Intelligent Decision Technologies 13 (2019) 295–303
DOI 10.3233/IDT-180003
IOS Press

Proficient 3-class classification model for confident overlap value based fuzzified aquatic information extracted tsunami prediction

Nikita Jain[a,b,*], Deepali Virmani[c] and Ajith Abraham[d]
[a]*University School of Information, Communication and Technology, Gobind Singh Indraprastha Universty, Delhi, India*
[b]*Bharati Vidyapeeth's College of Engineering, New Delhi, India*
[c]*Department of Computer Science and Engineering, Bhagwan Parshuram Institute of Technology, Delhi, India*
[d]*Machine Intelligence Research Labs, Scientific Network for Innovation and Research Excellence, Auburn, WA, USA*

AUTHOR COPY

Abstract. Tsunami occurrence has created havoc for humans. This unfortunate event however does provide some pre-alert signals which if carefully analyzed can help in pre-sensing this havoc. The signals can be in form of certain indicators in environment and in nature which can be sensed dynamically. Various studies have reported cases of animal behavioral signals prior to tsunami. These changes are a result of environmental changes before any such event occurrence. This paper proposes a confident fuzzified system derived over marine behavior to predict tsunamis ($3CC_{COV}FTP$). The system uses an overlap function based linguistic rule derived algorithm creating three class of classifications. Using this system, aquatic behavior is studied, analyzed and classified to produce alerts in real time. Initially, the behavioral attributes are identified for both turtle and earthworm dataset which do produce anomalous signals. The attributed data is further analyzed to retrieve fuzzy rules using which alert, pre-alert or no alert overlapped opinions are extracted. The dataset for analysis includes the following derived parameters: adaptive electromagnetic field, Underwater count of particular specie Deviation in angle of motion (calculated for both sea turtles and earthworms defining their navigation activity per month and per day). The proposed system generates criteria three class categorization on the basis of the derived inputs. From the result obtained, confidence level for each extracted rule is formulated to derive optimized rule set that can serve mathematical formulation to in time alert generation. For prediction of any similar activity in the coming years, 2004 has been utilized as the baseline opinion year with resulting constraint as default rule. The tertiary classification formulated using the proposed algorithm classifies the behavior into three alert categories: Alert, Pre-Alert and No-Alert. Based on the quantified confident opinions, alerts primarily based on aquatic animal behavior can be generated for future years.

Keywords: Aquatic behavior, sea turtle, earthworm, fuzzification, rules, opinion, confidence score, alert

1. Introduction

In 2004, huge underwater seismic waves commonly termed as tsunami was witnessed along the coast of Sumatra.

Since then various actions have been taken up by government institutions as well as research commu-

*Corresponding author: Nikita Jain, University School of Information, Communication and Technology, Gobind Singh Indraprastha Universty, Delhi, India. E-mail: nikitajain1210@gmail.com.

ISSN 1872-4981/19/$35.00 © 2019 – IOS Press and the authors. All rights reserved

nity to develop efficient solutions needed, where such seismic waves can be pre-sensed such to help saving human lives [1]. However, the reoccurrence of similar instances where no alerts were generated for abandoning the affected areas timely have raised concerns over the efficacy of such solutions. Here, the solutions referred to as what is commonly termed as Tsunami warning system (TWS). As per certain recent news articles, these TWS have somehow not been able to generate any timely alerts while they were designed for the same.

As per human experiences, certain gaps [2,3] have been identified with respect to these TWS which can and have served as action points for the scientific community for improvement:

1. The remote areas along the coastlines usually do not receive timely warning sirens.
2. Various local inhabitants are expected to monitor the coastline despite the presence of TWS.
3. From 2, the inefficacy of inhabitants in identifying or categorizing alarming situations might lead to false positives or false negatives in timely predicting mishaps.

Given these pitfalls or gaps which were identified from past instances of tsunami occurrence, a need to design and implement effective as well as efficient warning systems became inevitable [4]. Seismic waves give pre occurrence signals by both means i.e. geophysical as well as by nature. Natural precursors include the aquatic lives which do get affected by these underwater seismic waves. Any changes in their adapted environmental conditions make them behave anomalously. Such observations have been studied and reported by the research community as well as the affected population [5–8].

The current tsunami prediction systems are monitoring the geophysical conditions more than the natural responses. The geophysical responses that are being tapped mainly are earthquake magnitude, underwater bottom layer pressure, changed in tidal activities, waveform properties [9,10]. The sensor nodes that record these changes are deployed underwater for precise information capturing. We propose a 3 class classification model with a confident overlap based fuzzified algorithm based out of aquatic species change in behavior here: Sea turtle and earthworm both.

Marine life, can act as timely predictor to sense tsunami.

The research community has believed that aquatic animals do produce certain messages or signals in terms of behavioral responses which can act as predictive means to generate alerts [11]. Here, Apart from just generating signals in form of responses an integrated system where these responses are collected and analyzed together for generating awareness [12]; these messages if integrated to the current warning systems can help in generating an effective design and diverse warning system.

In existing state-of-art no global warning system produces aquatic animal behavioral alerts in concatenation to geo physical changes in environment. If analyzed well in time, the efficacy of existing TWS can be enhanced.

The specific contributions of this article are as follows.

An exhaustive categorization of existing TWS or existing techniques in literature has been presented. This has underlined the dire need of a special hybrid systems marking higher efficiency for timely prediction

Based on above observation, a hybrid prediction model ($3CC_{COV}FTP$) is proposed which combines the effects of two precursors that can derive timely tsunami prediction

The hybrid model uses novel quantified anomalous sea animals (Turtles and Earthworms) behavioral attributes obtained in response to changing environmental condition and performs a 3 class classification using fuzzified rule based extraction

The derived rules obtained using rated confident and overlap scores are classified into 3 different classes as tsunami-alert, tsunami-pre-Alert and tsunami-no-alert years. Here the classification is done on the basis of confident overlap function scoring. The resulting insights match with the historical data; again identifying year 2004 as an alert year.

In this paper, a confident overlap function based algorithm (COV_FMB) is proposed and implemented. This algorithm gives fuzzified linguistic rules evaluated from aquatic animal behavioral attributes. The 3 class classification here is defined as: Pre-Alert, No-Alert and Alert. 2004 being the known tsunami year, from this algorithm also comes to be the tsunami year as well. To evaluate these rules, confidence score is also calculated for each rule where the optimization of these rules is highlighted. Two datasets used here are from a public source which gives behavioral activities of Earthworms and sea turtles.

AUTHOR COPY

2. Related works

2.1. Tsunami warning system categorization

Earthquakes, landslides, volcanic eruptions all can lead to tsunami generation. In this section different categories of TWS have been discussed, describing about existing and proposed algorithm as well products

Tsunami is a hazard that is generated by short period underwater perturbations [13,14]. They can also be a result of ongoing volcanic eruptions or landslides or repetitive earthquakes. Based on the time period that it takes to propagate, tsunamis are categorized as either "ongoing" or "slowly creeping". The warning systems so designed generate alerts using different types of sensed parameters. From the different types parameters sensed, the current state of warning systems is being categorized into two: Geophysical systems and People oriented systems. Consequently, a hybrid system is further proposed, where both features can drive seismic alerts based on response of one from the other.

2.2. Warning systems based on geophysical features

Seismic perturbations can cause changes in environment conditions for egg: pressure underwater, tidal wave activity of waves, sea-level, and height of waves, temperature and salinity of the water [15,16]. As noted, these are all geo-physical features on which a TWS can be designed. The predictors used here show changes which are time dependent. For timely alerts quick changes needs to be tapped for getting an efficient warning system.

2.2.1. People based TWS

Community or people-reaction derived warning systems are designed to generate alerts using an individual observation that includes coastline fisherman, local inhabitants near sea shores etc. It's a response based model where the word of mouth further propagated can help in a timely evacuation. The analysis here is carried out on behavioral responses of humans towards the change in geophysical changes happening in the environment. These responses could also be there deep observations towards changes they are able to identify in natural elements like underwater animals and plants. Various content and people behavioral based warning models and studies have been discussed in [20].

2.2.2. Nature derived warning systems

Underwater animals as well as plants are inherently adapted to a stable and suitable environment as per the conditions they are subjected to [17]. Any inconsistency or deviation in the environmental conditions can lead to changes in feeding, locomotion, migration as well as positioning patterns of these creatures. Seismicity can lead to unwanted disturbances in the environment [18]. Hence Marine life in specific does get affected by any change in the adaptive environment they are already a part of. These changes have been observed sometimes days, month or months before the actual occurrence of this unfortunate event: Tsunami. Several researchers have highlighted such facts. One of the examples is the changes in behavior of a common toad much before the waves hit the Ruffino Lake in 2009 [19].

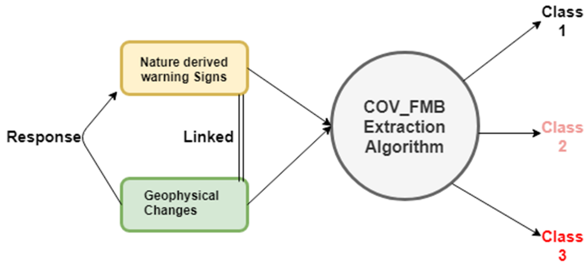

Fig. 1. $3CC_{COV}FTP$ architecture.

2.2.3. Hybrid systems

This paper therefore proposes an additional category of warning system which is an integrated solution. The proposed system is a hybrid of both the natural and geophysical parameters identified individually in the previous sections. Figure 1 presents an architecture block diagram of the hybrid system defined $3CC_{COV}FTP$ which is a 3 class classification system derived over confident fuzzified extracted linguistic rules over marine behavior attributes. From above discussion, A novel linked conjunction between geophysical changes and aquatic species response is a need.

A similar responsive association between behavior of sea species and geo-physical conditions was observed when 6 days before 2011 tsunami in Japan [18], a large amount of whales were found dead along the coastline. Similar instance of beaching was observed in New Zealand in 2015 [21]. Such incidents were based out of the inability of sea animals to adapt to the diversely changing environmental conditions. Hence, a responsive reaction by these animals can be sensed, pre-analyzed and an alert much before the occurrence of the event can be generated which will help in timely evacuation. It was also reported that in above mentioned instances the species who suffered from this "mass suicide" did not have any other disease. Hence,

AUTHOR COPY

the architecture in Fig. 1 shows a relational link between the two parameters.

Here, the parameters sensed are the change in electromagnetic force (EMF), its effect on sea turtle count (Cant) and Angle of Deviation (AOD) (monthly) as well as OD (Daily).

These parameters cover the impact of tsunami on both breeding and migration activities of these underwater species as discussed in [22].

2.3. *The need of a hybrid system: Why sea turtles and earthworms?*

The need of a hybrid system deriving alerts on bio system responses followed by geophysical changes has been highlighted in the previous section. The motivation behind such proposition is that tsunamis still are going undetected timely. From the examples cited, it is possible for such hybrid warning systems to generate alerts at least few to many days before the actual onset of such event. Any change in adaptive conditions such as electromagnetic field affects migration and locomotion pattern of underwater species. Such as sea turtles which use their inherent magnetic cues for finding direction to locate food or prey underwater. As any change leads to a complete deviation which therefore makes them food deprived causing a reduction in underwater count.

Here, on the basis of existing evidences and [23–25] reports that identify how electro-magnetic fields can affect the behavior of marine animals. Based on the effects of the changed electromagnetic field, the consequent changes in the behavior of aquatic species can be used one of the precursors in generating alerts [26]. Thus, the proposed system works by formulating new dimension to tsunami prediction on the basis of Sea Turtle and Earthworm behavioral patterns. Sea turtles have been used a case of study in respect to the results of an experiment conducted in [27]. Here, the turtles that were exposed to strong magnetic fields from north deviated to south direction giving a change in locomotion. Similar observations are highlighted for Earthworm behavior in [40].

2.4. *Three class classification using fuzzy rules*

Multiclass classification differs from binary classification to the number of output class. Here the given set of predictor attributes are used to map it with a finite set of categories (classes), i.e., each input is classified into one of the possible target class [27,28]. Multiple classes are considered simultaneously, it is complex than the binary classification where there are only two classes involved [29].

Usually classification as a concept is used as an initial step where the similar members of a group are always grouped together. Such preliminary analysis helps in obtaining a pattern detection scheme where a trend or a particular incoming instance based classification can be performed. In order to devise an algorithm for making a precise classification, learning the trajectories of data is needed. Various learning models have been used and proposed in past. Here, combination of classifiers has also been explored to obtain highly correlated results and maximized inter cluster (group) distance.

The methodology used by different classifiers is based on the representation of the input pattern as well as the measurement or the classifying criteria. For example: Kitler et al. in [30] have used a joint probability distribution based sum rule combination to classify the data. The criteria used here is a cost minimizing function to minimize the error obtained from above sum combination. Followed by above is a Naïve Bayes classifier [31] uses a conditionally independent probability for data analysis.

In probability concept, the classification rules are derived from the basic premise B (say) is objectively or subjectively estimated to be true. However, these classifications suffer from computational limitation when the input data comes out to be uncertain and dynamic [32].

Hence, fuzzy set theory introduced in [33,34] served as a mathematical foundation for modeling imprecise data. Various researchers in past have used this theory to model behavioral data to deal with inexactness or fuzziness of such data. Here a defined cluster analysis is performed to take in the vagueness of data through degrees of membership functions in form IF-THEN-ELSE decision rules. These rules are computed to be human readable.

3. Dataset description

The proposed COV_FMB algorithm works on two data sets prepared. One is obtained from Reunion Island near Indian Ocean coasts containing marine turtle behavioral statistics termed here as D1 [35]. Second is the same year window dataset (D2) [36,40] for Earthworm activity near coastlines of Indian ocean.

Following parameters are extracted from both datasets in form of attribute for particular specie [37,38].

AUTHOR COPY

- Deviation in angle of motion (between consecutive months) as AOD(M). For every year in the complete dataset D1 and D2 both, this parameter is formulated between each pair of months occurring consecutively. These parameters are partitioned under linguistic labels as shown in Table 1.
- Deviation in angle of motion (for existing values in both datasets separately) formulated between each pair of months occurring consecutively. This is calculated for each year in the whole dataset.
  The above parameters are calculated using tapped longitude and latitude values for both datasets where deviation was calculated using haversine equations as shown in [41].
- Underwater specie count (as turtle and earthworms both).
- Electromagnetic Field: Due to seismic activity, the adaptive electromagnetic field starts varying. during underwater seismic perturbations gets changed. From the existing dataset (both D1 and D2) a SQL query command is used to extract behavioral activity for a repeated timestamp. These changes in attributes are linguistically mapped as shown in Table 1. From the above process, there were some values missing for a particular timestamp for different attributes. The missing values of the attributed dataset also had values for days closer to 2004. This we assume to be a cause of unavailability or inability of sensors to track the information in advance to occurrence of such hazardous event or probably due to unwanted catastrophic failures, therefore it is one of the limitations here.

Table 1 represents the parameter description with value description for each variable as Low (L), Medium (M), High (H), Very High (VH) for both D1 and D2.

4. Methodology

In the current model, an aquatic animal behavioral rated algorithm COV_FMB is proposed and used. The used algorithm uses an overlap function over spanned years of dataset to find fuzzified rules. The given rules are then evaluated for confidence value to get the best possible rule base.

4.1. COV_FMB Algorithm

This algorithm uses 4 input parameters for all years of data taken into consideration.

<p1, p2, p3, p4>= AOD (D), AOD (M), Cnt, EMF.

The range of values of these parameters is defined below.

$$<p1> \rightarrow \text{Angle of Deviation (Day)} \rightarrow [\text{L, M, H, VH}] \quad (1)$$

$$<p2> \rightarrow \text{Angle of Deviation (Month)} \rightarrow [\text{L, M, H, VH}] \quad (2)$$

$$<p3> \rightarrow \text{Count} \rightarrow [\text{L, M, H}] \quad (3)$$

$$<p4> \rightarrow \text{Electromagnetic Field} \rightarrow [\text{L, M, H, VH}] \quad (4)$$

The above parameter values are extracted from [22, 23] where the range is specified as per the prediction algorithms.

Given a dataset (D) the activation hyperbox which extracts the minimum and maximum value for each parameter p for each year y is calculated as

$$\text{ActHB}_{yp} = [\min_{yp}, \max_{yp}] \quad (5)$$

The Overlap value is further formulated from Eq. (5) between two years y_1 and y_2 over all parameter values <p1, p2, p3, p4> using Eq. (6)

$$\text{Overlap}_{y1y2p} = \text{FindOverlap}[\text{ActHB}_{y1p}, \text{ActHB}_{y2p}] \quad (6)$$

Here the overlap value is calculated using the following function definition

FindOverlap(ActHB$_{y1p}$, ActHB$_{y2p)}$

{

$\text{Overlap} = (|(\min_{y1}, \max_{y1})| \cap |(\min_{y2}, \max_{y2})|)$

$\text{Minimumof}(|(\min_{y1}, \max_{y1})|, |(\min_{y2}, \max_{y2})|)$

} (7)

The above obtained Overlap is obtained and tested under three cases where the required actions are taken to generate the fuzzy prediction rule

Case 1: If

$$\text{Overlap}_{y1y2p} = 0 \quad (8)$$

Implies no overlap in behavioral attributes for parameter values stating that the gap between the considerable years is high where one is the tsunami year: 2004 hence giving no overlap

Case 2: If

$$\text{Overlap}_{y1y2p} < 0.55 \quad (9)$$

AUTHOR COPY

Table 1
Linguistic label characterization of both datasets

Parameter	Linguistic label	Range categorisation for D1	Range categorisation for D2
Angle of Deviation (month):	Low	$\leqslant 100$ degrees	$\leqslant 45$ degrees
AOD (M)	Medium	$\geqslant 100$ and $\leqslant 140$ degrees	$\geqslant 45$ and $\leqslant 70$ degrees
Angle of Deviation (day): AOD (D)	High	$\geqslant 140$ and <160 degrees	$\geqslant 70$ and <80
	Very high	$\geqslant 160$ degrees	$\geqslant 80$
Underwater specie count: Cnt	Low medium high	$\leqslant 3 \geqslant 5$ and $\leqslant 7 \geqslant 8$	$\leqslant 6 \geqslant 6$ and $\leqslant 9 \geqslant 10$
Electromagnetic field: EMF	Low high	$\leqslant 1$ nTesla $\geqslant 1$ nTesla till 4 nTesla	$\leqslant 1$ nTesla $\geqslant 1$ nTesla till 4 nTesla

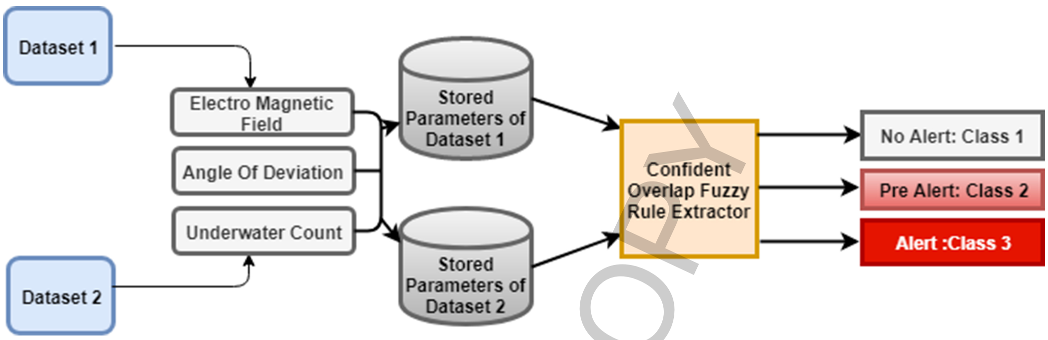

Fig. 2. COV_FMB workflow.

AUTHOR COPY

Implies a medium overlap in behavioral attributes for parameter values stating that the gap between the considerable yeNars is moderate where one is the tsunami year: 2004 hence giving a considerable overlap

Case 3: If

$$\text{Overlap}_{y1y2p} > 0.55 \tag{10}$$

Implies a high overlap in behavioral attributes for parameter values stating that the gap between the considerable years is less where one is the tsunami year: 2004 hence giving a high overlap.

The prediction rules are further formulated as function:

FindRules (Overlap)

{if (Overlap_{y1y2p} == 0){Extract fuzzy rule F from all attributes
for different combinations.
else (for each parameter $p_1, p_2 \ldots p_n$)
{
$X_{y1} \& X_{y2} = [\text{ActHB}_{y1p}, \text{ActHB}_{y2p}]$
$\text{Overlap}_{\text{Max}1\ldots n} = \text{Maximum}[X_{y1}] - \text{Maximum}[X_{y2}]$
$\text{Overlap}_{\text{Min}1\ldots n} = \text{Maximum}[X_{y1}] - \text{Maximum}[X_{y2}]$
if ($\text{Overlap}_{\text{Max}1\ldots n}$ || $\text{Overlap}_{\text{Min}1\ldots n} \approx 0$) then
{
$\text{Max}[X_{y1p}] = \text{Max}[\text{ActHB}_{y1p}]$
$\text{Max}[X_{y2p}] = \text{Max}[\text{ActHB}_{y2p}]$
}
else: **continue**
if ($\text{Overlap}_{\text{Max}1\ldots n}$ || $\text{Overlap}_{\text{Min}1\ldots n}$) then
{if
(
$\text{Max}[X_{y1p}] || \text{Max}[X_{y2p}] >$
Mean of [(p value in year y_1)
) then
$F \leqslant X_{y1p} || X_{y2p}\ as\ H$
else {$F \leqslant X_{y1p} || X_{y2p}\ as\ VH$
}
elseif
(
$\text{Max}[X_{y1p}] || \text{Max}[X_{y2p}] <$
Mean of [(p value in year y_1)]
) then
$F \leqslant X_{y1p} || X_{y2p}$ as L
else {$F \leqslant X_{y1p} || X_{y2p}$ as M}
end
/*Proposed Modification*/
ConfidentOptimise (F_n)
{Let F_n be the rule set obatained
$\text{COV}(F_i) = np^{+}(F_i)/n(F_i)$
}
Return F'
}

Using the above function the confident set of rules are obtained for all three cases classifying them in three classes. Equations (8)–(10) give the identifying condition for case division where a low overlap signifies no behavioral responses in earlier years than 2004. A higher overlap as in Eq. (10) signifies closer years to 2004 and similar responses by turtles and earthworms both as shown in year 2004. For Both datasets D1 and D2 having sea turtle and earthworm activity, mean overlap values are obtained and plotted for all parameters in all cases, shown in Figs 3–5. Similarly the dataset values for D1 are plotted in Figs 6 and 7.

Table 2
Retrieved confident optimized rule set for both D1 and D2

Rule number	Fuzzy rule	MeanOpSc	COV	Class category
Rule 1	IF EMF €[L; H] ∩ Cnt €[H] ∩ AOD (D) €[L; M; H; VH] ∩ AOD (M) €[L; M; H; VH] THEN Output = Z	−2.64	0.45	Class 3 Z = *No Alert*
Rule 2	IF EMF €[L] ∩ Cnt €[L; M; H] ∩ AOD (D) €[L; M; H; VH] ∩ AOD (M) €[L; M; H; VH] THEN Output = Z	−2.74	0.60	Class 3 Z = *No Alert*
Rule 3	IF EMF €[L] ∩ Cnt €[H] ∩ AOD (D) €[L] ∩ AOD (M) €[L; M; H; VH] THEN Output = Z	−1	0.42	Class 3 Z = *No Alert*
Rule 4	IF EMF €[H] ∩ Cnt €[M] ∩ AOD (D) €[VH] ∩ AOD (M) €[M] THEN Output = Z	+0.42	0.50	Class 2 Z = *Pre Alert*
Rule 5	IF EMF €[H] ∩ Cnt €[L] ∩ AOD (D) €[H] ∩ AOD (M) €[H] THEN Output = Z	+2	0.75	Class 1 Z = *Alert*
Rule 6	IF EMF €[H] ∩ Cnt €[L] ∩ AOD (D) €[VH] ∩ AOD (M) [VH] THEN Output = Z	+2	0.75	Class 1 Z = *Alert*

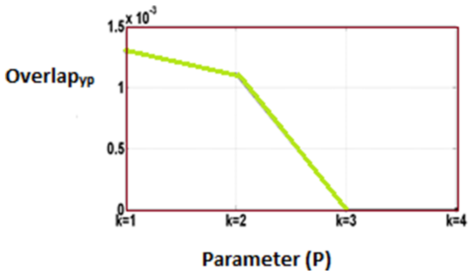

Fig. 3. Mean overlap values of both D1 and D2 for all parameters showing Case 1.

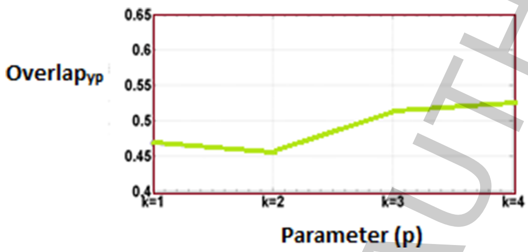

Fig. 4. Mean overlap values of both D1 and D2 for all parameters showing Case 2.

5. Results and discussion

To obtain the polarities between each rule for three class classification, Opinion Score as (OpSc) was calculated for every rule obtained in F using Eq. (11) which is an overridden score formulation from [38].

$$OpSc = N_L * \left(\log_2 \frac{N_L}{N_L + N_H} - \log_2 \frac{N_L}{N_L + N_H} \right) \tag{11}$$

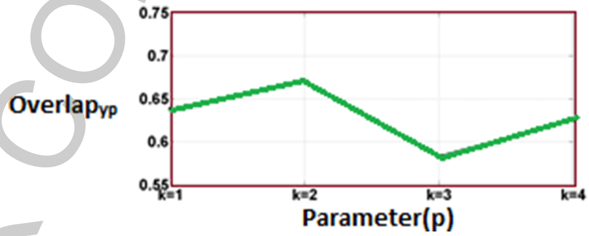

Fig. 5. Mean overlap values of both D1 and D2 for all parameters showing Case 3.

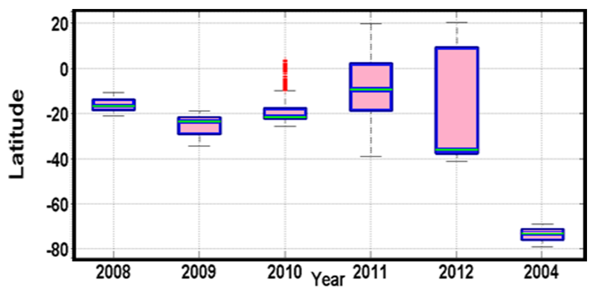

Fig. 6. Box plot of D1&D2 latitude values for every year.

From the above equation opinions for rule set F is obtained. Table 2 presents the extracted rule. Now, from these opinion polarities the three class classification is performed. However the rule set F gives various perm-uted rules. To rule out the permutation and extract F' the optimized rule set giving precise three class classification Confidence Score (COV) is calculated using Eq. (12) [39].

$$COV(F_1) = np^+(F_i)/n(F_i) \tag{12}$$

Here, $COV(F_1)$ is the confidence value of i^{th} rule in F set. $np^+(F_1)$ gives the number of positive or linguis-

AUTHOR COPY

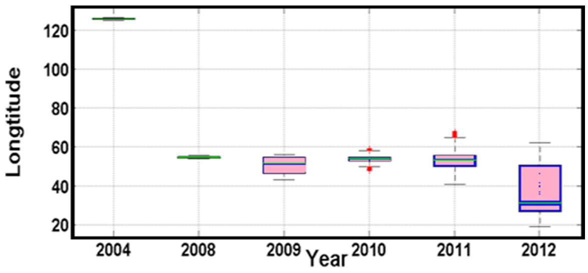

Fig. 7. Box plot of D1&D2 Longitude values for every year.

tically high values (here) in i^{th} rule of F set. Following $n(F_i)$ is number of samples covered by the rule. Clearly Rule 2, 4–6 standout be the more confident ones in terms of COV values obtained. Evidently they belong to three different classes of categorization taken in our problem for D1 and D2. Finally, this system has produce precise 3 class classification fuzzy rule sets from rated aquatic behavior conjuncted with geophysical changes.

6. Conclusion

The system proposed here, 3CC_{COV}FTP, produces marine behavior extracted three class classification based on polar opinions. These opinions are derived from a set of confident fuzzy rules. This system mines required information from the parameterized dataset of a sea turtle activity and Earthworm activity. This activity datasets contain values for 2004 which was a tsunami year. Different species both underwater and land have shown some anomalous behavioral signs in past prior to tsunami Using the proposed system a new dimension to Tsunami Warning can be added where nature also plays and equal role in seismic alert generation. The three class classification produce by the system is based on min-max fuzzified constraints. These constraints also called linguistic rules under the technique COV_FMB uses an overlap function to generate fuzzy rule set. This set is further evaluated using a confident score which places the final set of rules in parallel to the statistical reports stating similar evidences in marine behavior. A clear polarity change in opinion can be taken as the initial signs of existing tsunami warnings in animal responses. The OpSc ranges from $+2$ to -2.64 with a score of 0 for year 2004 being the Tsunami default year. For days closer to 2004 a higher opinion score is calculated, signifying the effects of pre-seismic perturbations which can affect marine behavior. The score opined from data values of 2004 is taken as a borderline or base score from which further deviations either positive or negative are calculated. This system adds a new dimension to existing systems and can generate animal behavior rated alerts globally. The proposed confident opinion-based fuzzification rules are further optimized using confidence scoring giving a three class classification to alert generation.

References

[1] Joseph A. Tsunamis: Detection, monitoring, and early-warning technologies. Academic Press. 2011.
[2] Løvholt F, Setiadi NJ, Birkmann J, Harbitz CB, Bach C, Fernando N, Nadim F. Tsunami risk reduction – are we better prepared today than in 2004? International Journal of Disaster Risk Reduction. 2014; 10: 127-142.
[3] Lassa JA. The west Sumatra earthquakes: Not learning our lessons? 2016.
[4] Schindelé F, Gailler A, Hébert H, Loevenbruck A, Gutierrez E, Monnier A, Rivera L. Implementation and challenges of the Tsunami Warning System in the Western Mediterranean. Pure and Applied Geophysics. 2015; 172(3-4): 821-833.
[5] Waltham T. The Asian Tsunami disaster, December 2004. Geology Today. 2005; 21(1): 22-26.
[6] Mott M. Did animals sense tsunami wascoming. In: National Geographic News 4. 2005.
[7] Corea Ravi. Nature: Eyewitness accounts. 2008; http://www.pbs.org/wnet/nature/can-animals-predict-disaster-ravi-corea/137/.
[8] Yamauchi H, Uchiyama H, Ohtani N, Ohta M. Unusual animal behavior preceding the 2011 earthquake off the pacific coast of tohoku, Japan: A way to predict the approach of large earthquakes. Animals. 2014; 4(2): 131-145.
[9] Grasso VF, Singh A. Early warning systems: State-of-art analysis and future directions. Draft Report. 2011; UNEP, 1.
[10] Beltrami GM. An ANN algorithm for automatic, real-time tsunami detection in deep-sea level measurements. Ocean Engineering. 2008; 35(5): 572-587.
[11] Tiwari R, Tiwari S. Animals: A natural messenger for disasters. Journal of Natural Products. 2011; 4: 3-4.
[12] Arce RSC, Onuki M, Esteban M, Shibayama T. Risk awareness and intended tsunami evacuation behaviour of international tourists in Kamakura City, Japan. International Journal of Disaster Risk Reduction. 2017; 23: 178-192.
[13] Monserrat S, Rabinovich AB. Meteotsunamis: Atmospherically induced destructive ocean waves in the tsunami frequency band. Natural Hazards and Earth System Science. 2006; 6(6): 1035-1051.
[14] Grilli ST, Vogelmann S, Watts P. Development of a 3D numerical wave tank for modeling tsunami generation by underwater landslides. Engineering Analysis with Boundary Elements. 2002; 26(4): 301-313.
[15] Cecioni C, Bellotti, G, Romano A, Abdolali A, Sammarco P, Franco L. Tsunami early warning system based on real-time measurements of hydro-acoustic waves. Procedia Engineering. 2014; 70: 311-320.
[16] Mulia IE, Asano T, Nagayama A. Real-time forecasting of near-field tsunami waveforms at coastal areas using a regularized extreme learning machine. Coastal Engineering. 2016; 109: 1-8.

AUTHOR COPY

[17] Stephen Messenger, Natural Sciences. Can whale strandings help predict earthquakes? 2011; https://www.treehugger.com /natural-sciences/can-whale-strandings-help-predict-earthquakes.html.

[18] Seaburn Paul. 160 beached whales may be a Japanese earthquake warning. 2015; http://mysteriousuniverse.org/2015/04/160-beached-whales-may-be-a-japanese-earthquake-warning/.

[19] Grant RA, Halliday T. Predicting the unpredictable; evidence of pre-seismic anticipatory behaviour in the common toad. Journal of Zoology. 2010; 281(4): 263-271.

[20] Suppasri A, Leelawat N, Latcharote P, Roeber V, Yamashita K, Hayashi A, Imamura F. The 2016 Fukushima earthquake and tsunami: Local tsunami behavior and recommendations for tsunami disaster risk reduction. International Journal of Disaster Risk Reduction. 2017; 21: 323-330.

[21] News Now. An overhaul of the current Civil Defence structure is on the cards after the Government ac-knowledged the current network is failing. 2016; https://www.tvnz.co.nz/one-news/new-zealand/failure-tsunami-warning-system-after-mondays-quake-sparks-civil-defence-overhaul. (Visited on 11/18/2016).

[22] Virmani D, Jain N. Intelligent information retrieval for Tsunami detection using wireless sensor nodes. in: Advances in Computing, Communications and Informatics (ICACCI). 2016 International Conference on IEEE. September 2016; 1103-1109.

[23] Schultz IR, Woodruff DL, Marshall KE, Pratt WJ, Roesijadi G. Effects of electromagnetic fields on fish and invertebrates (No. PNNL-19883). Pacific Northwest National Laboratory (PNNL). 2010; Richland, WA (US).

[24] Tricas T. Effects of EMFs from undersea power cables on elasmobranchs and other marine species. DIANE Publishing. 2012.

[25] Dodds WK, Robinson CT, Gaiser EE, Hansen GJ, Powell H, Smith JM, Kratz TK. Surprises and insights from long-term aquatic data sets and experiments. Bio Science. 2012; 62(8): 709-721.

[26] Lohmann KJ, Lohmann CM, Endres CS. The sensory ecology of ocean navigation. Journal of Experimental Biology. 2008; 211(11): 1719-1728.

[27] Kotecha R, Ukani V, Garg S. An empirical analysis of multi-class classification techniques in data mining. in: 2011 Nirma University International Conference on Engineering IEEE. December 2011; 1-5.

[28] Spangler WE, May JH, Vargas LG. Choosing data-mining methods for multiple classification: Representational and performance measurement implications for decision support. Journal of Management Information Systems. 1999; 16(1): 37-62.

[29] Grice JW, Iwasaki M. A truly multivariate approach to MANOVA. Applied Multivariate Research. 2007; 12(3): 199-226.

[30] Christmas WJ, Kittler J, Petrou M. Structural matching in computer vision using probabilistic relaxation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1995; 17(8): 749-764.

[31] Chen J, Huang H, Tian S, Qu Y. Feature selection for text classification with Naïve Bayes. Expert Systems with Applications. 2009; 36(3): 5432-5435.

[32] Pappenberger F, Beven KJ, Hunter NM, Bates PD, Gouweleeuw BT, Thielen J, De Roo APJ. Cascading model uncertainty from medium range weather forecasts (10 days) through a rainfall-runoff model to flood inundation predictions within the European Flood Forecasting System (EFFS). Hydrology and Earth System Sciences Discussions. 2005; 9(4): 381-393.

[33] Zadeh LA. Fuzzy sets, Information and Control. 1965; 8: 338-358.

[34] Wang L-X, Mendel LM. Generating fuzzy rules by learning from examples. IEEE Trans. on Systems, Man and Cybernetics. 1992; 22: 1414-1427.

[35] OBIS-seamap. Ocean biogeographic information system spatial ecological analysis of megavertebrate populations. http://seamap.env.duke.edu/.

[36] The global diversity information facility: http://www.gbif.org/what-is-gbif.

[37] Jain N, Virmani D. A novel navigation based decision algorithm to generate tsunami alerts using sensor nodes. Compusoft. 2018; 7(12), 2945.

[38] Jain N, Virmani D. Feature classification for underwater seismic prediction using wireless sensor nodes. in: Proceedings of the International MultiConference of Engineers and Computer Scientists. 2017; 1.

[39] Afzaal M, Usman M, Fong ACM, Fong S, Zhuang Y. Fuzzy aspect based opinion classification system for mining tourist reviews. Advances in Fuzzy Systems. 2016, 2.

[40] Elkano M, Galar M, Sanz J, Bustince H. Fuzzy rule-based classification systems for multi-class problems using binary decomposition strategies: On the influence of n-dimensional overlap functions in the fuzzy reasoning method. Information Sciences. 2016; 332: 94-114.

[41] Jain N, Virmani D, Gupta R, Gupta K, Bansal A. Mining underground alert signals for seismic detection using wireless sensor nodes. in: 2017 International Conference on Signal Processing and Communication (ICSPC) IEEE. July 2017; 274-282.

AUTHOR COPY