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Detection Of Semantic Events Using Changepoint and Ontology

DR. V. SESHASRINIVAS[1], V. THANUJA[2]
[1, 2]*Department of Information Technology R.V.R & J.C College of Engineering Guntur, India*

Abstract- With increased availability of time series data of oceanographic and environmental variables, there is a necessity for developing a way to recognize events out of continuous observation data. To solve the problem described above, this research offers a two-stages framework to recognize semantic events utilizing change point detection and ontology-based reasoning approach. At the first stage, change point detection techniques are used to identify significant events out of raw time series data. Pruned Exact Linear Time (PELT) algorithm is applied to find points of changes in statistical characteristics of data, like mean or variance. Detected change points divide time series into homogeneous parts, each of which can be considered as an event. At the second stage, semantic interpretation of detected parts is carried out based on ontology. Knowledge about domain is represented in the form of ontology that describes relationships between parameters of the system, such as threshold value, trend and environmental conditions. In accordance with described characteristics, each part is classified to meaningful groups of normal and risk conditions. For this project, I am using the Pelt approach.

I. INTRODUCTION

About 71% of the surface area of the Earth is covered by oceans. Oceans regulate the climate and maintain biodiversity and environmental balance. They function as reservoirs of heat and carbon and affect weather and ocean circulation and global climate systems. The monitoring of the state of the oceans is vital for the assessment of the environmental condition, forecasting the natural hazards, and sustainable management of the marine resources.

With the development of the ocean observation technology, new methods of collecting oceanographic data have been developed.[11],[14]. Some of the semantic approaches which can be adopted in the coding of domain knowledge and creation of relationships among various elements include ontology in the field of oceanography [1], [10], [17] Such observation instruments as moored buoys, drifting buoys, tide gauges, Argo floats, and remote sensing from satellites enable scientists to collect huge amounts of data on different aspects of the state of the oceans. The data collected using these devices include the measures of the wave height, sea surface temperature, salinity, sea level, ocean currents and other variables that can be classified as the Essential Oceanographic Variables (EOVs).

The abundance of the time series data collected through the ocean observations poses some problems in terms of their analysis. Ocean datasets may contain noise, missing and inconsistent values due to the limitations of the sensors and difficult environmental conditions. In addition, Conventional approaches for detecting events are mainly based on threshold-based techniques and statistical modeling. While these techniques may be able to recognize abnormal situations, they often lack a way to interpret those events in a meaningful way. Semantic techniques like ontology may be used to encode domain knowledge and establish associations between different entities in the oceanography domain. The use of ontology allows numerical values to be mapped into semantically interpretable information.

The presence of time series data from the ocean observing systems creates many challenges for the process of data analysis [16]. Data collected through ocean observation systems tend to be affected by noise, missing values, and inconsistency because of limitations with the sensors and the hostile environment. Furthermore, detection of any event through time series data is a difficult task since there will be many events like cyclones, tsunamis, harmful algal bloom, and high wave conditions. This research work suggests a novel framework that integrates Change Point Detection (CPD) and Ontology-Based Semantic Modeling to detect semantic events in oceanographic time series data. The Pruned Exact Linear Time (PELT) algorithm is employed to detect meaningful change points in wave height data by partitioning the time series into homogeneous segments. The detected change points are later mapped to ontology concepts. This novel approach not only improves the detection accuracy but also increases understanding of the events occurring in oceans.

Moreover, this research is an attempt to incorporate change point detection along with semantic modeling using ontologies in order to mitigate the shortcomings of existing approaches to detecting ocean events. The suggested framework uses PELT algorithm to detect significant changes within oceanic time-series data, and, with the help of ontology, provides semantic meaning for the detected events. Using both statistics and knowledge of the subject area, the framework converts numeric information into oceanic events, such as cyclone events, tsunami events, and wave events. Moreover, the suggested research proposes a hybrid approach for change-point detection in oceanographic data based on the PELT technique and semantic inference using ontologies. In contrast to traditional methods that use thresholds, the suggested approach allows recognizing statistical changes in time series data and mapping them to semantics reflecting the actual conditions of the ocean. This framework helps detect, classify, and interpret oceanographic events while providing higher explainability of the analytics outcomes. This research output is aimed at developing intelligent ocean monitoring frameworks with the capability of implementing early warning systems and environmental applications.

This research approach also provides an efficient way of analyzing massive ocean data coming from modern observation systems such as buoys, tide gauges, Argo floats, and satellite instruments. Through transforming numerical observations into semantic knowledge, this system helps scientists and policymakers understand complicated ocean processes. The outputs of this research are related to creating intelligent ocean monitoring frameworks for environmental assessment, disaster management, early warning systems, and sustainable management of marine resources.

II. CHANGEPOINT

Change Point Detection (CPD) is a statistical procedure employed in the identification of change points in a time-series dataset wherein significant changes in the nature of the data occur. [5] Changes may take place in various characteristics such as the mean, variance, distribution, trend, among others. In general, change points represent the point in the time series at which the data transitioned from one state to another.

Recent advances in change point detection have been driven by its extensive usage in a wide variety of fields like finance, health care, environmental monitoring, climatology, cybersecurity, and process control in industry. In particular, the main goal of CPD is the automatic detection of significant changes in a sequence without any prior knowledge about these transitions. Thus, through change point detection, we can gain insightful understanding on the behavior of the system being observed.[7]

In oceanography, huge amounts of time-series data are being collected from observation systems such as wave rider buoys, tide gauges, Argo float, and satellite sensors. [11],[12]. These data provide us with crucial information about the oceanic conditions in terms of wave heights, sea surface temperatures, salinities, wind speeds, and pressures, among others.

Changes in these parameters generally relate to actual occurrences like storms, cyclones, high waves, and environmental perturbations. With the adoption of ontology, numerical values can be interpreted into semantic information [2], [11], [12]. Hence, the detection of change points from oceanographic time-series is very vital for the study of ocean dynamics and environmental monitoring systems.

Conventional techniques of event detection often use predetermined thresholds and inspection of observation values manually. In many cases, such techniques fail to recognize the occurrence of transitions. Besides, manual event detection requires expertise in the concerned domain. In contrast, the technique of Change Point Detection overcomes all these problems by providing an automatic way of detecting changes in a dataset. In this method, a time series is divided into different segments that have similar statistical properties. The boundaries of these segments are the potential change points.

A time series can mathematically be represented as follows:
$X = \{x_1, x_2, x_3, ..., x_n\}$
where $x_1, x_2, ..., x_n$ are consecutive observations.
Change point detection is carried out with the intention of detecting the following change points:
$T = \{\tau_1, \tau_2, \tau_3, ..., \tau_m\}$

In such a way, the properties of the data under study are noticeably different in neighboring segments. among all the available approaches to CPD analysis, the Pruned Exact Linear Time (PELT) approach has proved to be among the most efficient ones due to its high precision and speed. This algorithm involves optimal partitioning together with pruning and allows detecting change points in near linear time. Thus, PELT is especially useful for dealing with big oceanographic data sets [8].

III. RELATED WORK

Change Point Detection (CPD) has become a significant approach for detecting structural changes in sequences of data. This technique has been extensively used in many domains including finance, environment monitoring, health care, climate, etc. The main aim of CPD algorithms is to detect points in a sequence when the statistical properties of the data change dramatically.

One of the earliest approaches for change point detection is the Cumulative Sum (CUSUM) method, extensively discussed by Basseville and Nikiforov [5]. Although CUSUM gives a good detection result for simple datasets, the detection quality reduces for more complicated cases when multiple change points exist in a sequence. The Binary Segmentation (BS) approach was developed for detecting multiple change points; however, this method suffers from a low accuracy of detecting close change points.

The Segment Neighborhood and Optimal Partitioning approaches increase the precision of change points estimation [6], [7]. Even though these algorithms give accurate results, they have a high complexity and cannot be applied to large datasets. To overcome this problem, Killick et al. developed the Pruned Exact Linear Time (PELT) algorithm approach [8].

The algorithm greatly decreases the computational effort needed for detection without decreasing the quality of detection.

It has been shown in recent researches that PELT is efficient in environmental monitoring and oceanography. PELT identifies important changes in the height of waves, temperature of the surface of water, and other oceanographic measures through segmenting the time series into homogenous segments. This research proposes an approach that will adopt both change point detection and ontology semantic modeling for identifying semantic events in oceanographic time series data [1], [7], [10]. Due to being accurate, scalable, and computationally efficient, PELT is one of the most popular algorithms used for large-scale change point detection problems. This research uses the PELT algorithm for identifying important transitions in oceanographic time series data. Change points found through this process are then analyzed for understanding changes in oceanic conditions.

Despite the fact that ontology offers the possibility of domain knowledge representation, it does not provide an opportunity for automatic temporal change detection [10], [17]. [9]. The technique has been used in environmental monitoring for detecting climate change, rainfall and temperature change. In the medical sphere, it was used to diagnose the anomalies in physiological functioning using data obtained from medical sensors [9]. In industries, it helps to detect equipment failure and process changes. Efficiency in detecting more than one change point without affecting computational efficiency has made it the most preferred modern change point detection algorithm.

In the sphere of oceanography, there are researchers who have applied change points detection for such characteristics as sea surface temperature, wave height, ocean current, and meteorological observations [11], [12]. The ocean environment is very dynamic in nature and there are environmental events like storms, cyclone, waves, and disturbances that are reflected as

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changes in data. Early detection of such changes is very important for environmental evaluation, safety of the marine environment, and disaster management. The traditional method of using thresholds fails to catch the change or creates false alarms.Of all the available methods, the PELT technique has proven to be highly effective in identifying meaningful transitions in time-series data related to oceanography. Being able to segment data into homogeneous regions helps in identifying environmental changes.

The segmentation abilities of this method make it possible to detect significant environmental events. Moreover, it works well with big data sets created by modern ocean observatories.

Binary Segmentation was developed to overcome these drawbacks. Binary Segmentation repeatedly splits the time series and locates the change points in each partition. While Binary Segmentation performs better compared to other techniques in locating multiple change points, it fails to detect changes when they occur very close to one another or when the changes are not very strong. Therefore, Binary Segmentation could become inaccurate for highly dynamic time series.

Segment Neighborhood approaches are capable of producing highly accurate results but they require increasing computation efforts with the growth of the dataset size. In turn, Optimal Partitioning is able to produce optimal solutions but its computation effort is also increasing.

Even though there are effective techniques for discovering statistical change points in time series, none of these techniques provides semantic interpretations of the discovered change points. In the same way, even though the ontology approach allows the representation of domain knowledge, it lacks the capability to automatically detect changes that occur in time. Consequently, a unified framework that combines these two techniques is necessary.

IV. PROPOSED METHODOLOGY

The proposed method attempts to detect important transitions in oceanographic time-series data using the Pruned Exact Linear Time (PELT) algorithm. Oceanographic data sets have characteristics such as continuity of measurements recorded by different monitoring systems as well as abrupt changes arising due to environmental factors like storms, cyclones, high waves, and ocean disturbances. Identifying these changes is crucial for understanding the dynamics of the oceans as well as environmental monitoring systems. This paper presents an integration of data preprocessing, change point detection, feature extraction and event identification to enable an efficient way of analyzing oceanographic time-series data.

The entire process includes five main phases which include data acquisition, data preprocessing, change point detection by PELT algorithm, feature extraction, and event identification. The whole process converts the raw ocean observations into useful information by detecting the statistically significant transitions in the data set.

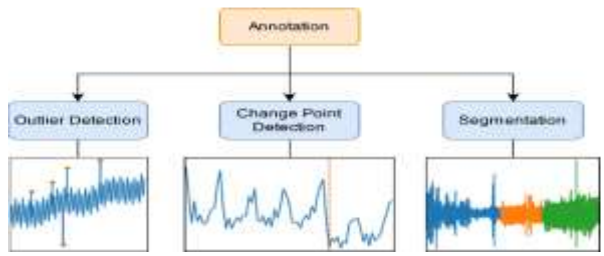

Fig. 1. Overall Framework of the Proposed Change Point Detection System.

1. Data Acquisition

Data acquisition is the first phase of the proposed methodology and involves collection of oceanographic data from monitoring systems such as wave rider buoys, ocean sensors, meteorological stations and satellite observation stations. The data sets consist of measurements of time-series from different monitoring systems that change over time.

The following are some of the observations made from the ocean parameters used in this study:
Wave Height
Wind Speed
Sea Surface Temperature
Atmospheric Pressure
Ocean Current Information

They are obtained at regular intervals and represented as time-series sequences. Due to their dynamics and sensitivity to the environment, they offer useful insights into significant ocean events.

2. Data Preprocessing

Inaccuracies in oceanographic observations may include missing data, noise, sensor errors and inconsistencies. As such, it is necessary to preprocess data before using the PELT algorithm.

3. Handling Missing Values

Missing values are estimated through interpolation techniques so as not to disrupt the continuity of the sequence of observations.

A missing value x_i is estimated through:
$x_i = (x_{i-1} + x_{i+1})/2$

The process uses surrounding observations to approximate any missing values.

4. Data Normalization

The different oceanographic measurements might be scaled differently and use different units of measurement. To ensure consistency, normalization of data is done.Data is normalized using the equation:
$x' = (x - \mu)/\sigma$
Where:
x = actual value
μ = mean value
σ = standard deviation

Normalization enhances the stability and efficiency of statistical analysis.

5. Noise Reduction

Measurements made for oceanography are usually influenced by noise and external perturbations. The moving average filter technique is used to filter out noise and minimize unwanted fluctuations.
$MA(t) = (1/n)\Sigma x(t)$

The output signal offers a more accurate depiction of the actual situation in the ocean.

6. Change Point Detection Using PELT Algorithm

After data processing, the Pruned Exact Linear Time (PELT) algorithm is implemented to determine changes in the time-series data.

Change point detection involves identifying points at which there is an abrupt change in statistical properties of observations. Such changes may include changes in mean, variance, distribution, or trend.

Let:
$X = \{x_1, x_2, x_3, ..., x_n\}$
denote the input time series consisting of n observations.

The goal of PELT is to obtain an optimal set of change points:
$T = \{\tau_1, \tau_2, \tau_3, ..., \tau_m\}$
where τ is the position of detected change points.
PELT algorithm uses the following optimization criterion:
$F(n) = \min [\Sigma\ C(y\tau(i-1)+1 : \tau i) + \beta m]$
where:
C = cost function of a segment
β = penalty function
m = number of detected change points
While the cost function determines the uniformity of a segment, the penalty prevents unnecessary segmentation and over-fitting.

PELT differs from other segmentation methods by its use of an effective pruning technique which eliminates sub-optimal candidate solutions during the computations. This leads to reduced computational complexity without any loss in detection performance.

7. Cost Function Evaluation

A cost function used in the segmentation procedure is responsible for assessing the variability of a segment and its model complexity[6],[8].

In case of segment starting at a and ending at b:
$C(y_{a:\beta}) = \Sigma(y_t - \bar{y})^2$
Where:
y_t – observation at time t;
$\bar{y}$ – mean of the segment.
Low value of cost function implies similarity of behavior of observations in the segment.

8. Feature Extraction

When change points are determined, the time series is split into several homogeneous segments and each segment is characterized with specific statistical features.

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Mean
It shows the average behavior of observations within a segment.
$\mu = (1/n) \Sigma x_i$

Variance
The variance reflects the scatter of observations relative to the mean.
$\sigma^2 = (1/n) \Sigma(x_i - \mu)^2$
Standard Deviation
$\sigma = \sqrt{\sigma^2}$

Trend Analysis
Trend analysis is used to determine the trend and its magnitude in a segment.
Trend = $\Delta y / \Delta x$
These statistics are useful to know the degree and type of ocean phenomena that were observed.

9. Identification and Analysis of Events
The statistical features obtained from a time series are analyzed in order to identify important oceanographic events. Segments with unusual statistical features are marked as an event.

Examples of such events are:
Sudden rise in wave height
Unusual ocean disturbance
Ocean with high energy level
Quick environmental transition

Detected events are characterized by the duration and intensity of the event and statistical features. The detected change points can give an idea about the dynamic behavior of oceanographic phenomena.

10. Advantages of the Suggested Method
The suggested method has the following advantages over the existing methods:

Accurate detection of multiple change points.
Decreased computation complexity due to pruning.
Ability to work on large scale time-series datasets.
Better detection of important oceanographic events.
Scalability for real-time monitoring application.

By preprocessing the data and using segmentation along with the statistical analysis of segments, a useful solution is obtained for the detection of important transitions in oceanographic time series.

V. PELT ALGORITHM PRUNED EXACT LINEAR TIME

The Pruned Exact Linear Time (PELT) algorithm is among the most effective and popular methods in multiple change point detection of time-series. PELT algorithm was designed to solve the computational problem of traditional segmentation techniques without compromising the optimum performance in detecting the change points[8]. The algorithm detects locations in time series where changes in statistical attributes like mean, variance, or distribution have occurred.

PELT algorithm differs from other methods which involve scanning all the possibilities since PELT uses pruning process which discards the suboptimal candidates of change points while computing. This makes it computationally efficient without altering the optimality of the solution.

In oceanography, sudden changes in wave height, sea surface temperature, atmospheric pressure, and wind speed could be signs of some events in environment. PELT algorithm successfully detects those changes by partitioning the time series into homogeneous segments.

Let
$X = \{x_1, x_2, x_3, ..., x_n\}$
be a time series with n observations.
The task of PELT is to find out the optimal set of change points:
$T = \{\tau_1, \tau_2, \tau_3, ..., \tau_m\}$
where τ is the points at which significant statistical changes are present.
The objective function to be minimized is:
$F(n) = \min [\Sigma C(y\tau(i-1)+1 : \tau i) + \beta m]$
where:
C(.) is the cost associated with the segment.
β is the penalty parameter.
m is the number of change points detected.
F(n) is the total cost associated with the segmentation.
A higher penalty value results in fewer change points being detected, whereas a lower value may cause over-segmentation.

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11. Principle of PELT Algorithm

The PELT algorithm is adopted in detecting change points in the wave height data[8]. All observations are treated as a potential candidate for change points at the start. The cost associated with each candidate is calculated and then retained only those candidates that may be useful in determining the optimum solution.
The pruning condition is as follows:
$F(t) + C(t+1) + K \geq F(s)$

where:
$F(t)$ is the optimum cost until t.
$C(t+1)$ is the cost associated with the segment.
K is the constant used in pruning.

If the above condition is satisfied, then the candidate can be discarded as it will not form part of the optimum solution.

This process significantly decreases computational complexities and makes the efficient processing of large data sets possible.

12. Steps in the PELT Algorithm
Inputs:
Oceanographic time-series data $X = \{x_1, x_2, ..., x_n\}$
Penalty parameter β
Output:
Change points T
Step 1: Acquire the oceanographic time-series data.
Step 2: Do the data preprocessing such as missing value treatment, normalization, noise reduction.
Step 3: Set up the cost function, candidate set, and boundaries for segmentation.
Step 4: Compute the cost of every segment based on the chosen cost function.
Step 5: Examine all candidates of the change points.
Step 6: Apply the pruning process.
Step 7: Recompute the optimal partition based on dynamic programming.
Step 8: Repeat the above steps until all data points are processed.
Step 9: Obtain the set of change points.
Step 10: Segmentation of the time series into homogeneous segments.
Step 11: Output the detected change points and segmented time series.

Fig 2: - Process of ChangePoint

1. Cost Function Calculation
The cost function is used to quantify the homogeneity of a segment. The cost of the segment with similar observations is smaller than the cost of the segment with abrupt changes.

The cost function of mean-based change point detection method is:
$C(y_{a:\beta}) = \Sigma(y_t - \bar{y})^2$
where:
y_t = Observation.
$\bar{y}$ = Segment mean.
The aim is to achieve minimum total segmentation cost and have appropriate change points.

2. Computational Complexity
Most change point detection algorithms like Segment Neighborhood and Optimal Partitioning require computational complexity of $O(n^2)$. These methods are not efficient in analyzing large data sets.

PELT pruning approach makes the computational process efficient and leads to near-linear complexity:
Complexity = $O(n)$

This makes the algorithm very useful for large oceanographic data sets collected using current sensor and observation networks.

3. Benefits of PELT Algorithm
Some benefits of using the PELT algorithm include:
Detects multiple change points accurately.

Achieves optimal segmentation performance.
Efficient in reducing computational complexity through pruning.

Suitable for large-scale time series data.
Very efficient in analyzing long-term environmental observations.

Reliable in detecting both sudden and gradual change points.

These make the PELT algorithm very efficient in oceanographic observation.

VI. PERFORMANCE METRICS

Several quantitive metrics have been used for evaluation of the proposed approach in terms of its performance.

1) Accuracy

Accuracy determines how correct the process of detecting change points is.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

where:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

Higher value of accuracy metric means that the performance of the approach is better.

2) Precision

This metric evaluates the proportion of true change points among detected.

Precision = TP / (TP + FP)

The high precision value means that there are fewer false alarms during change points detection.

3) Recall

Recall evaluates the ability of the algorithm to detect change points.

Recall = TP / (TP + FN)

The more the recall value is high, then most of the true changes can be identified.

4) F1-Score

It is a balanced evaluation of both recall and precision values.

F1-Score = 2(Precision × Recall)/(Precision + Recall)

The metric is highly applicable where there are unequal numbers of change and no-change observations in the data set.

5) Detection Delay

It refers to the time taken between the occurrence of the event and its detection by the algorithm.

Detection Delay = Detected Time – Actual Change Time

Lesser detection delay indicates faster identification of important events.

6) Mean Absolute Error (MAE)

It evaluates the mean absolute error.

$MAE = (1/N) \Sigma |y_i - \hat{y}_i|$

Where:

y_i = actual value

$\hat{y}_i$ = predicted value

The lower MAE value indicates good detection performance.

7) Root Mean Square Error (RMSE)

It is a square root of mean squared error.

$RMSE = \sqrt{[(1/N) \Sigma(y_i - \hat{y}_i)^2]}$

It punishes bigger errors and gives information about the detection.

8) Scalability

It measures the capability of an algorithm to process larger and larger data. Since the oceanographic monitoring systems generate big data continuously, scalability is of vital importance.

9) Computational Efficiency

Computational efficiency is analyzed using time required for execution and memory used.

Time Required For Execution = End Time - Start Time

The efficiency in execution time by the algorithm PELT is much less compared to other segmentation techniques owing to the pruning technique in PELT.

In conclusion, these performance measures help in analyzing the efficiency of the proposed change point detection algorithm.

These metrics are considered for evaluation of future implementations.

VII. RESULTS

Efficacy of the developed methodology is verified based on oceanographic wave height data collected from a wave rider buoy installed in Visakhapatnam region. In particular, the purpose of the experiment is to detect significant changes in ocean conditions by

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implementing the quality control process and utilizing Pruned Exact Linear Time (PELT) change point detection algorithm. The results of the experiment are examined in three main stages: raw data examination, quality controlled data examination, and change point detection examination.

13. Raw Data Examination

Initial dataset comprises raw wave height data obtained from ocean observation system. This type of data is characterized by real wave height observations made during certain period of time. Being taken from practical systems, raw data are not free of errors and include measurement noise, spikes, missing observations, and transmission problems.

Raw data demonstrate considerable fluctuations of wave height values caused by both natural factors and uncertainties of the observation system used for data acquisition. Many sharp peaks and irregularities can be seen in the dataset. This makes it hard to separate real environmental changes and inaccurate measurements of the wave height.

Nevertheless, despite these drawbacks, the raw dataset contains useful information about ocean behavior and is the base for further processing steps. The analysis of raw observations proves the need to implement quality control before proceeding with event detection.

14. Analysis of Quality-Controlled Data

In order to increase the accuracy and reliability of observations, the process of quality control was implemented on the raw data. As part of quality control, abnormal values, unrealistic spikes, missing observations, and satisfaction of the validation criteria were taken into account.

The result of quality control procedure was the dataset, which demonstrated much greater consistency compared to the original raw data. Almost all of the noise, which was characteristic of the original observations, was successfully filtered out. The processed data contained real features of the ocean waves behavior.

Thus, the quality-controlled data represent a more realistic picture of the ocean behavior. This makes them applicable for further statistical processing and change point detection.

Moreover, visual analysis of the quality-controlled data shows distinct patterns in the dynamics of waves. In particular, during stable periods there is little fluctuation in waves, while in dynamic periods waves demonstrate greater variations in heights and have more energy. It proves that the quality control process increases the understanding of the data.

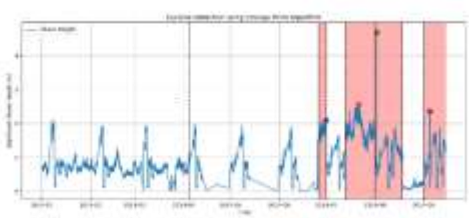

Fig. 3. Change Point Detection Results Showing Significant Ocean Events.

15. Results of Change Points Detection

After quality control, the application of the PELT algorithm to the processed time series data allowed us to find out significant changes in wave dynamics. It includes segmentation of time series into statistically homogeneous parts and finding out locations of the changes.

The obtained chart shows variations of wave heights, where vertical dashed lines show change points found using the algorithm[8]. Every change point indicates a location where there is a significant change in statistical properties of the time series. Such changes can be related to changing ocean conditions caused by various environmental influences, including storms, high-wave activity, or disturbances on the ocean surface.

Change points divide the data into segments that have different statistical properties. Stable ocean conditions are associated with small number of change points and smooth fluctuations of wave heights.

16. Discussion of Results

The findings prove that the proposed method is effective in finding meaningful changes in the time-series oceanographic data[7],[8],[9]. The combination of the quality control step and the change points'

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detection helps distinguish regular ocean variations from important environmental events.

The comparison of raw and quality controlled data shows the value of the pre-processing stage for better detection accuracy. Without pre-processing, noise and errors of the sensors can result in false change points that will decrease the reliability of the detection process. Quality control helps filter these inconsistencies and allows for reliable change points that mostly represent oceanographic processes.

The algorithm PELT performs well when detecting multiple change points and remains computationally efficient. The pruning technique used by the algorithm helps decrease the processing time of the algorithm. It makes the algorithm appropriate for ocean monitoring systems which require the detection of change points from the stream of sensor observations in real time.

The change points found during the detection process provide information about the temporal changes of the ocean state. Areas with a high concentration of change points usually reflect an active period of the ocean.

This type of information may be used for marine forecasting, environmental assessments, and prediction of extreme events on the ocean.

17. General Evaluation of the Results
Overall performance of the suggested system shows that the framework is an efficient way to detect changes in oceanographic data. Quality control makes the data more accurate and consistent, whereas the PELT algorithm is able to detect significant changes in the time series.

According to the experimental results, it is possible to conclude that in the case of stable ocean environment, there are no abrupt changes in wave height values and only several change points are found. In contrast, the abnormal state of the ocean implies higher wave heights, variability, and abundance of change points. Thus, the efficiency of the suggested methodology to differentiate between normal and abnormal ocean environment is confirmed.

In general, the suggested framework allows detecting changes in the oceanographic data and giving some information about the current environmental situation.

VIII. FUTURE WORK

Further research will entail the inclusion of more oceanic variables like water surface temperature, winds, and air pressure. Other approaches which can be adopted include advanced ontology and machine learning for better semantic event detection.

Future work will focus on integrating advanced ontology reasoning techniques and machine learning methods for improved semantic event interpretation [1], [10], [16], [17].

IX. CONCLUSION

Change point detection and ontology techniques are proposed to effectively discover and interpret semantic events from time-series of oceanic data. PELT algorithm is used to discover meaningful changes in the data by partitioning the data into segments having similar statistical properties.

PELT delivers fast and precise detection, whereas ontology enhances interpretation. As a result, the combination of these methods represents a practical and intelligent way of analyzing time-series data and discovering semantic events. The key idea was not only to find changes in data but also to interpret them. The PELT (Pruned Exact Linear Time) algorithm was applied for the purpose of discovering significant changes in time-series data. The algorithm is able to find points where statistical characteristics like mean or variance change and divide the data into segments with similar behavior. It enables recognition of important changes in ocean conditions, such as the rise in wave height.

To sum up, this project proves that combining change point detection technique with ontology gives a reliable and efficient way of discovering and interpreting semantic events in time-series data.

X. REFERENCES

[1] Al-Baltah, I.A., Ghani, A.A.A., Al-Gomaei, G.M., Abdulrazzak, F.A.H. and Kharusi, A.A.A., 2023. A scalable semantic data fusion framework for heterogeneous sensors data. Journal of Ambient Intelligence and Humanized Computing, 14(5), pp.5047–5066.

[2] Atemezing, G., Corcho, O., Garijo, D., Mora, J., Poveda-Villalón, M., Rozas, P., Vila-Suero, D. and Villazón-Terrazas, B., 2013. Transforming meteorological data into linked data. Semantic Web, 4(3), pp.285–290.

[3] Al-Baltah, I.A., Ghani, A.A.A., Al-Gomaei, G.M., Abdulrazzak, F.A.H. and Kharusi, A.A.A., 2023. A scalable semantic data fusion framework for heterogeneous sensors data. Journal of Ambient Intelligence and Humanized Computing, 14(5), pp.5047–5066.

[4] Atemezing, G., Corcho, O., Garijo, D., Mora, J., Poveda-Villalón, M., Rozas, P., Vila-Suero, D. and Villazón-Terrazas, B., 2013. Transforming meteorological data into linked data. Semantic Web, 4(3), pp.285–290.

[5] Basseville, M. and Nikiforov, I.V., 1993. Detection of abrupt changes: Theory and application. Prentice Hall.

[6] Lavielle, M., 2005. Using penalized contrasts for the change-point problem. Signal Processing, 85(8), pp.1501–1510.

[7] Truong, C., Oudre, L. and Vayatis, N., 2020. Selective review of offline change point detection methods. Signal Processing, 167, p.107299.

[8] Killick, R. and Eckley, I.A., 2014. changepoint: An R package for change point analysis. Journal of Statistical Software, 58(3), pp.1–19.

[9] Aminikhanghahi, S. and Cook, D.J., 2017. A survey of methods for time series change point detection. Knowledge and Information Systems, 51(2), pp.339–367.

[10] Cristani, M. and Cuel, R., 2005. A survey on ontology creation methodologies. International Journal on Semantic Web and Information Systems, 1(2), pp.49–69.

[11] Devaraju, A. and Kauppinen, T., 2012. Sensors tell more than they sense: Modeling and reasoning about sensor observations for understanding weather events. International Journal of Sensors Wireless Communications and Control, 2(1), pp.14–26.

[12] Velu, A. and Thangavelu, M., 2021. Hetero-GCD2RDF: Interoperable solution for climatic data. Wireless Personal Communications, 117(4), pp.3527–3551.

[13] Basseville, M. and Nikiforov, I.V., 1993. Detection of abrupt changes: Theory and application. Prentice Hall.

[14] Garrido, Á.L., Buey, M.G., Munoz, G. and Casado Rubio, J.L., 2016. AEMIX: Semantic verification of weather forecasts on the web.

[15] Gupta, S., Jain, I., Johari, P. and Lal, M., 2018. Impact of climate change on tropical cyclones frequency and intensity on Indian coasts. In: Springer Conference Proceedings, pp.359–365.

[16] Kaladevi, R., Revathi, A. and Sridhar, S., 2020. Development of background ontology for weather systems through ontology learning. International Journal of Recent Technology and Engineering, 8, pp.168–172.

[17] Kalibatiene, D. and Vasilecas, O., 2011. Survey on ontology languages. In: International Conference on Business Informatics Research, pp.124–141.

[18] Kambli, K., 2020. Throwback to a stormy year: A look at the 8 North Indian Ocean cyclones of 2019. The Times of India.

[19] Al-Baltah, I.A., Ghani, A.A.A., Al-Gomaei, G.M., Abdulrazzak, F.A.H. and Kharusi, A.A.A., 2023. A scalable semantic data fusion framework for heterogeneous sensors data. Journal of Ambient Intelligence and Humanized Computing, 14(5), pp.5047–5066.

[20] Atemezing, G., Corcho, O., Garijo, D., Mora, J., Poveda-Villalón, M., Rozas, P., Vila-Suero, D. and Villazón-Terrazas, B., 2013. Transforming meteorological data into linked data. Semantic Web, 4(3), pp.285–290.