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Tidal Data Analysis using ANN

Ritu Vijay, and Rekha Govil

***Abstract*—**The design of a complete expansion that allows for compact representation of certain relevant classes of signals is a central problem in signal processing applications. Achieving such a representation means knowing the signal features for the purpose of denoising, classification, interpolation and forecasting. Multilayer Neural Networks are relatively a new class of techniques that are mathematically proven to approximate any continuous function arbitrarily well. Radial Basis Function Networks, which make use of Gaussian activation function, are also shown to be a universal approximator. In this age of ever-increasing digitization in the storage, processing, analysis and communication of information, there are numerous examples of applications where one needs to construct a continuously defined function or numerical algorithm to approximate, represent and reconstruct the given discrete data of a signal. Many a times one wishes to manipulate the data in a way that requires information not included explicitly in the data, which is done through interpolation and/or extrapolation.

Tidal data are a very perfect example of time series and many statistical techniques have been applied for tidal data analysis and representation. ANN is recent addition to such techniques. In the present paper we describe the time series representation capabilities of a special type of ANN- Radial Basis Function networks and present the results of tidal data representation using RBF. Tidal data analysis & representation is one of the important requirements in marine science for forecasting.

***Keywords*—**ANN, RBF, Tidal Data.

I. Introduction

A tide is the periodic rise and fall of the seawater resulting from gravitational interactions between the sun, moon, and earth. Other factors influence tides; coastline configuration, local water depth, seafloor topography, winds, and weather alter the arrival times of tides, their range, and the interval between high and low water. A tide prediction can differ from the actual sea level that will be observed as a result of the tide. Predicted tidal heights are those expected under average weather conditions. When weather conditions differ from what is considered average, corresponding differences between predicted levels and those actually observed would occur. Generally, prolonged onshore winds (wind towards the land) or a low barometric pressure can produce higher sea levels than predicted, while offshore winds (wind away from the land) and high barometric pressure can result in lower sea levels than predicted. Thus mariners need to take local conditions into account when considering critical activities with tide prediction information.

The importance of the vertical change in the level of water is of fundamental importance to the mariner. The height of the tide will determine the depth of water as well as overhead clearances. This knowledge is essential in determining if a ship is able to make it into a particular harbor, able to pass safely, or has enough clearance or pass under a low bridge.

The National Ocean Service (NOS) produces worldwide tidal prediction tables annually. The tables are broken down into four volumes, each covering different regions of the globe. The tidal tables are used to predict the times of high and low water for several thousand-area substations.

Online dynamic tidal prediction requires a representation algorithm which is chip implementable and fast. Accurate tidal prediction and supplement is an important task in determining constructions and human activity in coastal and oceanic areas. The harmonic tidal level is conventionally used to predict tide levels. However, determination of the tidal components using the spectral analysis requires a long-term tidal level record (more than one year). In addition, calculating the coefficients abbreviated of tide component using the least square method also requires a large database of tide measurements. In the present paper we are presenting the results of application of the Radial Basis Function Network a class of Artificial Neural Network for predicting and supplementing the long-term tidal level using the short term observed data. The results of RBF modelling are also compared with those obtained using the other traditional approximation techniques namely i.e. Polynomial [1], Fourier series [2] and Wavelet approximations [3].

II. Neural Networks

During the infancy of the development of Neural Networks technology, one thing that excited people's interest was its analogy to biological systems. Even though not all has been understood about the learning processes of human neural systems, Artificial Neural Networks (ANN) have, without a doubt, provide the solution to problems in different application areas. The brain is a highly complex, nonlinear and parallel information processing system. It consists of about one hundred billion neural cells, each connected to about 10,000 neighboring neurons and receiving signals from there. The brain routinely accomplishes perceptual recognition tasks (e.g., recognizing a familiar face in a scene) in about 100-200 msec. The neuron, the basic information processing element (PE) in the central nervous system plays a very

Authors are with Department of Computer science and Electronics, Banasthali Vidyapith, Rajasthan - 304022, India (e-mail: rituvijay@yahoo.co.in).

important and diverse role in human sensory processing, control and cognition. The brain is able to do complex tasks by its ability to learn from experience. An Artificial Neural network is designed to model the working of human brain.

The ANN is usually implemented using electronic components (digital & analog) and/or simulated on a digital computer. It employs massive interconnection of simple computing cells called "neurons" or "processing elements (PE)" It resembles the brain in two ways:

- Knowledge is acquired by the network through learning process,
- Inter neuron connection strength (synaptic weights) are responsible for storing the knowledge.

The way the synaptic weights change is what makes the design of ANNs. Such an approach is close to linear adaptive filter theory, which is well established and is used in many diverse fields such as communication, control, sonar, radar, and biomedical engineering. There are three types of neural networks model.

Types of Neural Network Model

Multilayer Perceptron Network

Multilayer perceptron network (MLP) comprises a large class of feedforward neural networks with one or more layers of neurons, called hidden neurons, between the input and output neurons. In general, all neurons in a layer are connected to all neurons in the adjacent layers through unidirectional links. These links are represented by connection weights [6].

Radial Basis Function Networks

An RBF is a multidimensional function that depends on the distance between the input vector and a center vector. The basic topology of the RBF network consists of an input layer, one hidden layer, and an output layer. RBF have applications in interpolation, time series modeling, image processing, medical diagnosis etc. [6].

Cellular Neural Network

This kind of neural network is very powerful in signal processing. A basic cellular neural network has a two dimensional connection structure whose processing unit, called a cell, is connected only to its neighboring cells [9].

III. RBF Networks

The construction of a RBF network in its most basic form involves three entirely different layers. The input layer is made up of source nodes (sensory units). The second layer is a hidden layer of high enough dimension. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden unit space is nonlinear, whereas the transformation from the hidden unit space to the output space is linear. The hidden unit of RBF implements a radial activation function. The output units implement a weighted sum of hidden unit outputs. The input into an RBF network is nonlinear while the output is linear. Their excellent approximation capabilities have been studied in literature [4]-[5]. Due to their nonlinear approximation properties, RBF networks are able to model complex mapping [6].

Radial functions are simply a class of functions. In principle, they could be employed in any sort of model (linear or nonlinear) and any sort of network (single-layer or multi-layer). However, since Broomhead and Lowe's 1988 seminal paper [7], Radial Basis Function networks (RBF networks) have traditionally been associated with radial functions in a single-layer network such as shown in Fig. 1.

Radial basis functions are a special class of functions. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The centre, the distance scale, and the precise shape of the radial function are parameters of the model, all fixed if it is linear.

A radial basis function approximation in p-dimension ($x \in R^p$) has the generic form

$$f(x) = \Sigma a_k p(|| \; x - x_k||) \quad (1)$$

where $p(r) : R_+ \rightarrow R$ is a univariate function and where ($||x-x_k||$) denotes the Euclidean distance between the p vectors x and x_k. The basis function in (1) depends only on the distance to their corresponding grid point x_k and are thus called radial. The a_k are weighting coefficients that are typically determined by fitting the function to some data. In the classical interpolation problem, the function f is determined such that $f(x_k) = f_k$, where the f_k are some data value; in this case, there is exactly one linear constraint per basis function, and the corresponding linear system of equations invrertible under relatively mild condition [8]. The better known examples of radial basis function are p(r)=r (linear or membrane spline), $p(r) = r^2 \log(r)$ (thin plat spline), and $p(r) = \mathrm{sqrt}(c^2 + r^{2)}$(Hardy's multiquardric)

A typical radial function is the Gaussian which, in the case of a scalar input, is

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right). \quad (2)$$

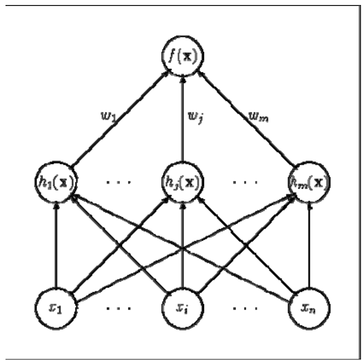


Fig. 1 Radial basis function network

IV. RBF Modeling of Tidal Data

Tidal data analysis of a particular station requires modelling of following two characteristics

- Cyclic variations representing the time dependence of tidal heights with some desired frequency (say half an hour)
- Day wise variation of low and high tides at the station.

In fact the second one can be derived from the first one; the steps involved in which case are as follows:

- The recorded time series tidal data of one full cycle of a particular station is presented to the input layer of the RBF neural network.
- The network architecture is chosen so as to provide the output of the test cases within the acceptable tolerance limits.
- The weight matrix thus obtained can be used to represent tidal data of any day of the year by forecasting.
- The times and heights of low and high tides could also be predicted.

Example: Here we have taken tidal data of a station having semi diurnal type of tide i.e. two high and two low waters each day spaced at about 6 hours each. Since the time series period is 30 days (one lunar month) hence hourly data of 30 days i.e. 720 points were taken as input to the RBF neural network. The iteration was stopped after achieving the convergence at each test point of less than e-0026.

The actual one-day data along with its approximation by all the four techniques under consideration is shown in Fig. 2. The rms error analysis of each technique as shown in Table I reveals that Fourier and Polynomial approximation do not make a good case to be used for Tidal data approximations.

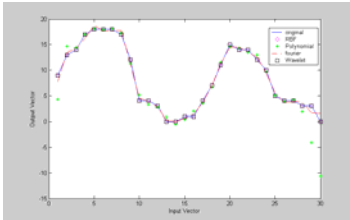
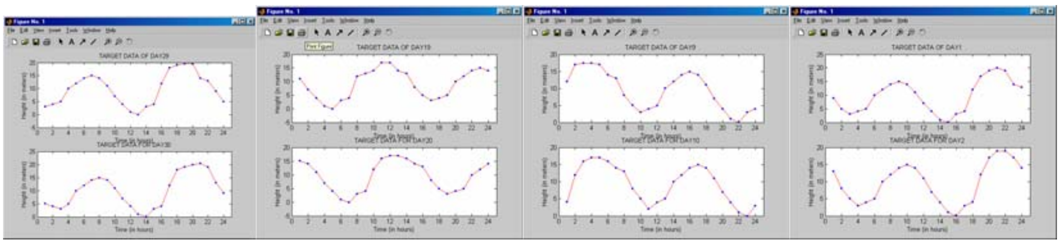


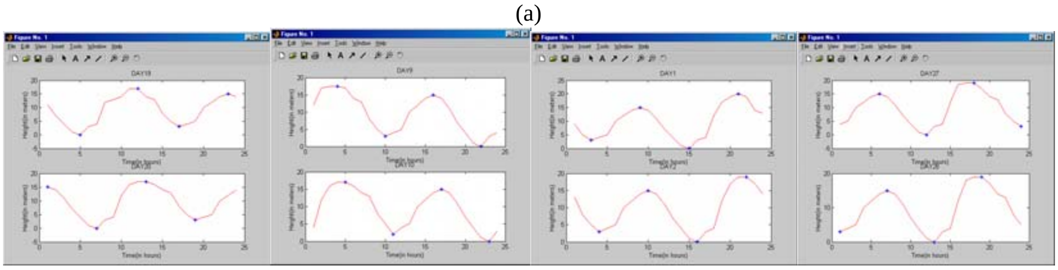
Fig. 2 Approximation of one day tidal data

TABLE I
RMS Error in Tidal data Representation

Technique	Fourier	Polynomial	Wavelet	RBF
Error	0.3971	6.4917	2.9286*e-030	3.0332*e-031



(a)



(b)

Fig. 3 (a) Simulated Results (b) Maxima Minima curve

V. Interpolation & Forecasting

Sea level heights are recorded continuously at the ports and communicated to the Geostation. This application requires a compact representation with capabilities of accurately making up of missing data using interpolation. Forecasting the times for maxima-minima of tidal heights is another required application of recording tidal heights.

RBF neural networks are able to fulfill both these needs as shown by the Figs. 4 and 5 respectively for a day's data where in Fig. 4 missing data is interpolated and in Fig. 5 one day's data is forecasted with maxima-minima prediction. Table II shows the rms error values for both the cases. The results obtained with other techniques are also given for comparison.

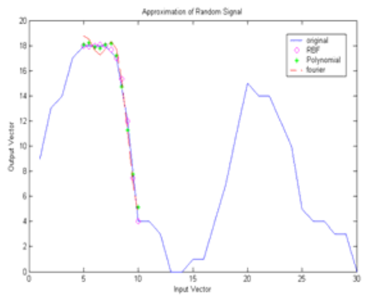
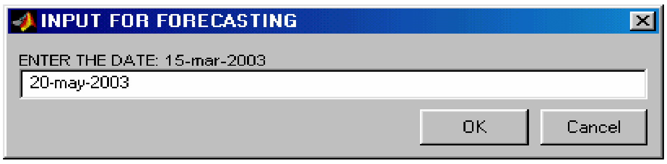
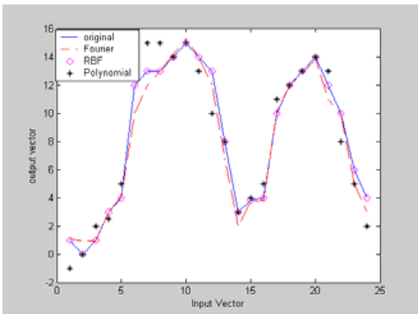


Fig. 4 Result of interpolation of tidal wave



(a)



(b)

Fig. 5 (a) User Interface (b) forecasting results

In fact we have developed software with user interface (Fig. 5(a) where the user could enter the data and the software provides the tidal data for the desired day (Fig. 5(b)).

The results show that the tidal level over long duration can be efficiently predicted or supplemented using only a short-term tidal record by RBF modelling.

VI. Conclusion

Tidal data all over the world are true time series data where the variability in the waveform is only geographic i.e. port dependent. This makes RBF a very suitable tool to be used for Tidal data representation, its compact storage and forecasting. In fact a software application has been developed in this work to demonstrate the accurate forecasting capability of RBF where one can predict the low & high tide times information of any day of the year by just training the network on one month tidal data of the port i.e. on one cycle time series data.

It must be noted that other techniques such as polynomial/ Fourier series approximation do not provide universal accurate representation in case of Tidal data. The results of interpolation for missing data also confirm the same. RBF results match Wavelet approximation accuracy or are even better in some cases, but wavelet technique is not chip implementable and consume enormous execution time [Polikar,1994]. DSP with RBF is more promising and needs exploring.

The VLSI implementability of ANN can prove a boon to signal processing science community to design embedded systems for such applications e.g. a tidal height & time predictor portable tool (expert system) for mariners.

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RituVijay, PhD is a Senior Faculty Member, Department of Computer Science & Electronics, University Banasthali Vidyapith, Rajasthan. She has more than 8 years of research experience. She has many papers to her credit in International/National Conferences & has given expert/invited talks in many Seminars. Her areas of research include Data Compression, Signal Processing.

TABLE II
Error Analysis of Interpolation and Extrapolation

rms error in	RBF	Fourier	Polynomial
Interpolation	1.1573*e-006	0.9572	22.7295
Extrapolation	1.1925*e-0023	.3256	7.9542