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ANN BASED TSUNAMI DETECTION ALGORITHM

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Abstract: Tsunamis cause damage by two mechanisms: the smashing force of a wall of water travelling at high speed, and the destructive power of a large volume of water draining off the land and carrying all with it, even if the wave did not look large. Earthquakes with an epicenter in the sea are not always tsunami genic. Direct detection in sea-level measurements is therefore essential to confirm the actual generation and propagation of a tsunami. Signals obtained from the bottom pressure recorders (BPRs) are commonly used for the automatic, real time detection of a tsunami within recorded signals. Only direct detection makes it possible to avoid false alarms and guarantees speed and accuracy in both the warning and the hazard assessment process. The tsunami detection algorithm works by first estimating the amplitudes of the pressure fluctuations within the tsunami frequency band and then testing these amplitudes against a threshold value.

This project aims at developing a Tsunami warning algorithm using artificial neural network (ANN). . Proposed algorithm is compared to the one developed under the Deep-ocean Assessment and Reporting of Tsunamis (DART) program run by the U.S. National Oceanic and Atmospheric Administration (NOAA). The algorithm is designed to detect the occurrence of tsunami using the data obtained from the data buoy. The ANN used for this process is feed forward multilayer network with back propagation training. Simulation and experimental results show that an improvement in detection performance can be obtained by using the ANN algorithm.

Keywords: Tsunami forcasting;Neural networks;Back propogation; Feed forward method

I. INTRODUCTION

A Tsunami warning system (TWS) is a system to detect tsunamis and issue warnings to prevent loss of life and property.It consists of two equally important components: a network of sensors to detect tsunamis and a communications infrastructure to issue timely alarms to permit evacuation of coastal areas.The Deep-ocean Assessment and Reporting of Tsunamis system is a component of an enhanced tsunami warning system.Each DART station consists of a surface buoy and a seafloor bottom pressure recording (BPR) package that detects pressure changes caused by tsunamis. When on-board software identifies a possible tsunami, the station leaves standard mode and begins transmitting in event mode. In standard mode, the station reports water temperature and pressure (which are converted to sea-surface height) every 15 minutes. At the start of event mode, the buoy reports measurements every 15 seconds for several minutes, followed by 1-minute averages for 4 hours.Deep-sea measurements (DSMs) are the main means of detecting tsunamis generated either by earthquakes or by submarine landslides. They are collected at a standard sampling rate of 15s by bottom pressure recorders (BPRs) located at water depths ranging from hundreds to some thousands of meters. Optimal use of BPR measurements depends both on instrument location and on the effectiveness of the detection algorithm. Earthquakes with an epicentre in the sea are not always tsunami genic. Only direct detection makes it possible to avoid false alarms and guarantees speed and accuracy in both the warning and the hazard assessment process. Using ANN algorithm’s closer prediction of both tide and other regular patterns makes it capable of a better filtering performance.

IIPROPOSED TSUNAMI DETECTION ALGORITHM

A. Method

In order to update the prediction of disturbing luctuations every 15 s, the algorithm presented here uses the feed-forward network shown in Fig. The two adaptive-weight layer networks is characterized by 4 input units plus bias, 6

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hidden units plus bias and one output unit (I4H6O1). The network's inputs consist of the same n-minute averages z of bottom pressure observations z as those used by the DART algorithm. These values are pre-processed so as to re-scale them linearly in the range [-1, 1]. More specifically, such a re-scaling is carried out by considering twice the original signal's maximum and minimum values. The function represented by the network diagram can be expressed as where t0, t00 and Dt are the same temporal parameters as those used in equation, ij and bj are the adaptive weights Connecting

$$\hat{\zeta}(t') = \tilde{g}\left\{ w_b^{(2)} + \sum_{j=1}^{6} w_j^{(2)} g\left[w_{bj}^{(1)} + \sum_{i=0}^{3} w_{ij}^{(1)} \bar{\zeta}(t'' - i\Delta t)\right]\right\}, \qquad (3)$$

Input units and bias to the hidden units, and j and b those connecting hidden units and bias to the output unit. Moreover, and represent the hidden and output unit activation functions. In particular, the logistic-sigmoid and the linear activation functions characterize the hidden units and the output unit, respectively. The structure of the algorithm network outlined is the result of investigating the effect of different numbers of both hidden layers and units, and of different activation function.

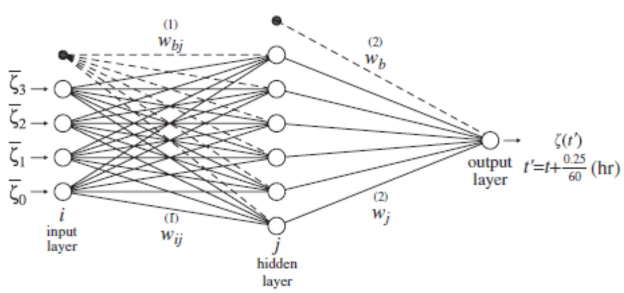

FIG: ANN FEED FORWARD NETWORK

Unlike the coefficients of the cubic polynomial (1), the adaptive weights of Equation result from the network's supervised learning. If a time series of actual observations z is available, it will be possible to present the network with an input array [z] and a corresponding output vector fzg, i.e. with a training set. The adaptive weights [w] result from minimizing the error function chosen to express the difference between the calculated f^zg and the actually observed outputs fzg. In particular, the network presented here uses:

(a) The mean square error (MSE) as the error function;
(b) The standard back-propagation technique to calculate
The MSE derivatives with respect to weights and
(c) The Levenberg–Marquardt optimization scheme for iteratively adjusting the network weights at the end of each epoch by means of the calculated derivatives

The way in which the adaptive weights are calculated makes the network performance dependent neither on the time interval n nor on the observed signal range. The interval n could therefore be chosen for the purposes of minimizing the extent to which a detected tsunami influences the filtered signal indirectly. Actually, the efficiency of the supervised learning relies totally upon how accurately the training set represents all the possible disturbing fluctuations and their composition. If it succeeds in this, the ANN algorithm error is expected to be nearly zero. This is especially so in the case of disturbing fluctuations consisting of regular wavy patterns such as the tidal one. On the other hand, the network training relies on actual data. This makes the resulting adaptive weights mainly tailored to a specific BPR location. In general, therefore, each BPR is characterized by a specific set of weights, although the same set might be used effectively in different BPRs if their locations are close enough to ensure that the devices are exposed to almost equal tidal and meteorological conditions.

B Implementation strategy

Although it is possible to implement the network learning and executing modules in a BPR, the need for memory (to store all the data necessary for learning) and for power (to run the learning procedure and therefore update the adaptive weights regularly) makes this strategy inconvenient. A far more practical solution would be simply to implement Eq. (3), i.e. just the executing module. Regularly downloading observed data makes it possible to carry out the network's supervised learning 'off-BPR'. Furthermore, the training set can be updated on the basis of progressively longer observation time series. The resulting adaptive-weight array [w] can be uploaded at the end of each new learning phase. Such a strategy clearly makes implementation as simple as that of the DART algorithm. It is worth noting that the length of the training set is not an absolute quality parameter of the supervised learning result (i.e. the adaptive-weight set). As previously stated, it is its accuracy in representing all the possible sea-level fluctuations (and their composition) that is of value. The length of the observation time series, on the other hand, is important. The longer the available time series, the more informative the training set obtained by selecting representative tracks of observations will be and, therefore, the result of the learning phase as well. Although a time series extending over a few days is sufficient to get the astronomic tide feature, only a longer time series is likely to contain a statistically significant number of examples of the way in which stochastic fluctuations (e.g. those due to atmospheric-pressure field variations) superimpose on tidal another regular long-period oscillations (e.g. planetary waves and gravitational normal modes on a geophysical basin scale).More quantitatively, a training set consisting of a 15-day continuous time series (i.e. half a lunar cycle) is sufficient to capture tide behavior with extremely high

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precision and can therefore guarantee that the algorithm is fully and effectively operative. Selecting a 30-day continuous time series (i.e. a full lunar cycle) so as to include significant sea level variations caused by meteorological perturbations clearly improves its effectiveness, however. A quick and easy way of constructing a suitable training set is to affect a preliminary harmonic analysis of the available time series. The training set can be chosen by looking for the period during which the residual signal shows a significant departure from zero. This makes it possible to gain an insight into the stochastic fluctuation due to atmospheric-pressure and wind fields. Short tracks of a few days containing other significant departures displayed by the residual signal during further different periods can be added to the basic 30-day continuous time series.

III .SIMULATION AND RESULTS

Tsunami algorithm developed by neural networks and general tsunami algorithm can be run in the MATLAB environment. The coding can be tested by using the values obtained from the buoy. There are two kinds of data that can be used to simulation one of them is reporting data and another is normal observation data. Simulation can be done in two ways initially by testing results using general algorithm later testing the data using neural networks algorithm.

Taking data from the data buoy 56001 dated between 8thmay2011 to 9thmay2011 and simulation with neural networks algorithm, figure 1 shows the predicted and actual data. The red curve indicates the prediction values and the blue curve indicates actual values since there is no event they correlate each other. It is also seen that the predicted values closely follows the trend of the actual data.

The regression plot of figure 2 is the another way of indication of tsunami, if there is no tsunami event then data representation(circles) is closely related to fitted line(blue) as shown in the above figure.

REPORTING MODE:

REAL TIME DATA SIMULATION:

TSUNAMI DATA TAKEN FROM BUOY NO.21418:

The data used here is taken from the buoy number 21418 which was recorded the pressure values when tsunami was generated near Japan recently within the date mar11, 2011-mar12, 2011, by simulating the data by using neural networks and the prediction results are shown in figure 3.we can see the regression fit between the two values the one with circles is data representation and blue line indicates the fit of the prediction data. The difference between them can give us the mean square error.

3.1 Figures and Tables

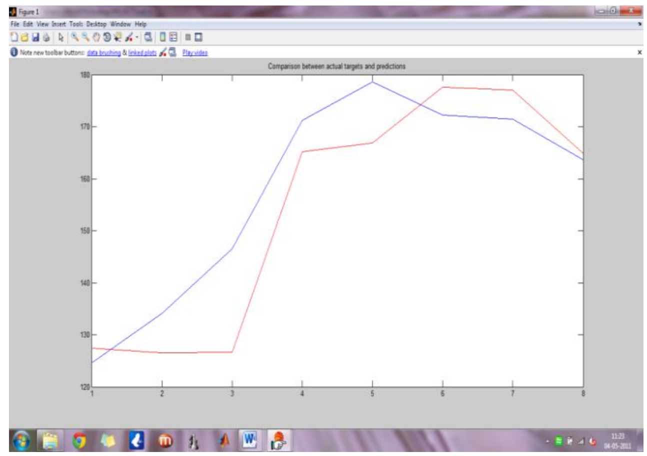

Fig 1: Predicted and actual data

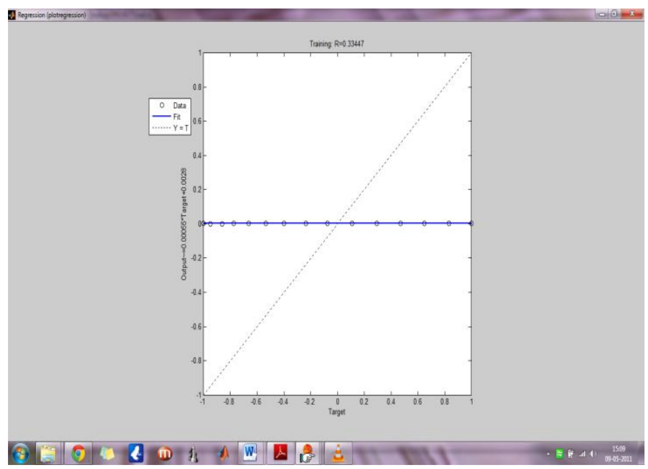

Fig 2: Regression plot for the Tsunami data

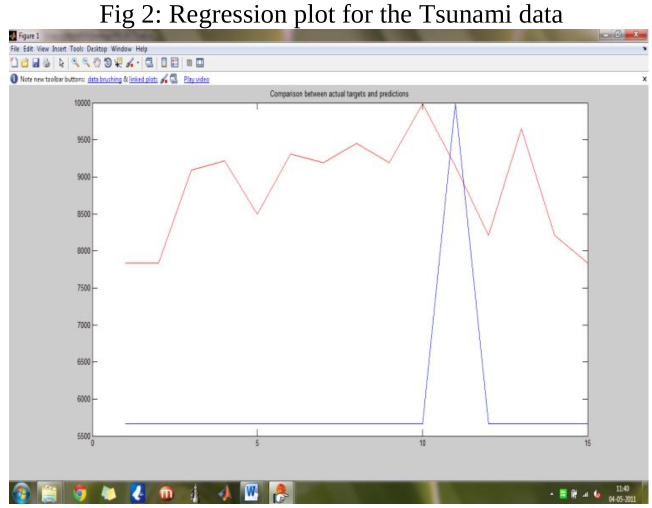

Fig3: Reporting mode plotting

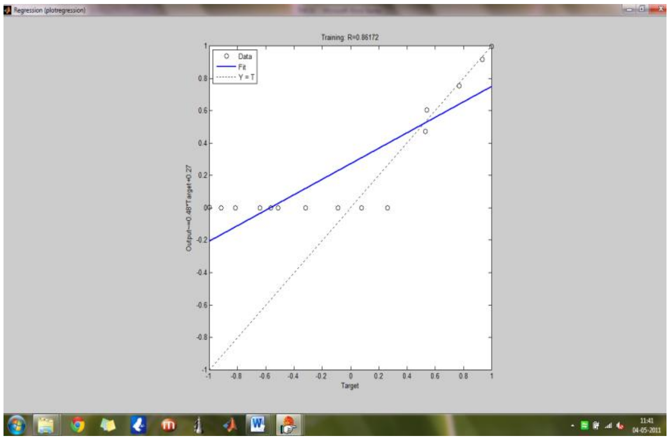

Fig: regression plot for reporting mode

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