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Estimation of Tsunami Direction and Velocity using Deep Sea Data

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Abstract

Objective: The long coastline and proximity to tsunamigenic zones mandate the requirement of an effective Tsunami forecasting system for India to minimize loss of life and property. **Methods/Statistical Methods/ Statistical Analysis**: In this paper, we discussed a tsunami forecasting model for Bay of Bengal using Artificial Neural Network (ANN) and network of eight Tsunami stations. The ANN algorithm at each station characterizes the tsunami detected, while velocity and direction are obtained from the specified arrangement of buoys. The effectiveness of the ANN algorithm in characterizing a tsunami is discussed using actual time-series data. **Findings:** It is observed that modification to the ANN algorithm in[7] can characterize a tsunami effectively, in terms of its amplitude and period. Analysis of the methodology is carried out using simulated data for obtaining the direction and velocity of tsunami. **Improvements/Applications**: Presently, the Indian Tsunami Warning System (ITWS) issue warnings based on the possible scenario selection from its exhaustive event database on the basis of inputs collected from various sources. **Applications:** This methodology could augment capabilities of ITWS by providing additional inputs on peak amplitude, direction and velocity of a detected tsunami for the proper scenario selection. This in turn helps in disseminating more reliable warnings.

Keywords: Artificial Neural Network for Tsunami, Bottom Pressure Recorders, Characterization of Tsunami, Sumatra Earthquake on 12th September 2017, Tsunami Direction and Velocity, Tsunami Warning

1. Introduction

Tsunami waves are caused by sudden geophysical disturbances which result in displacement of large volumes of water in oceans. Tsunamis are shallow-water waves with great wavelengths and tiny amplitudes[1]. The initial wavelength and amplitude are determined by the nature and size of phenomenon that produces the tsunami[2].

Initial speed, v, of tsunami is dependent on the depth d of the ocean, and can be given as

$$v = \sqrt{gd} \tag{1}$$

Where g is acceleration due to gravity. Considering an average depth of 3963 for Indian Ocean[2], the above relation suggests velocity in the range of 709.5 km/hr. As these waves approach shore, due to phenomenon of shoaling and coastal bathymetry the wavelength dwindles, while the amplitude get magnified many times and resulting in extensive damage to life and property.

The 9.1 magnitude earthquake off the coast of Sumatra (in 2004), which resulted in a deadly tsunami that hit the coasts of several countries in South and Southeast Asia, is recorded as one of the most devastating catastrophes to have occurred in the world. The extent of damage it caused exposed the vulnerability of a country like India, being surrounded by two Tsunami genic source zones with a coastline of 7500km. The most efficient method to mitigate the damage caused by a natural disaster is by establishing system which could reliably forecast the onset of an event and issue warnings about the impending disaster. In this regard, Ministry of Earth Sciences, Government of India has established an Indian Tsunami Warning System (ITWS) for the entire the Indian Ocean[3].

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ITWS acquires data from various sources :a network of land based seismic stations for detection of earthquake and its parameters, the Bottom Pressure Recorder (BPR) stations which measure water column height and coastal Tide Gauge network for monitoring sea level. ITWS uses Tsunami N2 model[4] to create a database of possible scenarios. Based on the magnitude and location of earthquake, the ITWS software selects appropriate scenario from the database to issue necessary warnings.

The Paper is organized as follows: Section 2 proposes an arrangement of BPR in the Indian Ocean; Section 3 discusses the algorithm used to characterize the detected tsunami (from the measurements of BPR); Section 4 discusses the estimation of direction and velocity of tsunami from a network of 8 stations; Section 5 discusses the results of the methodology on a simulated dataset and Section 6 concludes the paper.

2. Arrangement of BPR for Tsunami Detection and Characterization

An important component of any Tsunami Warning System is the accurate monitoring of sea-level. A Tsunami event is confirmed or denied based on the data from BPR installed in deep sea around 4000m of water depth. The BPR has a pressure transducer which measures the hydrostatic pressure of water column above it by using quartz-crystal beam type pressure sensor[5]. At such depths, long period waves like tsunami and tides can be detected by measuring the pressure at a fixed point on the sea-floor as deep ocean acts as an ideal low pass filter[6], filtering out the high frequency waves generated by winds and swells. The BPR is acoustically connected to a Tsunami surface buoy which inturn transmits the data to warning center using satellite telemetry. Each tsunami station consists of a BPR and acoustically connected the tsunami surface buoy. Figure 1 a depicts the two fault Zones, Makran and Sumatran. The BPR system is shown in Figure 1b and planned locations for the installation of BPR in the Bay of Bengal for augmenting the ITWS is given in Figure 1c.

The methodology discussed in this paper provides the characterization of Tsunami. The data from eight tsunami stations deployed in the Bay of Bengal and modification of the Artificial Neural Network (ANN) algorithm proposed [7] is used for determining velocity and direction of Tsunami wave.

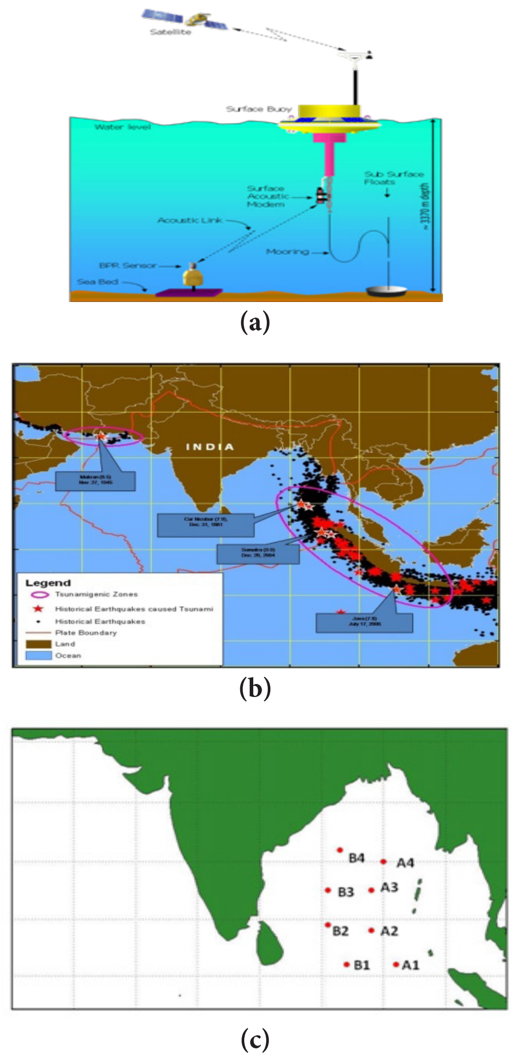


Figure 1. **(a)** Tsunami genic zones in the Indian Ocean[4] **(b)** Indian BPR system **(c)** Position of the BPR and tsunami buoys in the Indian Ocean covering the two faults.

3. Modified ANN Algorithm for Detection and Characterization of Tsunami

Beltrami discussed various algorithms used in BPR, Tidal gauges and Wind-wave gauges[8] for detection of Tsunami. The Deep-Ocean Assessment and Reporting of Tsunamis system (DART)[6,9] and ANN[7] algorithms, are able to closely predict the non-tsunami waves with BPR data. The former uses a cubic polynomial while the latter uses Artificial Neural Network (ANN) for prediction of the non-tsunami waves. Both these algorithms are based on amplitude discrimination in the sense that a tsunami is detected when difference between predicted wave amplitude and measured wave amplitude exceeds a predefined threshold (30 mm in Pacific Ocean). A modification to the ANN algorithm[7] in has been given in[10] for detection and characterization of tsunami. It consists of lengthening the time interval between the actual and the prediction time in order to delay the instant where a propagating tsunami start influencing the predictions.

The modification proposed in this paper stems from the fact that an ANN could closely predict the non-tsunami long period waves which is composed of sea-surface fluctuations (e.g. planetary waves, astronomical and meteorological tides or gravitational normal modes) and background sea noise. Assuming a perfect prediction of these non-tsunami waves, residual signal is essentially zero. The predictions from ANN could closely follow the observations by using training set encompassing all possible sea level variations. In case of perfect prediction, the residual signal contains only tsunami and seismic waves. The seismic waves are characterized by high frequency fluctuations which can be removed by simple low pass filtering. After applying a low pass filter, the residual signal will contain only tsunami waveform. Nevertheless, the actual residual signal will contain a noise component along with filtered tsunami waveform.

The network used for prediction is an adaptive-weight two layer feed-forward network given in Figure 2. It is characterized by 4 input plus bias with 7 Hidden units plus bias and one output unit. The input consists of n-minute (10 min) averages ($\bar{\zeta}$) of the observations by BPR ζ collected over the past 3 hours (same as used by DART[6,9] and ANN[7]). These values are rescaled in the range [0;1] by considering twice the original signal's maximum and minimum values. The network function corresponding to the architecture in figure 2 can be expressed as:

$$\hat{\varsigma}(t') = \tilde{g}\{w_b^{(2)} + \sum_{j=1}^{7} w_j^{(2)} g[w_{bj}^{(1)} + \sum_{i=0}^{3} w_{ij}^{(1)} \bar{\varsigma}(t'' - i\Delta t)]\} \quad (2)$$

Assuming t as the actual time, t'= t + 0.25/60h, t"= t – n/(2*60h) and Δt = 1h. This means that, the predictions are updated every 15s. $w_{ij}^{(1)}$ and $w_{bj}^{(1)}$ are the adaptive weights connecting the input units and the bias to the hidden units. $w_j^{(2)}$ and $w_b^{(2)}$ connect hidden and bias units, respectively, to the output unit. g(.) and $\tilde{g}$ are the activation functions which are linear and logistic sigmoid functions, respectively.

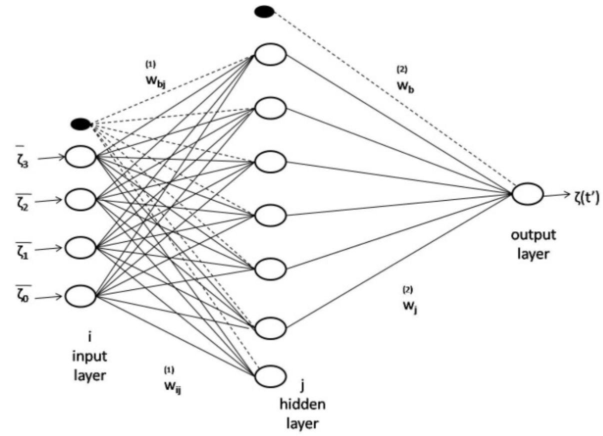


Figure 2. Diagram of the feed-forward ANN architecture used for prediction.

The adaptive weights and the bias are estimated from the network's supervised learning. In a supervised learning scenario, the network is fed with an input array ($\bar{\zeta}$) and the corresponding output vector (i.e. training set). The adaptive weights result from minimizing the difference between the calculated ($\hat{\bar{\zeta}}$) values and the observed (ζ) values during training.

In an ideal scenario, where the residual signal is zero, using the past predictions of the ANN as input to the network should not affect the network performance. However, in reality ANN is not capable of filtering out background pressure noise[10]. Even though the error in prediction becomes low with efficient training set, as time progresses errors accumulate and result in erroneous predictions. Therefore, in order to characterize tsunami, the modified ANN is proposed to work in two modes: standard mode and event mode. Standard mode is the normal mode of operation where input consists of ten minute averages ($\bar{\zeta}$ of the observations by ζ BPR (ζ)) collected over the preceding three hours and ten minutes. Event mode is triggered when the residual signal amplitude exceeds a pre-set threshold. The seismic waves, which accompany tsunami waves, travel much faster than the tsunami waves and trigger the system to event mode as the threshold exceeds. In the event mode, inputs to the system are taken from a sample set comprising of the measurements made by BPR till the time of trigger and past predictions made by the system from the time of trigger. This will help in filtering the noise generated due to seismic signal with an assumption that the predictions from the system closely follow the non-tsunami waves.

The amplitude of tsunami waveform can be found if the timestamp of trigger and settling time are estimated. The time stamp of trigger is the time at which the system is put into event mode. Settling time can be estimated by inspecting the residual signal. To find the time period of the tsunami waveform, the residual signal is subjected to low pass filtering which identifies the seismic waves. Having thus identified the seismic waves, we now proceed to the characterization of tsunami waves. Tsunami waves have approximately the form of N-wave. The period of such a wave can be identified as twice the period between maxima and minima. The maxima and minima can be detected from the residual signal when the settling time is reached.

4. Direction and Velocity of Tsunami Propagation

The estimation of direction becomes important in the prediction of travel times to issue accurate warnings. To estimate direction, a setup of BPR and tsunami buoy s as outlined in figure 1c is proposed. The following assumptions are made regarding the propagation of tsunami and the position of buoys:

1. Geometric spreading of waves where the amplitude ecay is proportional to 1/r, where r is the distance from source.
2. The BPR in each row are equidistant from the possible source of origin (Sumatran Fault).

The first assumption enables an upper limit approximation of the wave height as a function of distance from the source which can be given by

$$\mathbf{H} = \mathbf{H_0}\,\frac{\mathbf{R_0}}{\mathbf{R}} \tag{3}$$

Where Ro is the initial source radius, R is the distance the wave has traveled from the source, and Ho is the initial height of the source[11]. In a hypothetical case where energy spreads uniformly in all directions, the assumption 2 suggests that all the 4BPR in each row record same energy, and inturn same amplitude of the tsunami wave. However, in reality spreading of energy is not uniform. So an estimate of the tsunami amplitudes at each BPR can reasonably give the direction of tsunami. The amplitude of tsunami wave, at each BPR, is estimated using the modified ANN algorithm discussed above. The BPR where maximum amplitude recorded is calculated for each row. The look-up Table 1 gives the direction estimate. The bearings are calculated from the positions of each BPR in row A with respect to the positions of BPR in row B. Suppose the maximum amplitude in row A is detected at second BPR (A2) and maximum amplitude in row B is detected at third BPR (B3), the direction of propagation is given by 229°.

Similarly, the knowledge of time stamp of the maxima along with the distance between the stations in each row where maximum amplitude of tsunami wave is detected from the Table 2 can be used to get an estimate of the velocity of tsunami wave in Deep Ocean. The velocity thus obtained can be used for more accurate travel time predictions critical in issuing tsunami warnings compared to the approximation of tsunami velocity given by Eq.1. The discrepancy in using velocity given by eqn.1 can be deduced from the Figure 3 aand Figure 3b which depicts measurements made by BPR and Tide gauges, respectively, on September 12, 2007 during Sumatra earthquake of magnitude 8.2. According to the data from tide gauges (refer figure 3b.) the first waves hit Chennai coast, which is at a distance of 1348 km from the BPR which made the observations in figure 3a. 2.25 hours after the tsunami wave formation in Deep Ocean. The calculation of velocity yields approximately 600km/h instead of a shallow water wave assumption [12] of 709.5km/h.

5. Experiments and Results

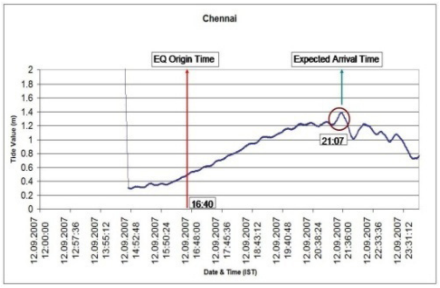
The modification suggested can be substantiated from the tests carried out on the data recorded by Station

Table 1. Bearing (deg)

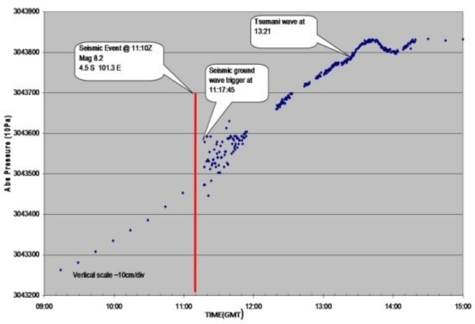
	B1	B2	B3	B4
A1	270.21	303.06	320.54	336.56
A2	213.6	278.51	315.82	341.03
A3	197.06	229.22	270.38	325.604
A4	198.44	219.15	240.78	286.98

Table 2. Distance between stations (NM)

	B1	B2	B3	B4
A1	442.34	720.11	941.45	1215.32
A2	399.85	388.12	545.13	824.26
A3	755.32	507.14	379.95	473.32
A4	1053.02	782.87	559.87	391.16



(a)



(b)

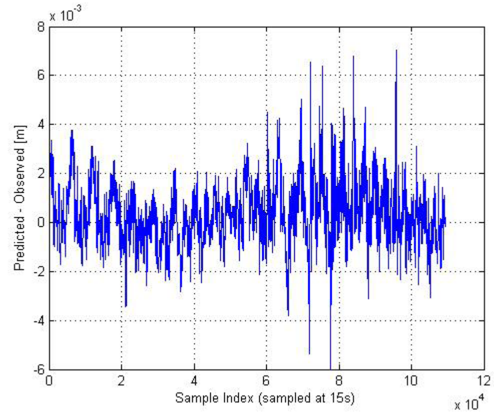
Figure 3. **(a)** The absolute pressure readings recorded by Indian Tsunami buoy on September 12, 2007 (Time in GMT). **(b)** Water level observations made by Tide gauges on the same day (Timein IST).

23401-600NM West-Northwest of Phuket, Thailand (8.905oN,88.537oE) available from NOAA site. The data consist of height (inmm) sampled at 15min. Aspline was fitted to generate a 15 ssampled data for all analysis purposes. The test data consists of continuous time- series spanning December, 2008 (1-20 days), January 2009 and May 2009. Table 3 shows the effect of length of training set on the standard deviation of filtered signal. The decrease in standard deviation of the filtered signal with an increase in the number of training samples supports the improvement in filtering performance of the ANN algorithm using training set comprising of extensive set of possible sea-level variations. This observation also follows from Figure 4. which depicts the filtered signal obtained for December 2008 data using training sets derived from 5, 15, 30 and 84 days, respectively. For all cases, the numbers of learning epochs were fixed at 1000.

Figure 5 shows the predicted and measured heights for the three datasets. From the figure it is evident that the error increases as the time progresses. But the figure also suggests that predictions follow the pattern of measured data in the depicted time interval (2000 samples is approximately 8 hours data). However, beyond 8 hours

Table 3. Comparison of standard deviation obtained for the test sets using training sets of various lengths

Span of Training Set (days)	Standard Deviation		
	December 2008	January 2009	May 2009
	0.05421	0.0576	0.0494
15	0.0020	0.0021	0.0020
31	0.0013	0.0014	0.0014
84	0.00092	0.00091	0.00090



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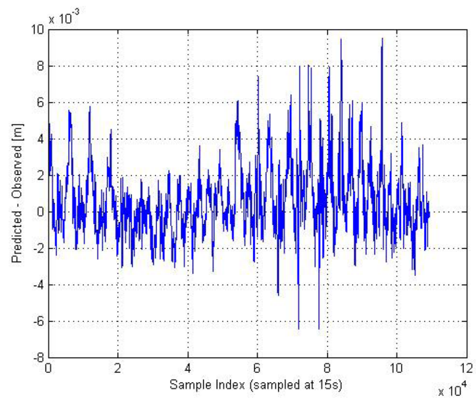

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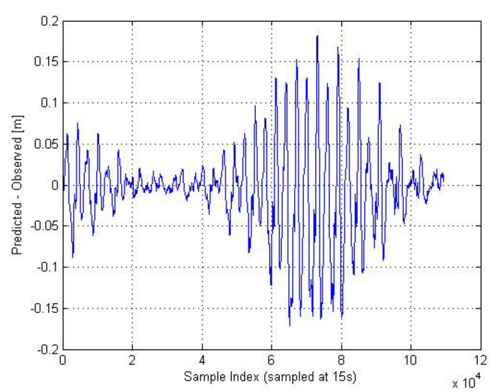

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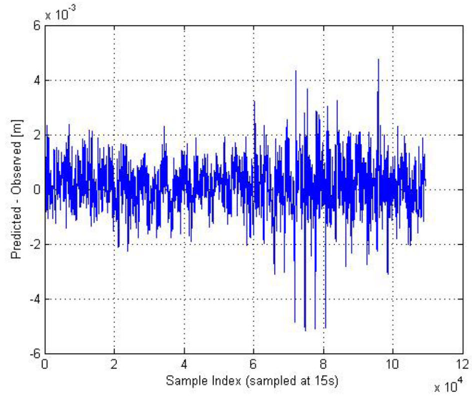
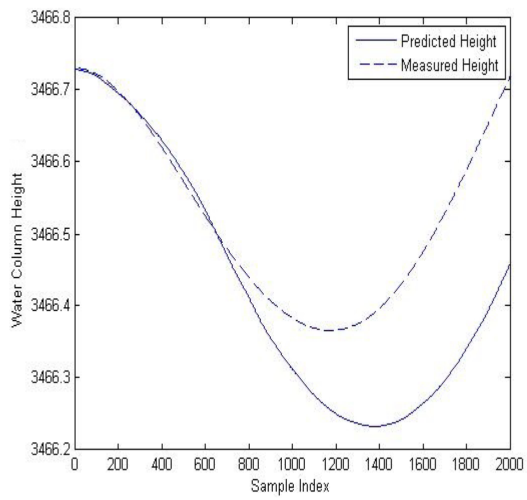


(d)

Figure 4. Filtered (predicted-observed) signal of the December, 2008 dataset using various lengths of training set **(a)** 5 days **(b)** 15 days **(c)** 30 days **(d)** 84 days.



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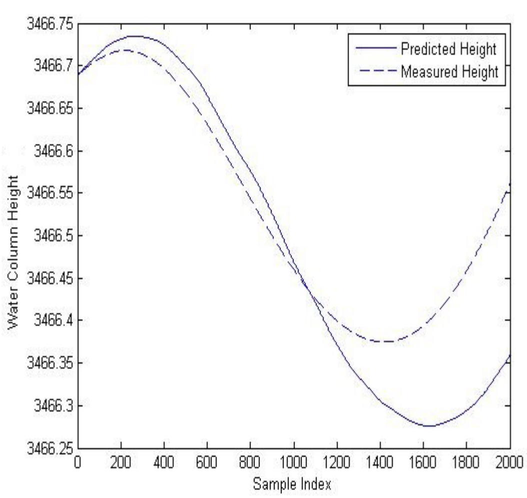

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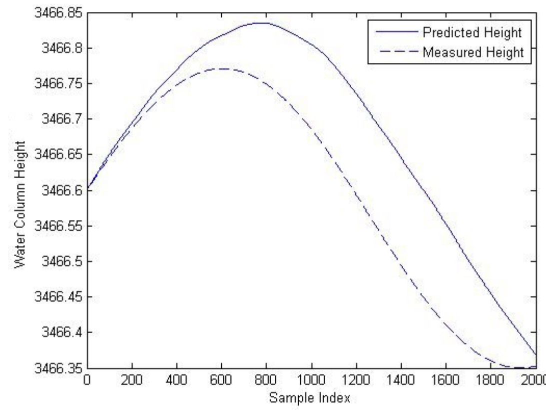

(c)

Figure 5. Comparison of the measured height (in mm) and the height predicted by the ANN algorithm (in mm) for **(a)** December, 2008 **(b)** January, 2009 **(c)** May, 2009.

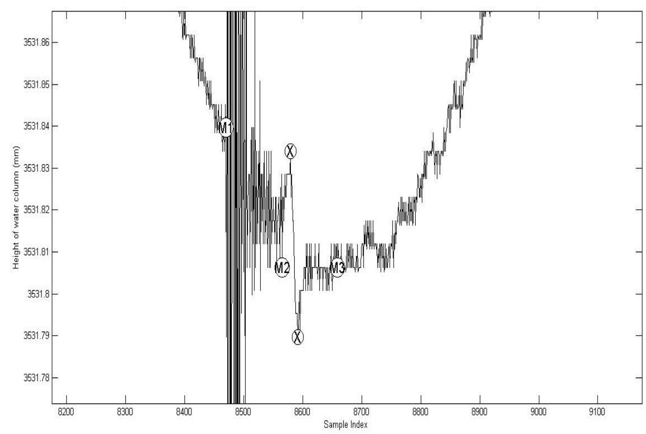

Figure 6. Result of applying modified ANN Algorithm on a real data. The data has been trimmed to display only the indices corresponding to tsunami.

the predictions digress wildly from the measurements made.

Figure 6 shows the extend of tsunami identified by the modified ANN algorithm on the data collected by Indian Tsunami buoy positioned at 9°N, 89°E collected during June, 2010. Three points are marked on the figure. M1-index where the threshold is exceeded (at this instant the system is put to event mode); M2-index depicting the start of tsunami wave; M3-index where the system is settled (beyond this time the system continues to be in standard mode). The amplitude of tsunami can be calculated by taking half of the difference between maximum and minimum amplitudes between the markers M2 and

Table 4. Estimation of direction using the modified ANN algorithm to the indices of maximum amplitudes of stations in rows A and B gives the direction of tsunami

Trial No	Peak Amplitudes at Station					Max. Amplitude Index		Bearing
	Row	1	2	3	4	@Row1	@Row2	
1	A	0.049150	0.049298	0.033152	0.049412	4	1	338
	B	0.044143	0.034708	0.041006	0.027838			
2	A	0.043575	0.045155	0.044863	0.037845	2	3	229
	B	0.038110	0.028424	0.039121	0.025637			
3	A	0.035538	0.030923	0.031943	0.046469	4	3	303
	B	0.038897	0.031342	0.044004	0.025689			
4	A	0.038775	0.037631	0.045310	0.045904	4	4	270
	B	0.028737	0.034795	0.033912	0.037926			
5	A	0.044187	0.045094	0.035521	0.043594	2	1	331
	B	0.038102	0.028252	0.027380	0.034967			
6	A	0.049195	0.036808	0.041705	0.034476	1	1	289
	B	0.040025	0.030102	0.035119	0.038982			
7	A	0.047818	0.049186	0.040944	0.032772	2	3	229
	B	0.027986	0.030150	0.041814	0.030086			
8	A	0.046286	0.034870	0.048585	0.037000	3	3	278
	B	0.028932	0.030022	0.037321	0.034466			
9	A	0.037033	0.046617	0.041705	0.040994	2	1	331
	B	0.043344	0.030717	0.040144	0.040075			
10	A	0.041376	0.039388	0.030238	0.036742	1	2	240
	B	0.028244	0.040886	0.031224	0.035571			

M3 which is found to be 2.2 cm. The extend of tsunami can be approximately calculated as 7 minutes (28 Samples) when sampled at 15s, which is twice the time between the maxima and minima between markers M2 and M3. The period of the wave has been estimated as 9.5 minutes by inspection.

Table 4 shows the direction (bearing) estimated using sets of simulated event data (due to the unavailability of data at all 8 stations as the deployment is still under progress)at each of the 8 BPR. The event data is obtained by super imposing asine wave on the data after manually removing the actual tsunami wave from the measurements. A trow A, the sine waves (tsunami waves) generated have amplitudes in the range 3 cm to 5cm.Considering the loss of energy, which results in the decrease of amplitude of the tsunami wave as the wave propagates given by eq.3, the amplitudes of sine wave atrow B are assumed between 2.5cm to 4.5cm for simulation purpose. The amplitude of the sine (tsunami) wave recorded in each station is calculated using the modified ANN algorithm discussed in section 2. The bearing corresponding to the station indices recording the maximum amplitude in each row is obtained from table 1 and it gives the direction of tsunami.

6. Conclusion

The proposed method could effectively detect and characterize tsunami wave. Further, the proposed algorithm along with the specified arrangement of eight Tsunami buoys could effectively estimate direction, peak amplitude and velocity of the Tsunami wave in the Bay of Bengal. These inputs could augment Indian Tsunami Warning Centers for generating information about travel times and other advisories.

7. Acknowledgement

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