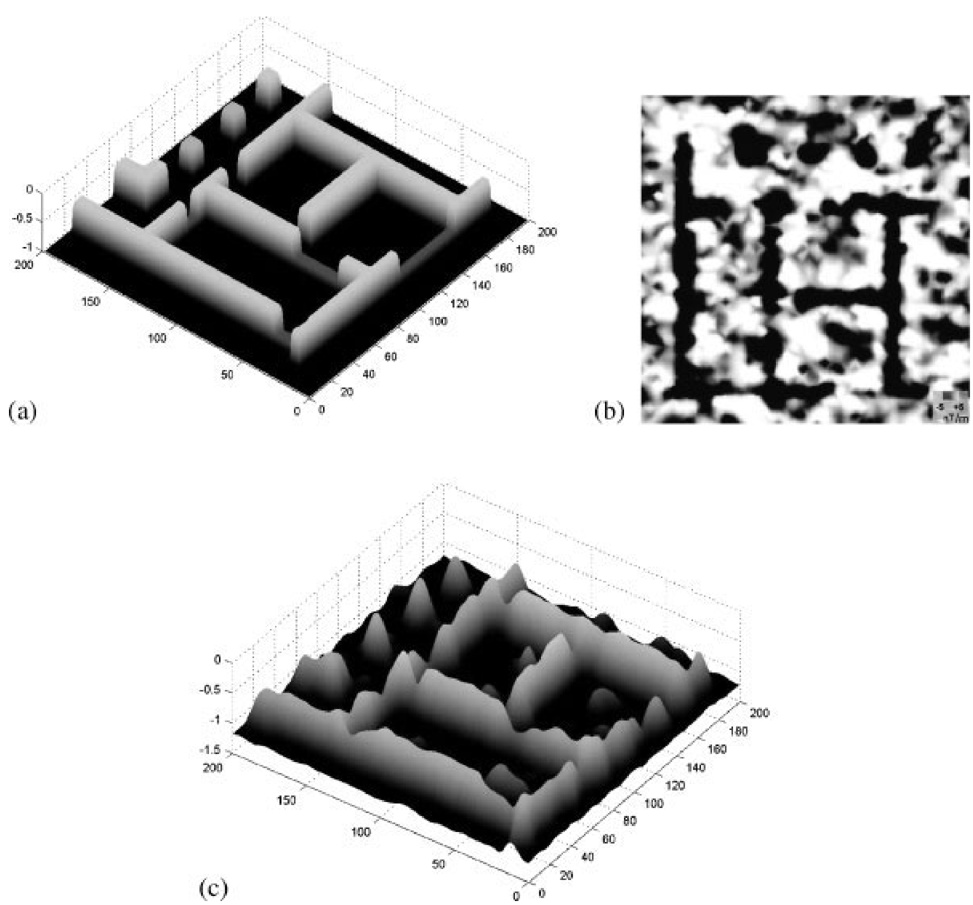

Figure 4. Forward modelled synthetic test data and corresponding network output. (a) Synthetic test data of buried wall sections used for network testing. (b) Corresponding forward modelled magnetic response of test data. (c) Network output showing predicted depth and shape of sub-surface features within test data.

Noise sampled from the magnetic survey data was again added to the forward modelled results for realism. The resulting synthetic magnetic data are shown in Figure 4(b) and the output from the network is shown in Figure 4(c). The root mean square (RMS) error for the network output, calculated by comparing the difference between the predicted results and the model data, was found to be 0.25 m, which compares well with the associated level of error predicted by the network.

Instead of using just one neural network to predict the burial depths of detected wall features, distinctly better results were achieved by combining the outputs of a number of identically trained networks. The use of what is known as a *committee* of networks has been found to offer improved overall generalization characteristics over a single network when processing new data, because networks generally converge to a local minima in error space during training and not a global error (see Bishop, 1995). Magnetic data were therefore processed using five networks, and their outputs combined by a weighted mean dependent upon the prediction errors associated with each network in the committee.

Once optimized using the synthetic test data, the committee of networks was applied to the magnetic survey data shown in Figure 2. Plate 2 shows the predicted depths of wall features overlaid onto the original magnetic data, while Figure 5 shows the same data displayed as a shaded relief plot, giving the three-dimensional, subsurface representation of predicted wall remains. It can be seen from the results that the committee is able to make realistic predictions for a number of limestone wall elements detected within the magnetic survey data. The majority of the predicted walls appear to be buried quite deeply at below −0.5 m, although there are also clusters of building remains with more shallow burial depths, i.e. within −0.25 m of the current surface. The relief plot of predicted subsurface remains in particular (Figure 5) shows an overall clarity over the original magnetic survey data giving a much less cluttered picture of the general settlement layout. The in-built discriminatory ability of the network to respond to anomalies representing predominantly limestone wall features, while being insensitive to other anomalous responses, seems effective when processing data at this spatial scale. It can be seen that in some cases the committee has made predictions for small discrete anomalies not likely to be associated with wall features, such as those recorded within the magnetically quiet area forming the southwest portion of the survey beyond the limits of the settlement. The anomalies interpreted as industrial activity above have also confused the committee. The limited amount of ground-truth data available within the excavated test trenches indicated an RMS error of 0.23 m between the predicted and excavated wall features.

Settlement burial depth and environmental change

It can be seen from the predicted results that the burial depth of remains in the western portion of the survey area, interpreted archaeologically as representing the remains of a large, late Roman townhouse or *domus* complex, are often significantly more shallow, many elements being within 0.5 m of the current ground surface. For a multiphase urban settlement, it generally would be expected stratigraphically that later phases would have a shallower burial depth, although this does not necessarily preclude the shallow survival of earlier phases of build. In particular, the rectangular building plan northeast of the peristyle, interpreted as a large hall or *triclinium*, has a consistently shallow burial depth, perhaps indicating that these seemingly later phases of settlement were preferentially sited at this location within the settlement.

A subsequent geoarchaeological investigation in the form of a transect of boreholes along the northwestern edge of the survey area indicated that the bulk of the settlement within this portion of the survey was constructed upon a gravel ridge, forming a topographically elevated headland. One of the most likely explanations for the observed clustering of later settlement remains might be that surrounding, lower lying areas became susceptible to flooding as a result of either overbank floods or rising groundwater levels (see Brown, 1997, Chapter 8). An increased

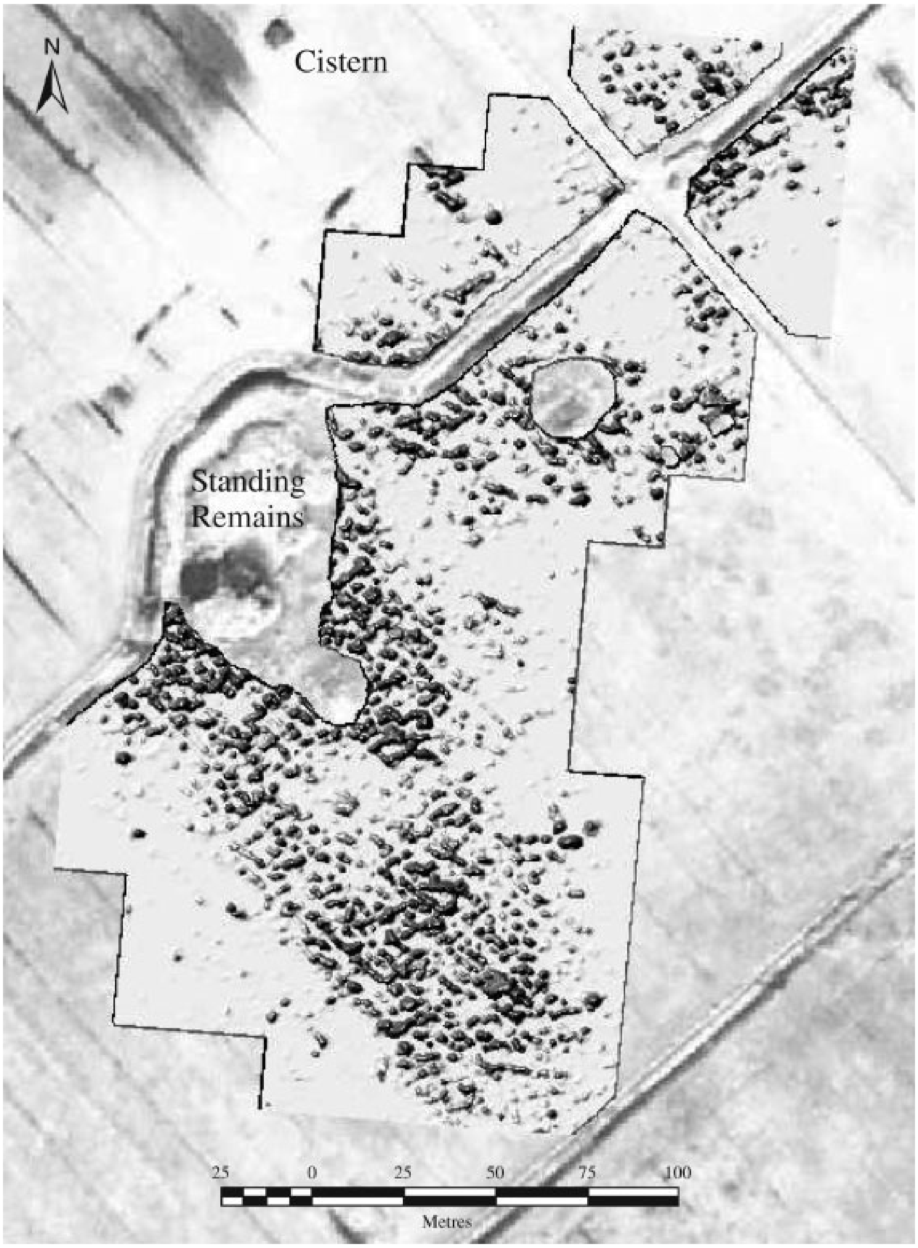

Figure 5. Subsurface relief plot of predicted wall remains.

risk of flooding might be the result of changes within the extensive catchment, or even linked to a rise in sea-level as a result of local tectonic changes, suggesting a potentially more sudden and relatively catastrophic change in the local environment (see Pirazzoli, 1996). There is strong evidence for a rapid succession of large tectonic events centred principally upon the eastern Mediterranean region, often referred to as the Early Byzantine Tectonic Paroxysm (Pirazzoli *et al.*, 1996). These types of event might also explain the size and layout of the late Roman domestic complex, which appears to cover several former *insulae*, if previous buildings had been badly damaged or destroyed during an earlier seismic event.

Conclusions

The processing of magnetic survey data using neural networks, leading to a subsurface reconstruction of surviving wall elements can be seen to have provided an enhanced interpretation of the survey data, useful both archaeologically and from the perspective of cultural resource management. Many of the hypotheses arising from the results obtained have been valuable in stimulating and formulating further research questions. The study has also shown how the data generated can be easily assessed in combination with geoarchaeological evidence to provide a more complete interpretation of settlement evolution.

The use of neural network techniques offers many interesting possibilities to the processing of geophysical data from archaeological sites, particularly in the field of inversion and signal processing, with many potential advantages in terms of speed and noise tolerance over existing techniques.

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