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Mapping ocean sediments by RBF networks

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Mapping ocean sediments by RBF networks

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Mapping ocean sediments by RBF networks

A. Caiti and T. Parisini

Executive Summary: The geoacoustic characteristics of the seafloor sediment play a major role in the propagation of sound at sonar operating frequencies. Hence, knowledge of the geoacoustic properties of the upper part of the marine sediment is required in order to model and predict acoustic propagation loss in the water column.

Available experimental methodologies for the measurement of the geoacoustic parameters of the seabed must compromise between accuracy and size of the area covered by the measurments themselves. One possible way to obtain wide area coverage while still preserving the detail of the measurements is to use very accurate local experimental techniques in selected points of the area of interest associated with suitable interpolation algorithms.

In this memorandum a class of interpolation algorithms based on the use of generalized radial basis functions (RBF) is explored as a means of correlating sparse measurements of seafloor geoacoustic properties. RBF-based algorithms have the important feature of a network computational structure that allows for their parallel implementation, greatly increasing their speed and performance.

The approximating properties of the algorithms are investigated, and it is discussed how these properties match with commonly encountered physical situations. A simple example is worked out from density data obtained by cores, showing good quantitative agreement between the actual measurements and the predictions of the interpolation algorithm.

Further testing of the class of algorithms described in this memorandum on larger data sets may assess the ability of RBF to obtain, in conjunction with existing databases, a complete quantitiative description of wide area geoacoustic parameters.

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Mapping ocean sediments by RBF networks

A. Caiti and T. Parisini

Abstract: Interpolation of sparse measurements of ocean-sediment properties by generalized radial basis function (RBF) networks is proposed. An RBF network is able to generate a continuous smooth approximation for sediment properties as a function of the x-y-z position, where z is the sediment depth. Advantages and disadvantages of the method are discussed, from both a physical and a computational viewpoint. An example using sediment density data obtained by sparse core measurements in a region of the Mediterranean Sea is presented.

Keywords: marine sediments ○ neural networks ○ radial basis functions ○ seafloor monitoring

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1
Introduction

A quantitative knowledge of the geoacoustic properties of ocean sediments (e.g. compressional and shear wave velocity and attenuation, density, porosity, grain size, etc.) is of great importance for predicting acoustic propagation loss at sonar operating frequencies. To this end, experimental methodologies are sought which are able to measure near-bottom sediment properties with high accuracy, and, at the same time, to cover the whole area of interest in a relatively fast and inexpensive way. These two requirements are conflicting, as the most accurate estimates of sediment properties are obtained by pointwise measurements (on cores or with *in situ* instrumentation), while the most extensive coverage leads to the identification of only gross sediment features (e.g. in velocity analysis of large seismic sections). One possible solution to the problem is to use suitable systems that allow local measurements of the quantities of interest in some selected regions of the area under investigation, and then to apply an interpolating algorithm able to correlate such measurements and provide an approximate map of the sediments over the whole area.

The topic of multivariable functional interpolation is certainly not new, but has received further attention in recent years as a consequence of the success and diffusion of artificial neural networks (NN). As pointed out by Poggio and Girosi [1] the use of NN for simple 'learning' tasks can be regarded as a specific method of function approximation. NN are designed to approximate or interpolate a function $f(\underline{x})$ by an approximating function $\hat{f}(\underline{c}, \underline{x})$ having a fixed number of parameters $\underline{c}$. When the range of the function $f(\underline{x})$ is a finite set, the problem that NN have to solve belongs to the class of pattern recognition and classification problems. It is in this field that NN were first succesfully applied. When the range of the function $f(\underline{x})$ is not a finite set, one has to face an interpolation problem in the standard sense. NN with the same structural characteristics of the ones used in pattern recognition have also been shown to be very effective for this kind of problem, and have been employed particularly in system planning and control for such tasks as kinematic inversion [5] and multistage dynamic optimization [6]. On the basis of this background, we have decided to test the use of NN to interpolate sparse measurements of marine sediment properties.

The main innovative aspect of this work is that the network selected does not belong to the popular class of feed-forward NN with sigmoid activation functions, but is a (generalized) radial basis functions (RBF) network. The reasons for selecting this particular network structure are detailed throughout the paper; however, the major points can be summarized as follows:

- RBF networks are mathematically derived from the application of regularization theory to the problem of approximation of functions, and can be shown to have the property of best approximating the function sampled.
- Due to their mathematical derivation, it is very easy to include *a priori* knowledge in the solution given by an RBF network. This is of major importance when measurements are obtained by using some inverse techniques (see e.g. [11]) that also rely on *a priori* assumptions. As a result, interpolation of measurements will be consistent with the procedure chosen for the measurements themselves.
- RBF networks are *linear in the parameters*, so that their learning stage, or parameter adaptation, can be achieved by a standard least-squares algorithm always convergent to the best parameter configuration.
- The usual drawback of RBF networks, i.e. the 'curse of dimensionality', is seldom encountered when dealing with geophysical measurements of the seafloor. The amount of data that can be collected on the field is two or three orders of magnitude smaller than that collected at sea by using, say, acoustic communication systems, like hydrophone arrays or side-scan sonar images. In practice an RBF network is not expected to grow to unmanageable size.

The results presented in this paper show how, under mild assumptions on data points, an interpolating RBF network is able to learn a smoothed approximation for the area of interest, while preserving, to some extent, measurement details. Moreover, the smoothing effect can be predicted in advance, as it is a mathematical property of the approximating algorithm.

Preliminary results of this work have been presented in [7,8]. Here we make a complete and detailed analysis of the network's properties, and of its application to the sea bottom/subbottom environment. This memorandum is organized as follows: the next section describes the network and its computational properties; in Sect. 3, the application of the network to the mapping of marine sediments is discussed; in Sect. 4, the approach is tested using sediment density data from cores taken in the Naples abyssal plain, in the Mediterranean Sea.

2

Regularization, approximation, and learning networks

Since research on feed-forward neural networks began, it has been pointed out that these networks are able to represent an unknown function to an arbitrarily high degree of accuracy (see e.g. [9,10]). However, in many practical applications, a very important issue concerns the possibility of using the available *a priori* knowledge about the function to be approximated. Classical neural structures, such as back-propagation networks, besides presenting learning problems, are not suited to embedding such knowledge. On the contrary, RBF networks are well suited to this task. In fact, Poggio and Girosi [1] noticed that this kind of network strictly derives from the application of regularization theory [3] to the problem of function approximation. As is well known, the regularization approach is a very classical mathematical tool for solving ill-posed problems embedding *a priori* knowledge on their solution. This is the main reason that led us to choose RBF networks to solve our problem.

In the following, we briefly describe both the application of regularization theory [3] to solve the problem of function approximation and its implementation with RBF networks (a more detailed discussion of these topics can be found in [1]).

Let $\mathcal{S} = \{(\underline{x}_i, y_i) \in \Re^n \times \Re, \quad i = 1, \ldots, N\}$ be a set of data that we want to approximate by means of a continuous function $f : \Re^n \rightarrow \Re$, with the property that $y = f(\underline{x})$ for every $(\underline{x}, y)$ in $\mathcal{S}$. The problem stated in this way is ill-posed, since there exist infinite functions f with the required property. Tikhonov's theory of regularization allows us to define a unique solution to this problem by imposing additional constraints in the form of *a priori* knowledge about the solution itself. In the most general case, the additional constraints take on the form of smoothness requirements on f. So we define *regularized solution* of the original problem the function f^* that minimizes the cost functional:

$$J(f) = \sum_{i=1}^{N} (y_i - f(\underline{x}_i))^2 + \lambda \parallel Hf \parallel^2, \qquad (1)$$

where H is the constraint operator (usually, a differential operator), $\|\cdot\|$ is the norm in the functional space $\mathcal{H} \supseteq \text{Range}(H)$, and $\lambda > 0$ is the regularization parameter that acts as a tradeoff weight between the regularity constraint and the requirement of minimum distance from the data. By means of variational arguments, it is possible to show that the solution of the minimum problem is given by

$$f^*(\underline{x}) = \frac{1}{\lambda}\sum_{i=1}^{N}(y_i - f^*(\underline{x}_i))\phi(\underline{x};\underline{x}_i), \tag{2}$$

where ϕ is a function satisfying the distributional differential equation

$$H'H\phi(\underline{x};\underline{y}) = \delta(\underline{x} - \underline{y}) \tag{3}$$

(the prime denotes the adjoint operator). In other words, ϕ is the Green's function of the operator $H'H$. Eq. (2) has N unknown coefficients $c_i = (y_i - f^*(\underline{x}_i))/\lambda$ that can be determined evaluating Eq. (2) at the data points $\underline{x}_i$. This leads to the system of algebraic equations

$$(\Phi + \lambda I)\underline{c} = \underline{y}, \tag{4}$$

where $\underline{c} = \mathrm{col}(c_i, i = 1, \ldots, N)$, $\underline{y} = \mathrm{col}(y_i, i = 1, \ldots, N)$, $\Phi_{ij} = \phi(\underline{x}_i, \underline{x}_j)$, and I is the identity matrix. Given the coefficients c_i derived from Eq. (4), we can conclude that the solution of the regularized approximation problem is given by

$$f^*(\underline{x}) = \sum_{i=1}^{N} c_i\phi(\underline{x};\underline{x}_i). \tag{5}$$

Note that, as $H'H$ is a self-adjoint operator, $\phi(\underline{x};\underline{y})$ is symmetric. Moreover, if H is rotationally and translationally invariant, ϕ is a radial function: $\phi = \phi(\| \underline{x} - \underline{y} \|)$, where $\underline{y}$ is called the *centre* of ϕ. In this case, we resort to a radial basis functions (RBF) expansion, a traditional technique for interpolating in multidimensional spaces [4]. Typical choices for ϕ are

$$\phi(x) = \begin{cases} x^2\log(x), & \text{thin-plate-spline} \\ (x^2+\sigma^2)^{1/2}, & \text{multi-quadric} \\ \exp(-x^2/\sigma^2), & \text{gaussian} \\ \exp(-x/\sigma), & \text{exponential,} \end{cases} \tag{6}$$

where σ is a real constant. Reference [1] shows how radial functions can be related to the constraining operator H; in particular, the two limit cases are represented by the gaussian basis functions, which are derived from $H = \sum_{i=1}^{\infty} \partial^i/\partial\underline{x}^i$, and the exponential basis functions, generated by $H = \partial/\partial\underline{x}$.

Note that the requirement for rotational and translational invariance of the constraining operator is very common in practical situations. Clearly, using non-radial operators leads one to employ appropriate non-radial basis functions, preserving all the approximation properties associated with the regularization approach.

In the practical case considered in the present memorandum, radial operators are sufficient and work very well; hence, from now on, we shall consider only radial basis functions.

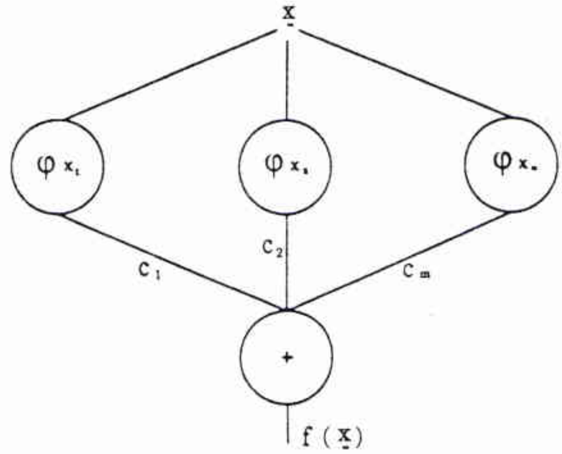

Figure 1 *Network implementation of the regularized interpolating function.*

Once a radial function ϕ has been chosen and the coefficients c_i have been calculated, Eq. (5) can be efficiently computed by a three-layer network, with one hidden layer composed of n units each one computing in parallel ϕ at a different centre $\underline{x}_i$ (Fig. 1).

The optimal solution obtained up to now is based on a network composed of as many hidden units as data points. This approach may be unfeasible if the amount of data is extremely large; in this case, we want to fix the number of hidden units to m, $m < N$, to find a suboptimal solution:

$$f(\underline{x}) = \sum_{i=1}^{m} c_i \phi(\| \underline{x} - \underline{\alpha}_i \|), \tag{7}$$

where the m centres $\underline{\alpha}_i \in \Re^n$ have now to be specified. There exist two possible approaches. The first consists in fixing the centres *a priori*, and in adaptively tuning the coefficients c_i by a least-mean-square (LMS) algorithm:

$$\begin{aligned} c_i^{(k+1)} =& c_i^{(k)} + \gamma \left\{ y_j - \sum_{i=1}^{m} c_i^{(k)} \phi(\| \underline{x}_i - \underline{\alpha}_i \|) \right\} \phi(\| \underline{x}_i - \underline{\alpha}_i \|), \\ & i = 1, \ldots, m; \quad J = 1, \ldots, N, \end{aligned} \tag{8}$$

where γ, the usual LMS step, is a fixed constant. In this fashion data points can be regarded as training examples for the network, which can then learn the correct configuration of its weights c_i. As the weights in the network are linear, inserting new data points is an easy task that involves just one more iteration of the LMS algorithm. A regular behaviour is guaranteed by the form of the function ϕ and by the truncated expansion, which is another regularization technique. However, a bad initial choice of the centres $\underline{\alpha}_i$ may lead to large errors in the interpolated function.

The second approach consists in adaptively tuning both the weights and the centres of the network. This means that we have to look for the m centres $\{\underline{\alpha}_j\}$ and the m

weights $\{c_j\}$ that minimize the cost function

$$J_m = \sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{m} c_j\phi(\| \underline{x}_i - \underline{\alpha}_j \|)\right)^2 + \lambda \| H \sum_{j=1}^{m} c_j\phi(\| \underline{x}_i - \underline{\alpha}_j \|) \|^2 . \quad (9)$$

This is a nonlinear minimization problem that can be solved by gradient descent methods, or even by stochastic minimization algorithms. A network that learns its centres is called a moving centre network, and is an extension of the usual RBF network (generalized RBF). Reference [1] also considers the adaptive tuning of a weighted norm $\| x \|_W = x'W'Wx$ in the space $\mathcal{H}$, and defines a still more general minimum problem which includes the coefficients of the matrix W as unknowns. In any case, the parameters of the network can be estimated by using the data points as training examples, and the minimization procedure (linear or nonlinear) closely resembles the learning phase of sigmoid-based neural networks.

Now, it is worth noting that *a priori* knowledge on the problem may be translated into a particular constraining operator. As shown below, in the case considered here, this means choosing a differential operator that reduces the space of functions to a specific smoothness class.

3
Smooth approximation of ocean sediment properties

The problem outlined in Sect. 1 will now be stated more formally. Suppose we have a set of n measurements of some sediment property, for instance, density:

$$\rho_i = \rho(\underline{x}_i), \qquad i = 1 \ldots n, \tag{10}$$

where ρ_i is the measured density and $\underline{x}_i = (x_i, y_i, z_i)$ is the location at which the measurement was made, assuming $z = 0$ at the sea bottom. Let $\underline{x} \in \mathcal{X}$, where $\mathcal{X}$ is the region in which density is to be estimated. A straightforward application of the interpolating network described in Sect. 2 leads to a final expression for density as

$$\rho(\underline{x}) = \sum_{i=1}^{m} c_i \phi(\| \underline{x} - \underline{\alpha}_i \|^2), \qquad \underline{x} \in \mathcal{X}, \tag{11}$$

where ϕ is the functional interpolating form (for instance, the gaussian function), $\underline{\alpha}_i \in \Re^3$ are the centres and m their number.

Care must be taken in choosing data points; the interpolation method proposed relies heavily on the regularity of the function $\rho(\underline{x})$ where no data are available. In the case of marine sediments, we deal with *piecewise regularity*: sediments may have smooth variations in their properties in a certain region; then they may be subject to abrupt changes, due to stratifications, faults, etc., depending on the geological and biochemical history of the site. In any case, Eq. (11) leads to a continuous approximation for $\rho(\cdot)$; however, such continuous approximation can be sharpened in the neighbourhood of the discontinuity region. One way to accomplish this is to penalize, in the minimization process, the parameters that may cause large deviations from the left and right limits of the true function at the discontinuity point. The discontinuity point and its left and right limits must be approximatively known, and the penalization effect can be obtained either by increasing the measurements around the discontinuity point, or by imposing a weighting on the norm of Eq. (1). The additional information needed is the locations of the critical discontinuity points. Such information can be obtained with state-of-the-art techniques, such as a preliminary seismic survey of the area of interest, a procedure that is often performed routinely. From the gross picture of the area, it is possible to select the points at which to make measurements to train the interpolating network.

Depending on the measurements made, moving centres may or may not be needed. In general, we expect to have few data points in the (x, y) plane. For each (x, y)

point we may have a large or small number of points along the z-axis. In the former case (large number of z-points), we use moving centres; in the latter, (small number of z-points), we can safely use fixed centres. Using fixed centres makes it very easy to update the network whenever a new data point is available: one need only add a new unit (opening one more connection), and perform one step of the LMS algorithm to update the network weights.

4

Testing the RBF approach: density recovery from sparse core data

As a simple example application, we decided to test this method by using density data from cores taken by SACLANTCEN from an area of the Tyrrhenian Abyssal Plain, in the Mediterranean Sea, off Naples (Fig. 2). An analysis of these data, along with descriptions of measurement procedures, can be found in [2]. An example of a density *vs* depth profile is given in Fig. 3. Wet density was measured on the cores at steps of 5 cm in depth; we stopped at a depth of 6 m; then, for each point in the (x, y) plane, we obtained 120 points along the z-axis. The error on this measure, reported in [2] is 6%. It is important to note the sharp density contrast in the region between 3 and 4 m, geologically due to turbidities or volcanic ash depositions. The area of interest showed fairly smooth variations in the sediment properties in the (x, y) directions, so we did not need to worry about sampling accuracy. We simulated the behaviour of the RBF network on a Sun 3 machine at DIST[1]. We choose exponential basis functions and a fixed-centre algorithm. The network was trained using all the core data in Fig. 2, except for core no. 53. Then the network was asked to predict the density at the position of core no. 53; a comparison between predicted and measured densities is given in Fig. 4. Figure 5 shows the prediction error as a function of depth, with an overall mean square error of 0.0037. Figures 4 and 5 clearly show that the network is able to learn the general trend of the density *vs* depth curve at a given location, and some but not all the structure of the sediment. In particular, the smoothing effect of the network makes it difficult to determine the exact depths of the different layers. On the other hand, the generalization properties of the network were good enough to generate a prediction with a very low mean square error, and with about 90% of the points within the experimental error. Changing the training set to predict densities at different core locations yielded similar results.

[1] Dipartimento di Informatica, Sistematica, e Telemetica, Università di Genova.

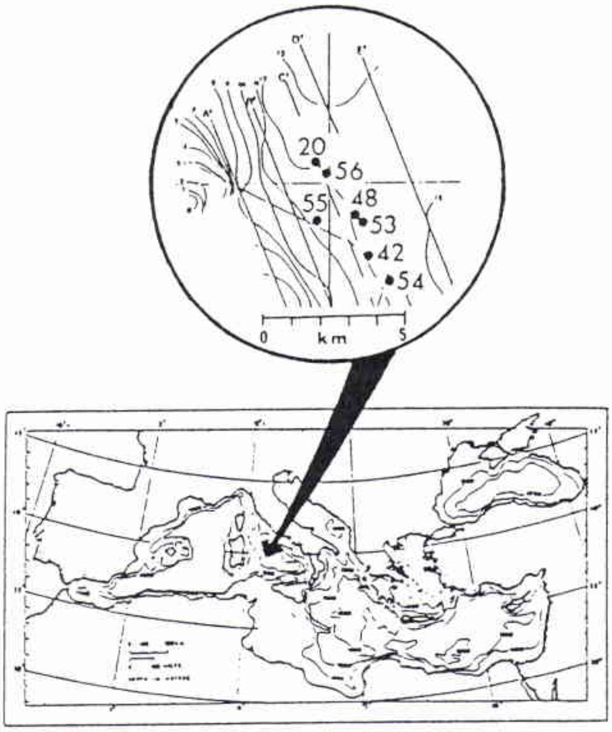

Figure 2 *Position of the SACLANTCEN cores taken in this study.*

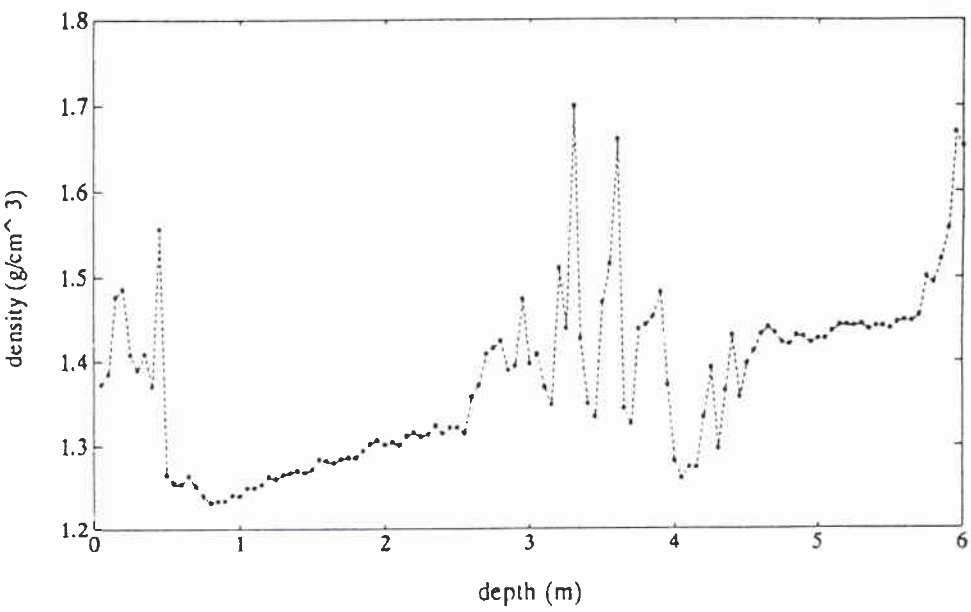

Figure 3 *Density vs depth profile measured on core n.48.*

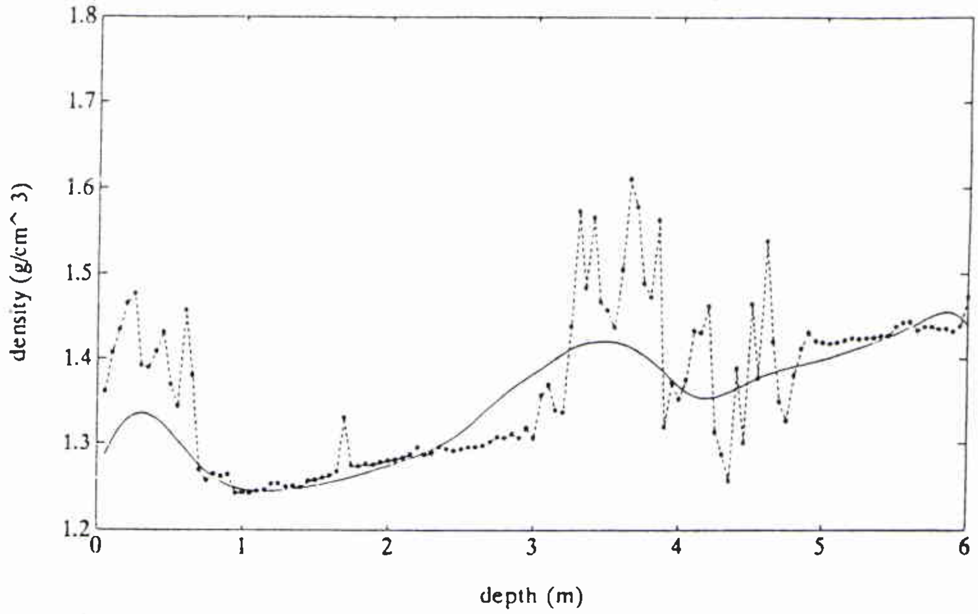

Figure 4 *Measured and predicted density at core n.53; *: measured data points, connected by dotted line; continuous line: predicted data.*

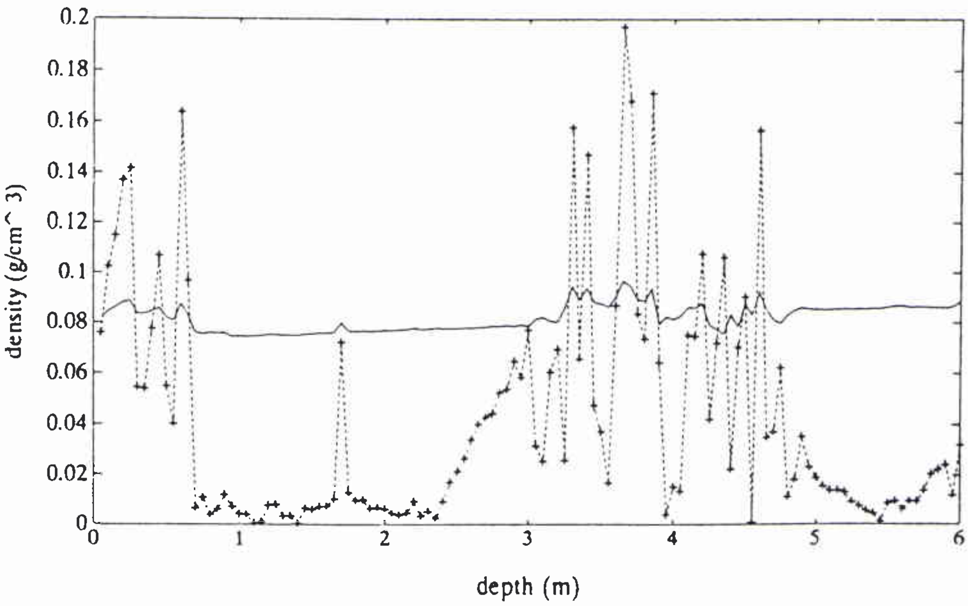

Figure 5 *Prediction error (absolute value) for core n.53. +: error points, connected by dotted line; continuous line: 6% threshold on the measured data (experimental error).*

5
Conclusions

A method for mapping marine sediment properties derived from sparse local measurements over a large area was introduced. The method is based on the interpolating properties of generalized RBF networks, and uses measured data as training examples to adaptively tune the internal parameters of an RBF network. It has general validity, and does not rely on any particular property of the measurement system used, nor on the physical parameters measured. Moreover, it can utilize the results of past measurements or of measurements obtained with different techniques. However, the following assumptions have to be met, in order to use the proposed technique consistently:

- The sediment property of interest is *piecewise regular* over the area under investigation, that is, it is a smooth function of its position except at a finite number of locations (discontinuity points).
- The location of the discontinutiy points is known in advance, and their presence is taken into account using one or both of the following techniques:
  1. increase the sampling of the sediment close to the discontinuity region;
  2. use a weighted norm to force the interpolated function to be close to the 'left' and 'right' limits of the true function at the discontinuity.
- The choice of the RBF activating function is made according to the *a priori* knowledge on the smoothness degree of the function that we want to approximate.

The above points make clear that the RBF interpolating network must be used in conjunction with large area qualitative information, such as that obtained from seismic surveys. Since seismic surveys are conducted routinely before quantitative area investigation, this requirement does not represent a limitation of the method proposed.

An example application using density data from cores taken in the Mediterranean Sea has been given. Results shows that the trained network is able to predict a smooth approximation for true data, as expected from theory.

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Title

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Abstract

Interpolation of sparse measurements of ocean-sediment properties by generalized radial basis function (RBF) networks is proposed. An RBF network is able to generate a continuous smooth approximation for sediment properties as a function of the x-y-z position, where z is the sediment depth. Advantages and disadvantages of the method are discussed, from both a physical and a computational viewpoint. An example using sediment density data obtained by sparse core measurements in a region of the Mediterranean Sea is presented.

Keywords

marine sediments, neural networks, radial basis functions, seafloor monitoring

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