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Object Relational Aerial Data Mining Via Topological Tree Based Feature Clustering Framework

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Abstract

In real world applications, lot of spatial events interrelate with each other based on time factor and demonstrate Spatio-temporal objects. Spatio-temporal objects help to recognize the events but a significant task is needed to be developed on identifying the relationship between the spatial and temporal features of these events. Although ample research on heterogeneous Spatio-temporal data modeling has been performed, very little work exists on how to implement the relationship between the individual and neighborhood aerial data features through object relational database techniques. Mining complex aerial variable however retrieves only limited relations between data objects. To ensure consistency on defining Spatio-temporal data relationship, a new framework is proposed in this paper. The proposed Topological Tree based Feature Clustering framework is combined with Object Relational Spatio-temporal Database (TTFC-ORSD) model to attain the solution for complex aerial variables. Initially, Topological Tree structure uses the Spatio temporal classified data to extract the features. The Topological Tree based structure simplifies the feature extraction process and extract the aerial features from the database. Next, Feature Time-Position Clustering approach is employed in the second step of TTFC-ORSD using the topological tree based feature extraction. Finally, Spatio-Temporal Object Relation between the features is identified using the meta-feature object relational value operator for relating aerial database objects. The main task of Meta-Feature Object Relational Value Operator is to identify the relational points between the features of dissimilar clusters. Experiment is conducted on factors such as features clustering rate, average neighborhood relationship identification time, efficiency on features relational analysis rate.

Keywords: Topological Tree, Feature Clustering, Object Relational Spatio-temporal Database, Meta-Feature Object Relational Value, Spatial Database.

1. Introduction

Spatio temporal objects have become very significant in the recent years. This is because of the fact that several applications and scenarios that include services based on location and information using Geographic data shows that it not only requires the spatial characteristics but also the temporal characteristics. Moreover, real world data objects include attributes consisting of both space and time. Efficient management of both space and time using existing RDBMS is not only a complex one but also has proved to be in-efficient, because of the multi-dimensional nature.

Temporal and Geographic Clustering (TGC) [1] compared the spatial and temporal distribution by obtaining a combination of patterns that provided an insight into socio economic neighborhood characteristics. However, sufficient research works on implementing the relationship between inter and intra cluster through object relational database techniques were not performed. Fast Fourier Transform (FFT) [2] performed a quantitative analysis using spatial and temporal changes in Land Surface Temperatures (LST) that was used to estimate the changing climatic conditions. But, mining complex aerial variable though retrieved only limited relations between the data objects.

Temporal data are highly ubiquitous in nature and used in several applications ranging from multimedia related information to temporal types of data mining. When compared to the static types of data, higher amount of dependency factors between temporal data makes the application more critical in temporal data processing. Temporal Data Clustering (TDC) [3] used a weighted function that captured intrinsic portions of dataset using weighted cluster ensemble algorithm. However, spatial type of data remained unaddressed.

Geographic Knowledge Discovery (GKD) [4] addressing spatial data was introduced for analyzing the moving data object. But voluminous amount of data remained a critical issue. A data mining approach introduced in [5] for time varying geographic environment to derive the key associations between geodata was introduced. A spatio-temporal analysis for disease classification was introduced in [6] using the Kulldorff's scan statistics that helped to identify several mental disorders.

The most significant approaches to address high-dimensional data are to use an efficient feature extraction process that maps the lower-dimensional space for retrieval of information and data processing in an accurate manner. Recurrent Online Clustering (ROC) [7] that identified spatiotemporal patterns by applying recurrent clustering algorithm. The method was proved to be efficient in terms of scalability. But the magnitude of data was not considered. Seismic Mass (SM) introduced in [8] provided a hybrid model including both time and spatial information for identifying irregularly shaped clusters. However, sequentially distributed data remained unaddressed.

Warped K Means (WKM) [9] provided a means for addressing sequentially distributed data using a multi-purpose clustering approach that not only reduced the computational cost but also preserved the order of magnitude. But, the method was proved to be highly sensitive. To address this issue, K Iteration Fast Learning Artificial Neural Network (KIFLANN) [10] was designed to improve the efficiency of the method in terms of classification accuracy.

Based on the aforementioned techniques and methods, Topological Tree based Feature Clustering framework is combined with Object Relational Spatio-temporal Database (TTFC-ORSD) model for complex aerial variables is presented. The contributions of the proposed Topological Tree based Feature Clustering framework with Object Relational Spatio-temporal Database is given as follows:

a) To attain solution for complex aerial variables using Topological Tree based Feature Clustering framework with Object Relational Spatio-temporal Database (TTFC-ORSD) model.
b) To simplify the feature extraction process and efficient feature extraction with the application of Topological Tree structure with Spatio temporal classified data.
c) To employ Feature Time-Position Clustering approach in TTFC-ORSD using the topological tree based feature extraction for efficient clustering.
d) To efficiently identify relational points between the features of dissimilar clusters using Meta-Feature Object Relational Value Operation.

The organization of the paper is as follows. Section 1 provides the framework for spatial and temporal data classification for object relational. Section 2 includes a detailed comparison with other state-of-the-art works. Section 3 details the Topological Tree based Feature Clustering framework with Object Relational Spatio-temporal Database, Similar feature position-time clustering, followed by a detailed algorithm and architecture diagram and meta-feature object relational value operator. Section 4 provides the experimental setups followed by Section 5 that includes the analysis of the results. Finally, Section 6 includes the concluding remarks.

2. Related Works

Developing classification methods for hot spot occurrences is considered to be one of the important activities in the fire prevention program. An improved ID3 Decision algorithm [11] designed a spatial decision tree to obtain higher accuracy on training set. However, with respect to time the classification of hot spot occurrences was proved to be fatal. To address this issue, SwiftRule [12] constructed a dynamic classifier rather than a static one for efficient extraction of rules using Gaussian and diagonal covariance matrix. However, comprehensibility of rules remained unaddressed. Classification on spatio-temporal relationships [13] was introduced with the help of object oriented model and was applied on diversified rules.

Movement is considered to be one of the most significant processes involved in the effective design of physical environment. With the highly increasing mobility of users integrated with certain advancements in ubiquitous computing, technologies has resulted in the increasing volume of data. Geovisual analysis tool [14] was designed by clustering spatio temporal clustering of data resulted in efficient classification of user task. However, pattern analysis was not performed.

Key concepts related to the moving objects and its characteristics were observed in [15] by interpreting cluster analysis on the basis of spatio temporal clustering. However, with the extensive movement in the objects, the method was proved to be fatal. A Variable length Markov Model (VMM) [16] was introduced to obtain and measure the objects movements resulting in higher accuracy.

One of the most important attentions received in the recent years is the behavior of uncertain databases. Superseding Nearest Neighbor (SNN) [17] on uncertain spatial databases was introduced to an extensive algorithm that evaluated and measured the SNN core by avoiding the entire superseding graph. The method resulted in the increase of number of instances per object with relatively lesser computation time. However, computation overhead also increased with the number of instances being derived.

A spatial clustering model using an approximate kNN-based framework was introduced in [18] to address computational complexity for indexing in multi-dimension. But complexity of the nature of data was not addressed. Spatio temporal clusters using time and space was introduced for multi-dimensional data type in [19]. However, congestion remains unaddressed. R-Tree [20] for Spatio temporal access using massive multi-dimensional data was addressed and obtained the object relationships which resulted in fast data retrieval.

Based on the above techniques discussed, we provide a topological tree based feature clustering framework with object relational spatio-temporal database for complex aerial variables.

3. Topological Tree Based Feature Clustering Framework With Object Relational Spatio-Temporal Database

Complex Spatio-temporal data objects from aerial database is the main focus of this work that relates the spatial and temporal objects of individual and neighboring clustering group using the Topological Tree based Feature Clustering framework. The proposed framework uses the object relational database technique for building efficient relationship between aerial database objects. In TTFC-ORSD model, the spatial and temporal attribute information are combined together to extract effective features. The temporal data obtains the start time, end time and transaction time of aerial data objects and simultaneously spatial data includes the theme and positional information. In the proposed Spatio-temporal Object Relational Database (ORSD) model, a topological framework based feature extraction is supported to enhance the flexibility. The topological tree structure is illustrated in Figure 1.

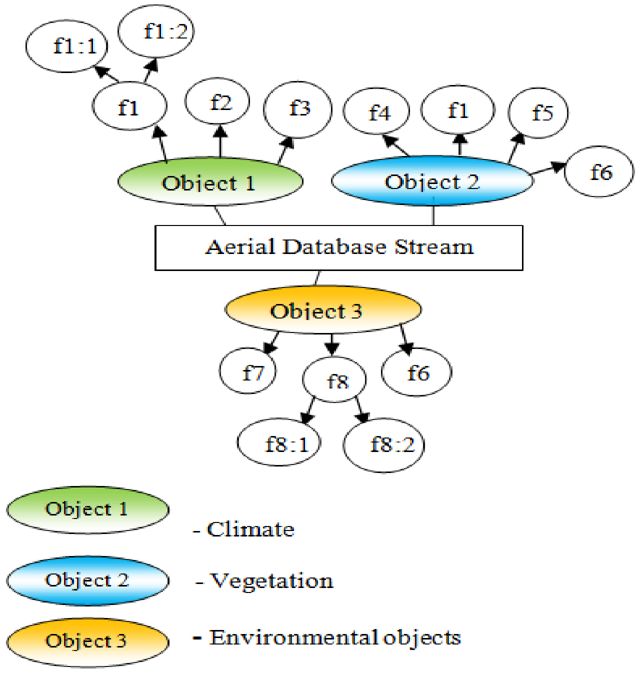

Figure 1 Topological Tree based Feature Extraction

The topological tree structure classifies the Spatio-temporal features for easier way of feature extraction using TTFC-ORSD model. The objects of aerial database are described and each object features are extracted and denoted as ‘f1,f2…fn’. Similarly each feature and sub features are denoted as <f1:1>, where ‘f1’ is the first feature whereas the succeeding 1 denotes the sub feature of the features. The topology is an arrangement of different aerial data objects for easier feature extraction. The data object level classifies the features of each objects present in the next sub level. In a similar manner, all the object features are classified using the topological tree structure.

The Topological Tree based feature extraction is used in TTFC-ORSD model for the efficient extraction. The topological representation of feature is used on locating the spatial objects for varying time period. For instance, the aerial database stream consists of different objects. The objects are of Spatio-temporal (i.e., different position on varying time rate). The climatic object includes different temperature on varying seasonal period. The vegetation in the aerial database shows dissimilar vegetation carried out on each seasonal period. The specific visualized objects are environmental objects. These features extracted are sometimes similar to each other.

The feature position on different temporal series is extracted to perform clustering operation. Similar Spatio-temporal objects are clustered using Similar Feature Time-Position Clustering approach. A conceptual feature clustering framework on Spatio-temporal data uses the topological tree based feature extraction. The similar features on different Spatio-temporal object are clustered mutually. Similar Feature Time-Position Clustering approach is applied in TTFC-ORSD Model for effective clustering of complex aerial database objects. Clustering approach used in the proposed work for identifying the relativity between complex Spatio-temporal data present in the aerial database. The clustered complex Spatio-temporal data is mapped using the object relational database model. The architecture diagram of TTFC-ORSD Model is illustrated in Figure 2.

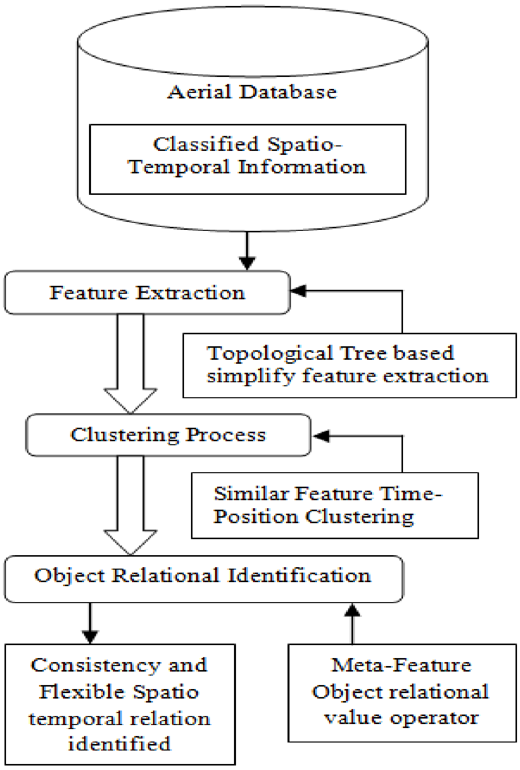

Figure 2 Architecture Diagram of TTFC-ORSD Model

As illustrated in Figure 2, an aerial database classified with Spatio-temporal information is used for feature extraction. The feature is extracted through Topological Tree based simplify feature extraction process using TTFC-ORSD Model. The topology tree holds the classified features at each sub-level of the tree for easy clustering of similar complex Spatio-temporal data. The extracted features are clustered if the various objects carry similar features in TTFC-ORSD Model. The clustering in TTFC-ORSD Model is carried out using the Similar Feature Time-Position Clustering approach. The clustered Spatio-temporal object features are used to identify the object relativity. The object relational is carried out in proposed work using the Meta-Feature Object relational value operator. With this, the relational of complex Spatio-temporal object is carried out with higher flexibility rate.

Topological Tree based Feature Extraction

The tree structure based on topological form yields the extracted features in a simplified form. A new approach implemented on the selected aerial data objects extract the features of each objects. The sub features are also extracted in subsequent computations based on the space function. The space function extracts the features of aerial objects. The space function is formularized as,

$$Space\ Function\ (s) = n\ (Obj) \rightarrow Obj^3 \quad (1)$$

The space function (s) denotes the value used on object extraction in TTFC-ORSD Model. The '3' objects 'Obj' are taken for experimenting the work with the

$$TT_{feature} = F_{q\in\alpha}|n - q| \quad 2)$$

The topological tree TT_{feature} of three aerial data objects are used to extract the features 'F' of the 'q' samples. 'α' denotes the level set of the topological tree structure. The total sample objects in the data object 'n'is used to extract the feature values.

Similar Feature Time-Position Clustering

The TTFC-ORSD Model group similar time and position features, so that similar aerial data objects are clustered. The shared property of clusters is administered in TTFC-ORSD Model to group similar Spatio-temporal data objects. Time-position clustering is described as,

$$TP\ Clustering = C\ \{S(Obj1_f + Obj2_f + Obj3_f) \quad (3)$$

The similar 'S' aerial objects 'Obj' feature 'f ' are grouped together through sharing property. $TP\ Clustering$ is based on the time-position of features. The TP clustering procedure is formularized as,

//Feature Time-Position Clustering
Begin
Input: Extracted Features TT *feature* Used for clustering
Output: Similar features of Spatio-temporal objects are grouped
1: Initialize the features for clustering
2: Performs inter-cluster by using the space and time domain attributes
3: Carries the same feature set
4: Performs the intra-cluster by using the space and time domain attributes.
5: Carries the different feature set when compared with inter-cluster features
6: Intra-cluster points carry the features depending on specific position and time range
7: Shared property is administered to perform the inter-cluster and intra-cluster formation
End

The feature time-position clustering clusters the complex Spatio-temporal objects. The clustering approach in TTFC-ORSD Model helps in identifying the flexible relativity between the aerial data objects. The individual (i.e., inter-cluster) and neighborhood aerial data (i.e., intra-cluster) features are identified and grouped together. The grouped objects use the object relational database techniques named Meta-Feature Object Relational Value Operator for relating the complex objects.

Meta-Feature Object Relational value operator

Object Relational Spatio-temporal Database (ORSD) model uses the Meta-Feature Object Relational Value Operator to improve the data object relativity. Clustered Aerial Object Relationship in TTFC-ORSD Model is shown in Figure 3.

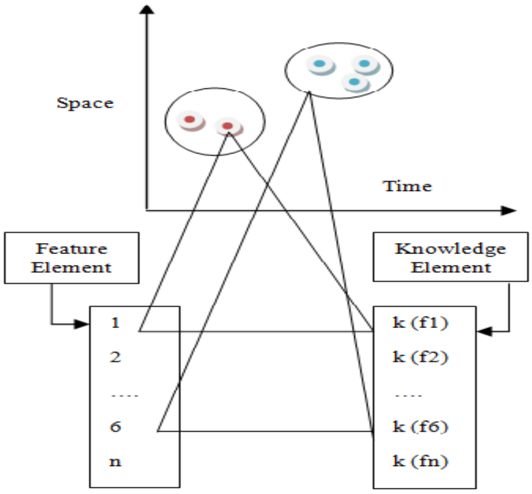

Figure 3 Representation of Clustered Aerial Object Relationship

In Figure 3, the interrelation between the aerial data objects is performed using two different elements namely, feature elements (1, 2, 3,.., n) and knowledge elements (k(f1),k(f2)…k(fn)). The feature element comprises of the feature name and object it belongs whereas the knowledge element in TTFC-ORSD Model provides the knowledge information about the features for efficient analysis of relativity. The feature element uses the knowledge of the aerial objects and performs the relationship between spatial objects using the clustered information.

With the introduction of Meta-Feature Object Relational Value Operator in TTFC-ORSD model, effective mapping relationship between the intra-cluster features is performed. With the intra-clustered features, the relationship between the Spatio-temporal objects is also identified. The relational value operator is represented as,

$$Database\ Table\ (Objects, Meta\ feature\ (R(c1), R(c2), R(c3) \ldots . R(cn))) \quad (4)$$

Meta feature relationship 'R' of aerial data objects 'Objects' is analyzed through clustered information $((c1),(c2),(c3) \ldots .(cn))$. A relationship between the row (i.e., time) and column (i.e., objects) are computed to identify the relativity of different clusters. Complex aerial database object allows the efficient relationship between meta-features in TTFC-ORSD Model using Meta-Feature Object Relational Value Operator. In this manner, similar functionality is related easily which leads to easier identification of net relationship and as a result, balance the variability.

4. Experimental Evaluation

Topological Tree based Feature Clustering framework is combined with Object Relational Spatio-temporal Database (TTFC-ORSD) model performs the experiment on JAVA platform using Spatio-temporal data on aerial database. TTFC-ORSD uses El Nino Data Set extracted from UCI repository. The E1 Nino Data Set includes the oceanographic and surface meteorological readings taken from a series of buoys positioned throughout the equatorial Pacific. The aerial data was collected using the Tropical Atmosphere Ocean (TAO) array which was developed by the international Tropical Ocean Global Atmosphere (TOGA) program. The TAO array consists of almost 70 moored buoys spanning the equatorial Pacific, compute oceanographic and outside meteorological variables. These variables are used widely on improving the relational identification between the spatial objects.

The El Nino/Southern Oscillation (ENSO) cycle neither predicted nor detected awaiting it was near its peak. The need for an ocean observing system (i.e. the TAO array) hold up studies of large scale ocean-atmosphere interactions on seasonal-to-inter twelve-monthly time scales. TTFC-ORSD model compares the proposed work with two existing works namely Temporal and Geographic Clustering (TGC) [1] method and Fast Fourier Transform (FFT) [2] method. The parametric factors used are features clustering rate, average neighborhood relationship identification time, efficiency on features relational analysis rate, CPU execution time.

The features clustering rate in TTFC-ORSD model is measured by combining both the spatial *Space Function (s)* and temporal information *TP Clustering* given below that are obtained from (1) and (3). It is measured in terms of percentage (%).

$$FCR = \text{Space Function (s)} \cup \text{TP Clustering} \quad (5)$$

The average neighborhood relationship identification time $ANRI_{time}$ is the average time taken to perform the individual (i.e., inter-cluster) $inter\text{-}cluster_{time}$ and neighborhood aerial data (i.e., intra-cluster) features $intra\text{-}cluster_{time}$ given below. It is measured in terms of milliseconds (ms).

$$ANRI_{time} = \frac{inter\text{-}cluster_{time} + intra\text{-}cluster_{time}}{2} \quad (6)$$

The effectiveness on features relational analysis rate is obtained from (4). This is measured in terms of percentage (%).The CPU execution time *CPU* for TTFC-ORSD model is the product of average number of cycles per spatial temporal instruction $Cycle_{ST}$, time per mapping relationship TMR and number of spatial temporal instructions per task $Insn_{ST}$. It is measured in terms of milliseconds (ms).

$$CPU = Cycle_{ST} * TMR * Insn_{ST} \quad (7)$$

5. Results Analysis Of TTFC-ORSD Model

In order to features and functionality of the TTFC-ORSD model, the performance is measured and accessed in a quantitative manner on the basis of twelve attributes, such as date, latitude, longitude, zonal winds and so on obtained from El Nino Data Set extracted from UCI repository and compared the analysis with the existing TGC [1] and FFT [2]. The obtained experimental results using JAVA are compared and analyzed using the values in the table and graphical figurative representation is shown as given below. To deliver with a detailed performance, in Table 1 we apply Feature Time-Position Clustering algorithm to obtain the Features Clustering Rate and comparison is made with two other existing techniques, TGC and FFT respectively. Features clustering rate in TTFC-ORSD model refers to the rate or the percentage at which the features are clustered using topical tree based feature clustering framework with respect to the number of features. Higher features clustering rate results in the improvement of the model.

Number of Features (f)	Features Clustering Rate (%)		
	TTFC-ORSD	TGC	FFT
3	58.35	53.33	42.30
6	63.21	58.19	47.16
9	70.33	65.31	54.28
12	75.45	70.43	60.40
15	71.67	66.65	55.62
18	82.65	77.63	66.60
21	84.32	79.30	68.27

Table 1 Tabulation for Features Clustering Rate

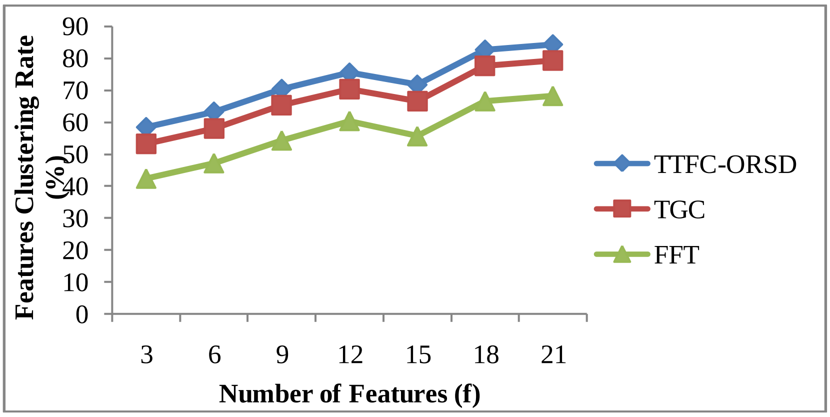

Figure 4 Measures of Features Clustering Rate

Figure 4 show that the proposed TTFC-ORSD model provides higher features clustering rate when compared to TGC [1] and FFT [2] with respect to the number of features provided as input. This is because of the application of Topological Tree based Feature Clustering framework using which the spatial and temporal information are combined which intensely results in the improvement of Features Clustering Rate by 5.95 % – 8.60 % compared to TGC. In addition to that with the use of effective temporal features like start time, end time and transaction time of aerial data objects and spatial features like theme and positional information, the features clustering rate is increased naturally by 19.03 % – 27.50 % compared to FFT respectively.

Number of observations (n)	Average Neighborhood Relationship Identification Time (ms)		
	TTFC-ORSD	TGC	FFT
5	0.132	0.154	0.169
10	0.154	0.176	0.191
15	0.183	0.205	0.220
20	0.165	0.187	0.202
25	0.195	0.207	0.222
30	0.206	0.228	0.243
35	0.225	0.247	0.262

Table 2 Tabulation for Average Neighborhood Relationship Identification Time

Average neighborhood relationship identification time refers to the time taken to identify the neighborhood aerial data features through the object relational database techniques. The comparison of Average Neighborhood Relationship Identification Time is provided in table 2 with respect to different observations noted at the same time of the day in the range of 5 – 35 observation. With increase in the number of observations being made, the average neighborhood relational identification time is also increased though reaches to saturation when 15 observations were conducted and a drift change occurred when the observation was noted to be 35. This is because the E1 Nino Data Set used contains the temperature factor which is not same throughput the day. As a result, the variations are also noted.

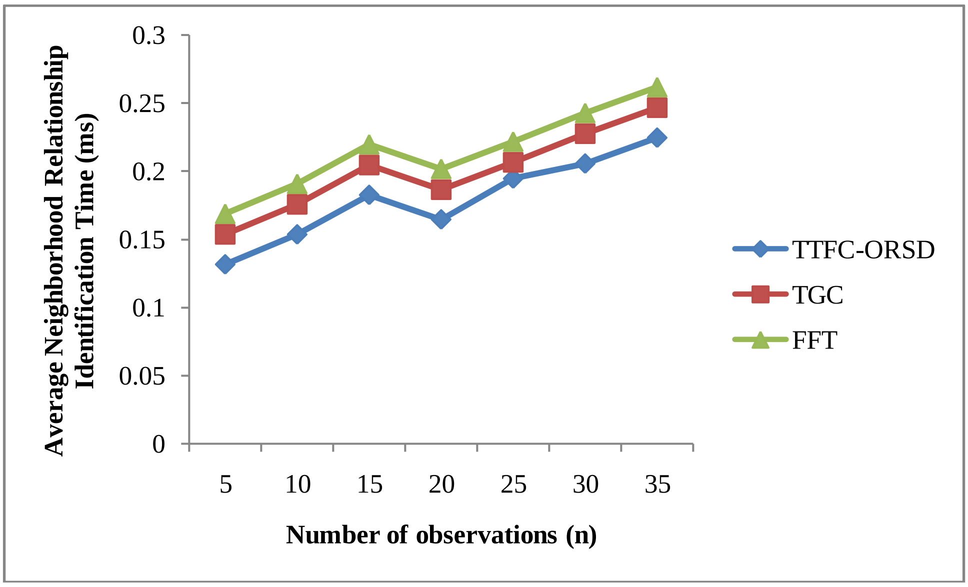

Figure 5 Measures of Average Neighborhood Relationship Identification Time

In figure 5, the Average Neighborhood Relationship Identification Time is depicted with respect to several observations of range 5 – 35 that are considered for the experimental purposes in JAVA. From the figure, we can observe that the value of average neighborhood relational identification time achieved using the proposed TTFC-ORSD is lower when compared to two other existing works Temporal and Geographic Clustering (TGC) [1] method and Fast Fourier Transform (FFT) [2] method. Moreover, we can also observe that by varying the number of observations being made, the identification time is increased but comparatively improvement is observed using the proposed TTFC-ORSD. This is because with the application of similar feature time-position clustering the clustering is based on the time-position of features. With complex Spatio-temporal objects, the flexible relativity between the aerial data objects is identified reducing the average neighborhood relationship identification time by 9.77 % – 16.66 % and 16.44 % – 28.03 % compared to TGC and FFT respectively.

Number of Features (f)	**Features Relational Analysis Rate (%)**		
	TTFC-ORSD	**TGC**	**FFT**
3	65.32	60.30	53.30
6	68.45	63.43	57.43
9	71.45	66.43	59.43
12	73.55	68.53	61.53
15	70.25	65.23	69.23
18	75.55	70.52	63.52
21	78.45	73.41	67.41

Table 3 Tabulation for Features Relational Analysis Rate

The effectiveness on Features Relational Analysis Rate measures the rate at which the analysis between the features is made using Object Relational Value Operator. The Features Relational Analysis Rate using TTFC-ORSD is provided in an elaborate manner in table 3. We consider the approach with different number of features acquired from the UCI repository using four attributes for experimental purpose using JAVA.

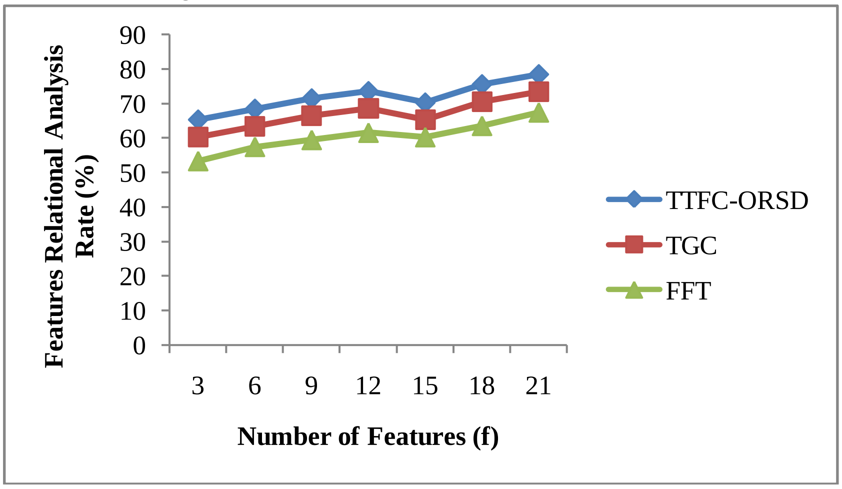

Figure 6 Measures of Features Relational Analysis Rate

The targeting results of the Features Relational Analysis Rate using TTFC-ORSD with two state-of-the-art methods [1], [2] in figure 6 is presented for visual comparison based on the varied features. Our approach differs from the TGC [1] and FFT [2] in that we have incorporated the Meta-Feature Object Relational Value Operator for handling both spatial and temporal data that improves the features relational analysis rate by 6.42 – 7.68 % and 14.07 – 18.40 % compared to TGC and FFT respectively. By applying two different elements, called feature and knowledge elements, efficient analysis of relativity is performed using the clustered information that results in the improvement of effectiveness on features relational analysis rate.

Number of observations (n)	CPU Execution Time (ms)		
	TTFC-ORSD	TGC	FFT
5	0.243	0.276	0.299
10	0.265	0.298	0.314
15	0.294	0.327	0.353
20	0.276	0.309	0.335
25	0.306	0.329	0.355
30	0.317	0.350	0.376
35	0.336	0.369	0.395

Table 4 Tabulation for CPU Execution Time

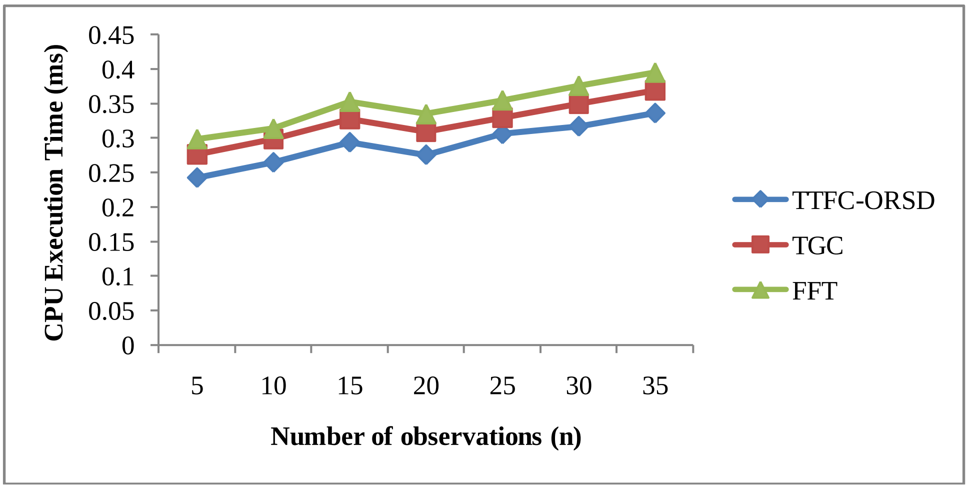

Figure 7 Measures of CPU Execution Time

Table 4 and Figure 7 shows the mining efficiency in terms of CPU Execution Time using E1 Nino Data Set and comparison is made with two other existing works namely, TGC [1] and FFT [2] versus increasing number of observations from n = 5 to n = 35. The CPU execution time improvement returned by E1 Nino Dataset over TGC and FFT increases gradually as the number of observations gets increased. For example for n = 15, the percentage improvement of TTFC-ORSD compared to TGC is 11.22 percent and compared to FFT is 20.06 percent, whereas for n = 20 the improvements are around 11.95 and 21.37 percent compared to TGC and FFT respectively. The mining efficiency in terms of CPU execution time is minimized by performing effective mapping relationship between the intra-cluster features by 7.51 – 13.58 % compared to TGC. Furthermore, to identify the relativity of different clusters, two important factors row and column are observed using time and objects respectively that results in the minimizing the CPU execution time by 16.01 % – 23.04 % compared to FFT respectively.

6. Conclusion

In this work, a Topological Tree based Feature Clustering Framework is combined with Object Relational Spatio-temporal Database (TTFC-ORSD) model to ensure consistency on defining the Spatio-temporal data relationship on E1 Nino Data Set. The TTFC-ORSD model utilizes Topological Tree based Feature Clustering framework and Object Relational Spatio-temporal Database model to mine the complex aerial variables. With the Topological Tree based simplify feature extraction process the, complex aerial variables are addressed that results in efficient feature extraction. Next, with the introduction of Similar Feature Time-Position Clustering, efficient clustering is performed using shared property to perform inter-cluster and intra-cluster formation. Finally, with the application of Meta-Feature Object relational value operator, consistent and flexible spatio temporal relationship is identified resulting in the efficient object relational identification. Experimental results demonstrate that the proposed TTFC-ORSD model not only leads to noticeable improvement over the parameters features clustering rate and feature relational analysis, but also outperforms average neighborhood relationship identification time required to perform inter-cluster and intra-cluster compared over other state-of-the-art works.

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