AN APPROACH OF DISCOVERING SPATIAL-TEMPORAL PATTERNS IN GEOGRAPHICAL PROCESS

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ABSTRACT:

Spatial data mining focuses on searching rules of the geographical statement, the structures of distribution and the spatial patterns of phenomena. However, many methods ignore the temporal information, thus, limited results describing the statement of spatial phenomena. This paper focuses on developing a mining method which directly detects spatial-temporal association rules hidden in the geographical process. Through such approach, geographical process can be extracted as a particle which exists in spatial-temporal- attribute dimensions. By setting customized fixed-window, geographical process in one time interval is organized as a record with attribute value and spatial orientation change. Spatial-temporal association rules can be found in geographic process mining table.

$$[TimeInterval_i, MovingDirection_m,P] => [TimeInterval_i, MovingDirection_n,Q]$$

To verify this mining approach, it is applied on AVHRR MCSST thermal data for extracting Indo-Pacific warm pool's frequent movement patterns. The raw data provided by PO.DAAC, whose time spans of 20years from 1981 to 2000 with 7days' time particle, has been used to mining spatial temporal association rules. In the experiment, we extract warm pool within 30°N-30°S, 100°E-140°W and use 28°C as temperature threshold. After which Warm Pool's geographical process table is established so as to describe the variation of warm pool in spatial-temporal-attribute dimension. In the mining process, 18 spatial-temporal process frequent models can be found by setting minimal support threshold at 10% and confidence threshold at 60%. The result shows such a methodology can mine complicated spatial-temporal rules in realistic data. At the same time, the mining result of warm pool's frequent movement patterns may provide reference for oceanographers.

1. INTRODUCTION

In data mining, Association Rule Mining (ARM) is a popular and prevailing researched method for discovering interesting relations between variables in large databases. Previously Spatial Association Rules Mining (SARM) and Sequence Mining (SM) are two different subareas on spatial rules and temporal rules respectively. SARM interests on how to find connection rules which is represent by spatial topology, such as "is_Close" and "is_Next_To", among spatial objects(Koperski and Han 1995). So a spatial association rule (SAR) is an association rule where at least one of the predicates is spatial(Shekhar and Huang 2001). On the other hand, SM concerns how to dig association rules under temporal constraints(R. Agrawal 1995; Zaki 2001). However, with the development of information capture devices, data containing both time stamp and location information is recorded. Especially, when process Geographical Information System (PGIS) (Fen-zhen SU 2006) is under discussing, mining spatial- temporal rules are expected. Therefore a burning question is how to find a solution that could mine spatial-temporal association rules.

From research objects prospects, spatial-temporal association rules can be divided into two parts. One is to find rules from group objects, the other focuses on mining movements of one object which has flexible shape and moving patterns, such as Warm Pool. In this paper, we propose an approach that takes into account spatial-temporal attributes to mine the frequent trajectory patterns of flexible shaped objects. Such approach contains three steps. Fundamentally, we scan entire database and organise geographic process. Then the process record pre-processing is required. Finally, we apply Apriori-based algorithm to mine spatial-temporal association rules. To prove validation of such approach, we set an experiment using AVHRR remote sensing image provided by PO.DAAC, whose time spans is 20 years from 1981 to 2000 with 7days' time particle, to mine Indo-Pacific warm pool's frequent trajectory. Some interesting rules are found which comply to the general rules of Warm Pool's seasonal fluctuation, while leaving some rules still unresolved.

2. RELATED WORK

From analytical prospective, the target of STARs mining is to search the correlations hidden behind objects' spatial and temporal data. Automatic statistic approaches are used for extracting such correlations from 2-dimensional table structure which covers realistic objects' statement or abstracted objects process. Such statistic approach is well developed by related database techniques and traditional data mining algorithms. In traditional data mining, R.Agrawal etc(Rakesh Agrawal 1993) proposed an Apriori algorithm to mine frequent item set from transactional database. The form of the rule is abstracted as X=>Y. The algorithm employs prior knowledge of frequent item set properties, which are all non-empty subsets of a frequent item set that must also be frequent. Under such prior knowledge, the number of candidate sets' combination is reduced prominently. Apriori algorithm sets a mile stone in ARM. Two years later, J.Han(Jiawei Han 1995) developed Agrawal's research and proposed an algorithm which utilised Multi –Level logic structure to abstract target rules and mined cross level schema so that complicated logic rules could be described.

After such fundamental work, many data mining researchers (R. Agrawal 1995; J.Pei 2001; Zaki 2001;

Hwang, Wei et al. 2004; Winarko and Roddick 2007; Kong, Wei et al. 2009)demonstrated how to combine both temporal information and other attributes into sequence rules and temporal rules. In rich temporal description forms, from basic time stamp representation to process representation, temporal topology was introduced. From the view of data structure, Zaki et al's SPADE algorithm decomposed the original mining problem into several smaller sub-problems so that each sub-problem could be independently solved in memory, while J.Pei et al's PrefixSpan algorithm reduced search space and accelerated the mining process by using the projected databases. In temporal topology, Kong et al proposed an algorithm which used four kinds of temporal topology predicates, namely before, during, equal and overlap, to mine temporal association rules. Despite temporal topology, Winarko et al proposed a method called ARMADA, whose accommodating temporal intervals offered rules that were richer still.

Geographic researchers discussed ways of taking advantages of multi level logic structures and cross mining schema in Geographic Information System so as to automatically find dependent patterns in spatial data. Han etc al (Koperski and Han 1995) set multilevel concept descriptions for spatial rules, such as "g_clse_to", "not_disjoint, close_to", "Intersects, Inside, Contain, Equal" to show the spatial topology, the final rules can be represented as "is_a(x, house) A close_to(x, beach) → is_expensive(x) (90%)". Their work made spatial information and none spatial-temporal information consistant. AGM algorithm (Inokuchi, Washio et al. 2000) and FSG algorithm (Kuramochi and Karypis 2001) used an Apriori-based approach to combine frequent sub-graphs mined at the previous level to generate all candidates at the next level. Appice etc al (Appice and Buono 2005) summarizes advantages from this taxonomic knowledge on spatial data to mine multi-level spatial association rules. Bembenik etc al (Bembenik and Rybiński 2009) defined the neighborhood in terms of the Delaunay diagrams, instead of predefining distance thresholds with extra runs.

However, how to handle both spatial and temporal data is still under research. But rear works have been published yet. Lee etc al (Lee, Chen et al. 2009) developed an approach using TI-lists structure and GBM algorithm to find trajectory patterns. Huang etc al (Huang, Kao et al. 2008) summarized the correlation between sea salt and temperature in spatial-temporal distribution. The final rules can be described as "if the salinity rose from 0.15 psu to 0.25 psu in the area that is in the east–northeast direction and is near Taiwan, then the temperature will rise from 0° C to 1.2° C in the area that is in the east–northeast direction and is far away from Taiwan next month", which set temporal constraints that limit temporal information in two adjacent time intervals. Verhein etc al (Verhein and Chawla 2008) proposed source-thoroughfare-sink model describing trajectory pattern, while left none connection charts unexplained. In conclusion, traditional algorithm may lose some important information during searching frequent trajectory patterns of flexible shaped objects.

3. GEOGRAPHIC PROCESS MINING APPROACH

This section describes the concepts associated with applying the association rule mining to discover spatial-temporal patterns. Some definitions will also be given before describing the proposed algorithm. Figure 1 below shows the steps of processing.

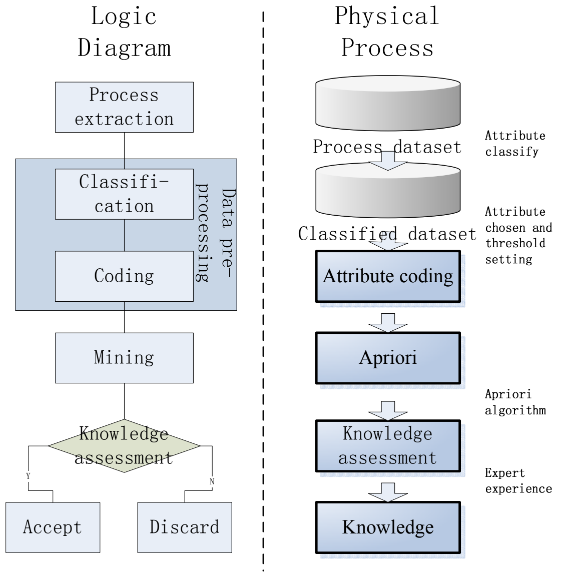

Figure 1. Mining approach flow chart

3.1 Description of geographic process

Modern physics shows that time and space form an indivisible entirety called four-dimension space. In this space, continuity dominates every attribute of existing objects (low speed), which means objects' snap shot always exists. In geography, modern science provides powerful devices to capture such snapshot of geographic phenomena rapidly and continuously. Therefore, to mine geographic patterns from these primary data needs strict organization and description of spatial-temporal statement.

Definition 1: In 4-dimensional space, given exactly T_i, objects I can be represented as I=[$Time_i$, $Location_i$, $Attribute_i$] , $i \in N$, $T_i \in (-\infty, -\infty)$. Location is the object's spatial vector, usually Location = [Longitude, Latitude, Altitude]^T, Attribute is the object's attribute vector.

Every objects can be described as I=[T_i , L_i, A_i]. Attribute A is a high dimensional vector, whose item depicts object from different aspects. To represent flexible appearance object's geometry, kinds of index can be used, such as degree of fragmentation, and fractal feature (M Coster 1985). Therefore, flexible shaped object can be recorded as kinds of index. And the description of spatial–temporal statement is compatible with 2-dimensional table structure, which means the characterization of object can be stored into formalized database table (Table 1).

ID	Time	Longitude	Latitude	Temperature	Area (million km^2)
1	1981-11-3	156.62	2.61	28.96	42.55
2	1981-11-10	158.57	1.43	29.44	42.1
3	1981-11-17	160.9	0.17	29.47	42.42
4	1981-11-24	161.46	-1.17	29.23	40.77

5	1981-12-1	163.04	-1.50	29.33	38.84

Table 1. An Example of Spatial-temporal statement table

Definition 2: Geographical Process (GP) is the change from starting statement to ending statement. Given fixed time window TI, TI = [T_i,T_j], i < j and i, j∈N, GP = $^{\Delta}$I=[TI, $^{\Delta}$L, $^{\Delta}$A].

Definition 3: Time interval in GP is the process particle marked as PP.

Geographic process, which reflects object's spatial movement in time evolution, is composed by sets of quantification or qualification statement. Object's spatial change $^{\Delta}$L contains the change of reshaping and moving. To simplify such variety, we view target object as a point.

Definition 4: Abstracted object as a point, called spatial-temporal point.

As a point, by introducing the orientation model, spatial topology is limited to just moving direction (Table2) so that the complexity of association rule is reduced.

TI ID	Direction	Temperature	Area (million km^2)	Start Time	End Time
1	N	-0.10	-6.98	1981 Winter	1982 Spring
2	NE	-0.24	4.50	1982 Spring	1982 Summer
3	SE	0.09	1.25	1982 Summer	1982 Autumn
4	SW	-0.06	-7.72	1982 Autumn	1982 Winter
5	NW	-0.26	-2.04	1982 Winter	1983 Spring

Table 2. An Example of Spatial-temporal process table (PP = 3 months)

From logical view, the description of spatial-temporal association rule is the instantiation of the form of target knowledge. Spatial-temporal association rule format prepares the foundation data set for pre-processing. As from mining view, it is the goal of the final result.

Definition 5: Geographic Process Association Rule is one kind of spatial-temporal association rule, defined as GPAR: GP_m=> GP_n, m,n∈N

Precisely, spatial temporal process association rule is written as [TI_m, $^{\Delta}L_m$, $^{\Delta}A_m$]=> [TI_n, $^{\Delta}L_n$, $^{\Delta}A_n$], m,n∈N. Such rule is distinguished from traditional association rule in three characters:

a) Spatial-Temporal scalability. The spatial or temporal information can be divided into different scale. In question-driven data mining process, the detail of final patterns is influenced by spatial-temporal particle.

b) Evolution entirety. As process association rule contain spatial temporal coupled information. So the process association rule describes the integrated 4-dimensional change process. In this experiment, setting time particle of Indo-Pacific warm pool's movement as 3 month，every statement change will be recorded while each attribute will be combined together for providing entirety of spatial- temporal information.

c) Rule flexibility. The formation of rule is just a description of process; it separates mining algorithm. So different mining target GP_m=> GP_n can be interpreted into diverse meaning. To take advantage of such character, different mining algorithm shares the same process of data sets.

3.2 Geographic Process data pre-processing

This section contains three parts. In the above, the pre-processing approach is discussed. Then, Geographic Process Mining Table (GPMT) is organized through pre-processing. As target GPAR rule described above, a mining method has been developed based on Apriori algorithm.

3.2.1. Process data set pre-processing

Data pre-processing is an approach which extracts data from primary concept level to upper ones. It is a question-driven procedure. All attribute's spatial-temporal particle, which directly influences the statistics in final rules is classified. After extracting the dataset of geographic process, one record in the table is called meta-process. Different attribute has different kind of classification threshold in the way of raising its concept level. Such as Table 2, using variance based binning method, to classify "Temperature". By setting 3 bins which represents "fall", "remain practically unchanged", "rise" in turn. The result is shown below.

class	Lower threshold	upper threshold
0		< -0.1140654
1	>= -0.1140654	<= 0.1126115
2	> 0.1126115	< 0.067004

Table 3. Classification after Binning

Reorganization and conversion makes every subset of process consistent (Figure 2). In this experiment's process [TI, $^{\Delta}$L, $^{\Delta}$A], as using orientation model, the number of changing domain "$^{\Delta}$L" sets 8, and the number of changing domain "A" are both 3. So taking the first row in Table2 as example, the result of coding is saved as "421" (Table 4).

Meta process: XXXXXXXXXX
└X is classification number

Figure 2. Coding Format

TI_ID	process	Start Time	End Time
1	111	1981 Winter	1982 Spring
2	201	1982 Spring	1982 Summer
3	411	1982 Summer	1982 Autumn
4	610	1982 Autumn	1982 Winter

Table 4. Process Dataset

3.2.2. Building GPMT

Definition 6: GPAR's Time Span (TS) is the time span between TI_m and TI_n. So the TS∈[1,K], K= (Starting Time – Ending Time) / PP,K∈N.

The temporal connection hidden in the GPAR: GP_m=> GP_n is limited. For example, in this experiment, the maximum TS in 20 years is 75. To mine such GPAR, GPMT should be constructed by connecting Process Dataset joint with Cloned Process Dataset with TS time intervals' lag. (Figure 3)

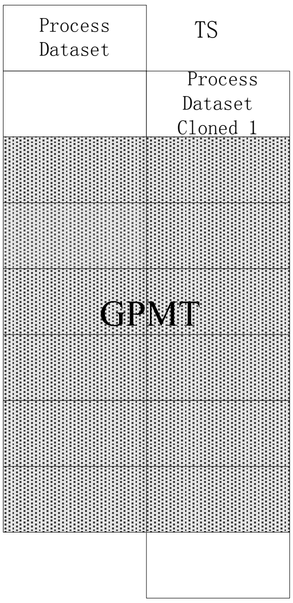

Figure 3 Geographic Process Mining Table (TS = 1 process)

3.3 Process association rules data mining

In this section, we introduce Apriori algorithm (Rakesh Agrawal 1993)to mine GPARs based on GPMT. By setting Maximum length of association rules and Support threshold = min_sup (support(A=>B) = P(A ∩ B)), confidence threshold = min_conf (confidence(A=>B) = P(B|A)), the Apriori algorithm traverses process dataset is not larger than such maximum length times. After first Scan, Apriori captures frequent set rule Length equals 1 and whose support and confidence are not less than min_sup and min_conffidence. Then build Length+1 candidate, and then Scan DB the second times, using Apriori traits pruning false candidate, generate Length+1 candidate. Such procedures continue until no Length+1 frequent sets can be found or Length equals Maximum length.

Pseudocode:

(1)L1= {large 1-item sets} //Scan DB once, capture frequent set, L1
(2)for (k=2; L_{k-1}≠ϕ; k++)
(3){ C_k=apriori-gen(L_{k-1})//according to L_{k-1} frequent set, digging new candidate sets, Ck
(4) for each t ∈D
(5) { Cspt =subset (C_k, t);
(6) for each c ∈C_t c.count ++;
(7) }
(8) Lk={c∈C_k|c.count≥minsupp}
(9)}
(10) L=$\cup_k L_k$;

4. EXPERIMENTAL RESULTS AND ANALYSIS

In this section we present realistic remote sensing images and the mine spatial temporal association rules generated from them. To analysis results, we quoted some oceanographer's work to assess rules mined.

4.1 SST Data introduction

These experiments using AVHRR sensor's SST to analyze the data provided by PO.DAAC whose size is 2048*1024pixel^2. Under Mercator's projection, spatial resolution is 5.689 pixels per Longitude and 2.845 pixels per Latitude. Temporal resolution is 7 days and the data covers 20 years (1981-2001). According to Wang etc al (Wanying 1998), the Indo-Pacific warm pool forms an entire Warm Pool (WP) and its envelope should be 100°E-140°W,30°N-140°S within which the warm pool influences the weather of Eastern Asian mostly. Meanwhile, we use 28°C as Warm Pool's edge accepted by many oceanographers (Zhang Qilong and Weng Xuechuan 1997; Enfield, Lee et al. 2005) to extract geometries. (Figure 4)

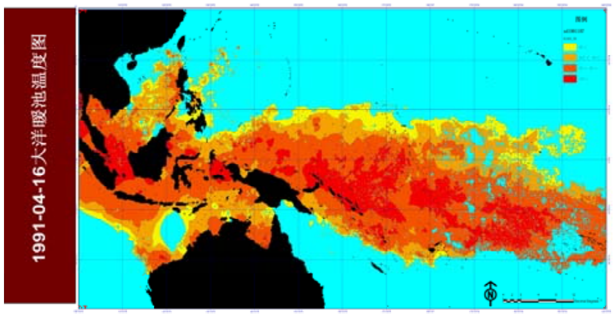

Figure 4. Warm Pool extraction image

4.2 Experiment

Using data processing approach mentioned above, the Warm Pool is described as the quantitatively and spatial-temporal statement table of Warm Pool which is captured by sensor in 7days. Set the maximum sequential rules is 3, min_support is 10%, confidence is 60%. We consider the temporal scales are 3months so as to slice data into big scale part.

4.2.1 Experiment

4 solar terms are chosen like spring, summer, autumn and winter. So the split points are Spring Equinox, Summer Solstice, Autumnal equinox and Winter Solstice. Seasonal process recorded (Table5) can be attained From Table2.

TI-ID	Direction	Temperature	Area change (million km^2)	Start time	End Time
1	1	-0.10	-0.70	Spring	Summer
2	2	-.24	4.50	Summer	Autumn
3	4	0.95	1.25	Autumn	Winter
4	6	-0.06	-7.72	Winter	Spring
5	7	-0.27	2.04	Spring	Summer

Table 5 Seasonal process table

The Top 4 GPARs Results are listed:

Conseq-uent	antece-dent	GPAR	support %	Confidence %
Summer to autumn = 111	Autumn to winter = 511	[Summer to autumn, N,1,1] is_before [Autumn to winter, S,1,1]	27.78	80
Winter to Spring = 511	Spring to Summer = 810	[Winter to Spring , S,1,1] is_after[Spring to Summer, NW,1,0]	16.7	100
Autumn to winter = 512	Spring to Summer = 810	[Autumn to winter , S,1,2] is_after[Spring to Summer , NW,1,0]	16.7	66.7
Summer to autumn = 112	Spring to Summer = 111	[Summer to autumn ,N,1,2]is_after [Spring to Summer ,N,1,1]	16.7	66.7

Table 6 Mining Results

4.2.2 Rule analysis

El Niño-Southern Oscillation (ENSO), is a climate pattern that occurs across the tropical Pacific Ocean on average every five years, but over a period which varies from three to seven years, and is therefore, widely and significantly, known as "quasi-periodic." The two components are coupled: when the warm oceanic phase (known as *El Niño*) is in effect, surface pressures in the western Pacific are high, and when the cold phase is in effect (*La Niña*), surface pressures in the western Pacific are low. (K.E. Trenberth, P.D. Jones et al. 2007) Southern Oscillation is an oscillation in air pressure between the tropical eastern and the western Pacific Ocean waters. Low atmospheric pressure tends to occur over warm water and high pressure occurs over cold water, in part because deep convection over the warm water acts to transport air.(Figure 5) Normal equatorial winds warm as they flow westward across the Pacific. Cold water is pulled up along west coast of South America. Warming water is pushed toward west side of Pacific.(http://en.wikipedia.org/)

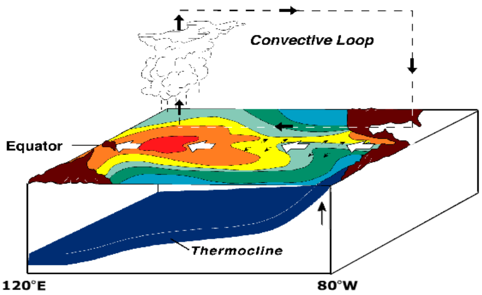

Figure 5 Normal Pacific pattern (http://en.wikipedia.org/)

The movement of warm water forms a periodical geographical process. After mining, GPARs may have association with Southern Oscillation. Here is the comparison.

GPAR1: In the same year, if during autumn to winter, Warm Pool moves South without Temperature and Area change prominently, then in the previous summer to autumn, Warm Pool moved North without Temperature and Area change prominently. This rule reflects warm pool's annual latitude infatuation. Two none spatial-temporal attributes remain unchanged. The rules appeared in 1984, 1992, 1993, 1995, 1997. Almost Earlier than all this rules El Niño phenomena happened. El Niño happens between October to next years February. It occured in 1982-1983,1986-1987, 1991-1992, 1993, 1994-1995, 1997-1998.And this rules are just after El Niño, excluding 1984. But during 1982-1983 ,one of the most powerful El Ninos happened , so the connection of GPAR1 and El Ninos have shown some kind of relation which needs further research or explanation.

GPAR2: In the same year, if during Spring to Summer, Warm Pool moves Northwest with Area shrinking prominently, then during winter to spring, Warm Pool will move South without Temperature and Area change prominently. Unlike GPAR1, rules applied in 1993, 1998, 1999, with 100% confidence and warm pool dominant area shrink prominently. In all dataset, during spring to summer, the area of Warm Pool shrink just appeared in 4 years in 1993, 1997, 1998, and 1999. This phenomena may be explained by too many rains above sea or powerful cold stream. It still needs oceangrapher to explain.

GPAR3: In the same year, if during Spring to Summer, Warm Pool moves Northwest with Area shrinking prominently, then during Autumn to winter, Warm Pool will move South with Area expanding prominently. Such rules happened in 1998, 1999, with pool dominant area shrink in spring to summer, expanding right into autumn to winter. In all dataset, during spring to summer, the area of Warm Pool shrinking just appeared in 4 years , which are 1993, 1997, 1998, 1999, while during autumn to winter in 1988, 1989, 1996, 1998, and 1999, more rules would be generated if data classification scale expaned. However,this rule may also be just a coincidence because its support and confidence are not high enough.

GPAR4: In the same year, if during spring to summer, Warm Pool moves North without Temperature and Area change prominently, then during summer and autumn, Warm Pool will move North with Area expanding prominently , just the same as GPAR3.This rule needs more data to prove.

So each of GPARs listed here has high support and confidence. The index of Lift which defines as Confidence / Support, are all greater than 1, which means all these rules are strong rules showing GP1=>GP2 are positively correlated. Despite these statistics, the appearance years of these GPARs may really correlate with El Niño and Southern Oscillation. Many oceanographers have worked on such areas and found patterns between Warm Pool and Southern Oscillation. (M. J. McPhaden 1990; Brijker, Jung et al. 2007; Cheng, Qi et al. 2008)

5. CONCLUSION

In this paper, an approach is proposed for mining spatial-temporal association rules of a flexible-shaped object. Such approach has three steps: geographic process is firstly generated from original image by designing process table. Then the attained table is processed so as to make attributes of geographic process consensus to form the GPMT table. Finally, spatial temporal association rules are mined using Apriori algorithm with rich spatial temporal information.

Although we have shown the rules mined by such approach some issues still need to be addressed in the future research. Above all, how to enrich spatial- temporal topologies so that rules can be represented in a more complicated way and can be dealt with is a sophisticated question. Anyway, the GPARs described in this paper is just an example to spatial–temporal association rules, it could also be used for other applications such as mobile advertisements, shoppers' trajectory analysis, and animal trajectory analysis to find other interesting rules.

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