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Research of MDCOP Mining Based on Time Aggregated Graph for Large Spatio-temproal Data Sets

Zhanquan Wang[1,2], Taoli Han[1], and Huiqun Yu[1,2]

[1] Department of Computer Science and Engineering, East China University of Science and Technology, Shanghai 200237, China
zhqwang@ecust.edu.cn, 2730023187@qq.com, yhq@ecust.edu.cn
[2] Shanghai Engineering Research Center of Smart Energy, Shanghai, 200237, China

Abstract. Discovering mixed-drove spatiotemporal co-occurrence patterns (MDCOPs) is important for network security such as distributed denial of service (DDoS) attack. There are usually many features when we are suffering from a DDoS attacks such as the server CPU is heavily occupied for a long time, bandwidth is hoovered and so on. In distributed cooperative intrusion, the feature information from multiple intrusion detection sources should be analyzed simultaneously to find the spatial correlation among the feature information.In addition to spatial correlation, intrusion also has temporal correlation. Some invasions are gradually penetrating, and attacks are the result of cumulative effects over a period of time. So it is necessary to discover mixed-drove spatiotemporal co-occurrence patterns (MDCOPs) in network security. However, it is difficult to mine MDCOPs from large attack event data sets because mining MDCOPs is computationally very expensive. In information security, the set of candidate co-occurrence attack event data sets is exponential in the number of object-types and the spatiotemporal data sets are too large to be managed in memory. To reduce the number of candidate co-occurrence instances, we present a computationally efficient MDCOP Graph Miner algorithm by using Time Aggregated Graph. which can deal with large attack event data sets by means of file index. The correctness, completeness and efficiency of the proposed methods are analyzed.

Keywords: Network spatiotemporal co-occurrence pattern intrusion detection, mixed-drove spatiotemporal co-occurrence pattern, large spatiotemporal data set, Time Aggregated Graph (TAG), file index.

1. Introduction

In network security area, intrusion detection is the detection of any intrusion that attempts to compromise the integrity, confidentiality, or availability of computer resources. Intrusion detection collects and analyzes the information of key nodes in a computer network or system to detect the behaviors and signs of security policy violations and attacks in the network or system, and to respond accordingly.

The first element of intrusion detection is data source, which usually includes host-based data source and network-based data source. The current intrusion behavior is gradually changing from the messy, unorganized and single invasion behavior to the distributed, organized and cooperative invasion behavior. In distributed cooperative intrusion, multiple attackers and multiple IP addresses can spy on and attack a common target simultaneously. In this collaborative intrusion behavior, the invasion of the attack from multiple points to invasion by the invasion of the source of the information is very fragmented, from a single intrusion detection information source may can't see anything suspicious, cannot determine whether have intrusion behavior, only at the same time analysis of characteristic information from multiple source of intrusion detection, is likely to determine the intrusion behavior. The correlation between the feature information of this intrusion is called spatial co-occurrence.

In addition to spatial co-occurrence, intrusion also has temporal co-occurrence. Some invasions are gradually penetrating, and attacks are the result of cumulative effects over a period of time. Analysis from some intrusion behavior, for example, the characteristics of the information can be found that Δ t period of network packet with the same source IP address, the address is trying to establish multiple connections with the same target host system. For this kind of intrusion behavior, if any time just thinks of this time period in isolation of characteristic information can reflect the attack, must consider all the feature information Δ t period.

Intrusion detection which takes spatial and temporal into account is mixed-drove spatiotemporal co-occurrence patterns detection.

As the volume of spatiotemporal data continues to increase significantly due to both the growth of database archives and the increasing number of spatiotemporal sensors, automatic and semi-automatic pattern analysis becomes more essential. It is meaningful and challenging for us to extract interesting patterns from these large spatiotemporal attack event data sets. Co-occurrence Pattern represents subsets of different object-types whose instances are co-located together for a significant fraction of time.

Given a large spatiotemporal attack event database, a neighbor relationship and mixed-drove interest measure thresholds, our aim is to discover mixed-drove spatiotemporal co-occurrence patterns (MDCOPs). To mine co-occurrence patterns, Celik et al. proposed MDCOP-Miner and fast MDCOP-Miner[14]. The two methods are based on the join-based collocation algorithm proposed by Huang et al.[18]. The basic co-occurrence pattern mining procedure involves four steps, as shown in Fig.1. First, candidate co-occurrence instances are gathered from the spatiotemporal data sets. Then, prevalent co-occurrence pattern sets satisfying the given prevalence thresholds are filtered. Finally, co-occurrence patterns satisfy the given prevalence thresholds are generated. Most of the computational time of co-occurrence pattern mining is devoted to finding co-occurrence instances. The approach is Apriori-like algorithm, which is costly as it enumerates all possible co-occurrence instances over all time instances. Thus, we propose adding a step for materializing the neighbor relationships to increase the efficiency of co-occurrence mining.

While the volume of the spatiotemporal data set is large, we find discovering the MDCOPs in a relatively small computer memory are difficult by using the existed methods. Mining the co-occurrence patterns is meaningful to network security.

1.1. Contributions

This study makes the following contributions:

We propose a novel method for materializing the neighbor relationships in order to perform efficient mixed-drove spatiotemporal co-occurrence patterns detection.

This work provides a new storage method for mining MDCOPs from large spatiotemporal attack data sets. The experimental results show that the proposed storage method and the pattern mining algorithms are correct, complete and efficient.

The framework of experimental design and the comparisons of existing approaches are provided in the paper.

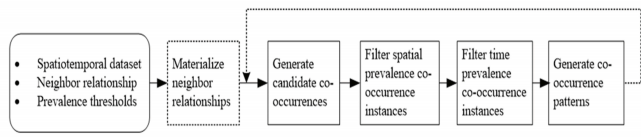


Fig. 1. Basic procedure of co-occurrence pattern mining

1.2. Scope and Outline

This work is aim to addresses the co-occurrence pattern mining for large volume of spatiotemporal attack data sets. Our system achieves superior performance of computation efficiency to existing work like fast MDCOP-Miner [3]. Determining thresholds for MDCOP interest measures and inserting object-types at arbitrary time intervals are not the scope of this paper.

The rest part of this paper is organized as follows: Section 2 reviews related works. Section 3 presents basic concepts to provide a formal model of MDCOP Graph and the problem statement of mining MDCOPs. In Section 4, we presented our proposed MDCOP mining algorithms. Analysis of the algorithms is given in Section 5. Section 6 presents the experimental evaluation and section 7 presents conclusions and future work.

2. Related Works

Previous studies for mining spatiotemporal co-occurrence patterns can be classified into two categories: the approaches of mining uniform groups on large attack event data sets and the approaches of mining mixed groups on large attack event data sets. MDCOP belongs to the latter. Audit Data Analysis and Mining is one of the known data mining projects in an intrusion detection, which uses a module to classify the abnormal event into false alarm or real attack proposed by Barbara′ et al. [4]. It is an online network-based ID, which used two data mining techniques, association rule and classification. Shi-Jinn Horng et al. [8] investigate using both a linear and a non-linear measure linear correlation coefficient and mutual information, for the feature selection. Jau Tsang et al. [19] proposed fuzzy rule-based system is evolved from an agent-based evolutionary framework and multi-objective optimization. Gudmundsson et al. [10] proposed an algorithm for detecting flock patterns in spatiotemporal datasets. Kalnis et al. [13] defined the problem of discovering moving clusters and proposed clustering-based methods to mine such patterns. If there are many common objects between clusters in consecutive time slots, such clusters are called moving clusters. The moving cluster patterns can be unified or a mixed object group [14]. However if there are no overlaps between the clusters in consecutive time slots, their proposed algorithms for mining moving clusters will fail to discover MDCOPs.

The MDCOPs problem differs from the co-location pattern. Previous approaches of MDCOP mining can use a spatial co-location mining algorithm for each time slot to find spatial prevalent co-locations, and then apply a post-processing step to discover MDCOPs by check their time prevalence. To mine co-locations, Huang et al. firstly proposed the mining of co-location patterns(different subset of instances of object types are adjacent to each other) from spatial datasets, then they proposed a join-based approach [20]; Cao et al. proposed a co-location approach from some period in spatiotemporal datasets, which can find out the co-location instances from continuous time slots [2]; Yoo et al. proposed a partial join-based and a join-less approach [18][11][12] which used nearby star and instance methods. Celik et al. [14]formalizes the problem, propose a new monotonic mixed-drove interest measure to discover and mine MDCOPs, and also propose an efficient algorithm (MDCOP-Miner).

MDCOPs represent object types co-located over space and time forming a spatial network (edges between objects in the network indicate existence of a neighborhood relationship) that dynamically changes over time. A common and naive approach to model such a network is to use time expanded graph, as described by Köhler et al. [6] where the network is replicated across discrete time instants. Ding et al. [5] proposed an alternative approach where attributes at each node and edge of the graph are used to model state and topology changes respectively. A more efficient method of modeling temporal spatial networks was proposed by George et al. [7], by incorporating the properties of nodes and edges in the graph as a time series. This paper also proposed efficient algorithms for computing the shortest path and connectivity in time dependent networks modeled using time aggregated graphs. The problem of mining MDCOPs with high spatial and time prevalence is described by Celik et al. [14]. However the approach is similar to Apriori like and involves candidate generation, which is costly as it enumerates all possible cliques over all time instances. A. Garaeva, M. Tang, Z. Wang, etc. [15][1] developed a framework implemented in Apache Spark environment for co-location patterns mining in big spatio-temporal data, which make evaluation of applied algorithms from the point of their efficiency and scalability.

Considerable achievements in MDCOP mining have been obtained in the last few years. However, dealing with large amount of spatiotemporal datasets is still challenging due to the accuracy and efficiency issues. In this paper, we materialize the neighbor relationships for efficient co-occurrence pattern mining, and solve the problem of efficient storage of MDCOPs by using the Time Aggregated Graph model and create our own storage model MDCOP Graph for mining MDCOPs. Finally, we provide an accurate and efficient co-occurrence pattern mining algorithm in large spatiotemporal datasets.

3. Co-occurrence Pattern Mining

In this section, we present basic concepts to provide a formal model of MDCOP Graph and the problem statement of mining MDCOPs. In the paper, we use multiple prevalence measures, which use threshold-spatial prevalence and temporal prevalence to determine whether one pattern is co-occurrence pattern. Meanwhile, we use time aggregate graph as data storage structure.

3.1. Mixed-drove Prevalence Measure

The focus of this study is to mine MDCOPs with multiple prevalence measures from large spatiotemporal data sets. Co-occurrence pattern represents subsets of different object-types whose instance are co-located together for a significant fraction time. Mining co-occurrence patterns from spatiotemporal datasets is based on the mining of spatial co-location patterns from spatial datasets. Co-location pattern is the dataset of the frequent and closely adjacent spatial characteristics in the geographical space. Spatiotemporal co-occurrence patterns are the co-location patterns which satisfy the time prevalence measure.

The basic MDCOP algorithm [14] defines two interest measures namely spatial prevalence θ_p and a time prevalence measure θ_{time} .

The spatial prevalence measure is used to determine if the pattern is spatially prevalent in a specific time slot. The time prevalence measure is used to determine if the pattern is frequent in all time slots. These threshold values are mostly domain-specific. It is difficult to determine suitable interest measure thresholds to identify MDCOPs without domain knowledge. If the values of thresholds are too small, there are many unnecessary patterns will be generated. Otherwise, there are too few patterns. It's possible to miss some significant candidate MDCOPs if they are too large.

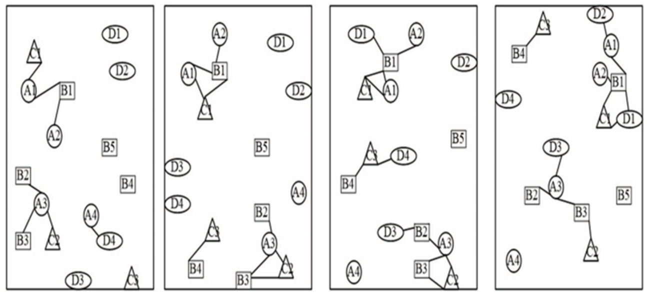
If a candidate pattern satisfies the following inequality, we can take this pattern as a spatial co-location pattern.

$$Prob_{t_m \epsilon TF}(s\_prev(P_i, time\_slot \quad t_m)) \geq \theta_p \tag{1}$$

Where, $Prob(.)$ is the probability of overall prevalence time slots; s_prev stands for spatial prevalence measure; θ_p is the spatial prevalence measure. Hence, a pattern is defined as an MDCOP if it satisfies the following inequality.

$$Prob_{t_m \epsilon TF}[s\_prev(P_i, time\_slot \quad t_m)) \geq \theta_p] \geq \theta_{time} \tag{2}$$

Where, $Prob(.)$ is the probability of overall prevalence time slots; θ_p stands for spatial prevalence measure; θ_{time} is the time prevalence measure. For example, in Fig. 2a, AB is an MDCOP because it is spatial prevalent in time slots 0, 1, 2, and 3 since its participation indices are no less than the given threshold 0.4 in these time slots, and is time prevalent since its time prevalence index of 1 is above the threshold 0.5. In contrast, BD is not a MDCOP. Although it is spatial prevalent in time slot 2, it is not time prevalent since its time prevalence index is no more than the given time prevalence threshold 0.5.



(a)

Mixed-Drove Co-occurrence Patterns	Spatial prevalence index values				Time prevalence index values
	time slot()	time slot1	time slot2	time slot3	
AB	3/5	3/5	3/5	3/5	4/4
AC	2/4	2/4	2/4	0	3/4
BC	0	3/5	3/5	3/5	3/4
ABC	0	2/5	2/5	0	2/4

(b)

Fig. 2. (a) An input spatiotemporal data set. (b) A set of output MDCOPs

Time Aggregated Graph (TAG) Spatiotemporal network is a spatial network whose topological relations and attribute information change with the passage of time. Spatiotemporal network model has many applications, such as real-time traffic planning, optimal shortest path selection and so on. These applications need to create a spatiotemporal network model which can be queried and calculated efficiently.Kohler et al. proposes a spatiotemporal network model-time expanded graph. Spatial network for each time slot is established in this model, which results in a large duplication of node information. With the increase of time slots, the time-consuming of establishing time expanded graph also significantly increased. To solve this problem, George et al. proposes a more efficient method-time aggregate graph, which takes time series as the attribute of node and edge. The duplication problem is solved by using this method, while it is difficult to efficiently obtain the location relationships between target object and other objects in all time slots. Currently, modeling spatiotemporal objects by time aggregate graph is an ideal spatiotemporal network model, which has low storage consumption, high query efficiency.

To take the advantage of time aggregate graph, we propose a graph based data structure to capture the information required to mine MDCOPs from the spatio-temoral data set. This data structure is motivated by Time Aggregated Graphs (TAG) [7] which models time varying road conditions as time series on the edges of a road network.[7] defines the time aggregated graph as follows.

$$TAG = (N, E, TF, f_1 ... f_k, g_1 ... g_m, w_1 ... w_p | f_i : N \rightarrow R^{TF}; \quad g_i : E \rightarrow R^{TF}; w_i : E \rightarrow R^{TF}) \tag{3}$$

Where N is the set of nodes, E is the set of edges, TF is the length of the entire time interval, $f_1 ... f_k$ are the mappings from nodes to nodes, $g_1 ... g_m$ are mapping from edges to edges, and $w_1 ... w_p$ indicate the dependent weights (eg.travel times) on the edges.

Each edge has an attribute, called an edge time series that represents the time instants for which the edge is present. This enables TAG to model the topological changes of the network with time.

Fig. 3a, 3b, 3c shows a network at three time instants. The network topology and parameters change over time. For example, the edge N2-N1 is present at time slot 0, time slot 1 and disappears at time slot 2, and its weight changes from 1 at time slot 0 to 5 at time slot 1. The time aggregated graph that represents this dynamic network is shown in Fig. 3d. In this figure, edge N2-N1 has two attributes, each being a series. The attribute (0, 1) represents the time instants at which the edge is present and [1, 1, -] is the weight time series, indicating the weights at various instants of time.

TAG models the network which has topology change with time passage, it can stores and combines spatial and temporal information efficiently. Thus it can save a lot of memory space and easily get all approaching slot information when querying examples of spatial relationships. Using the above-mentioned advantages of TAG model, we expand on this model and propose spatiotemporal co-occurrence storage model MDCOP Graph.

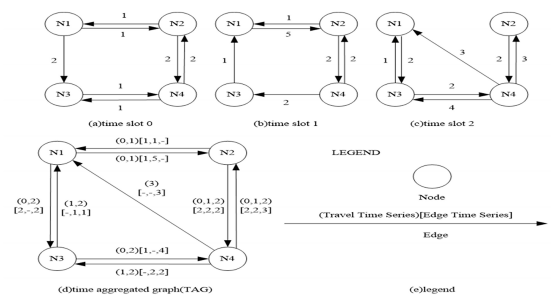


Fig. 3. (a), (b), (c) Network at various time instants. (d) Time Aggregated Graph (TAG). (e) Legend

3.2. Modeling MDCOP Graph

In this paper, we propose MDCOP Graph which based on TAG (Time Aggregated Graph) network model to store instances of close relationships, and obtain information for the process of mining co-occurrence patterns through visiting MDCOP Graph. Thus it can avoid a large number of join operations and complex space region split, which can improve the computational efficiency.

Given a set of spatiotemporal mixed object-types E, a neighborhood relation R, a set of time slots TF, a threshold pair (θ_p, θ_{time}), MDCOP Graph can be represented as a neighbor graph in which a node is an object type and edge between two nodes represents the neighbor relationship over all time slots. We use MDCOP Graph to materialize neighbor relationships. As we know that most of the computational time of co-occurrence pattern mining is devoted to finding co-occurrence instances. By means of MDCOP Graph, we don′ t need to generate all possible candidate co-occurrence instances. We just generate real co-occurrence instances through visiting the MDCOP Graph. Thus, we can increase the efficiency of co-occurrence mining.

Definition 3.1 Given a set of co-occurrence instances CI, instance type level graph (IG) is used to captures the existence of co-location instances between two instance types over time. We define instance type level graph as follows.

$$IG = (I, CI, TF, f_0...f_{k-1}, e_0...e_{n-1}, |f_i : I \rightarrow R^{TF}; e_i : CI \rightarrow R^{TF}) \qquad (4)$$

Where I is the set of instances of all object-types, CI is the set of co-location instances, TF is the length of the entire time interval, such that TF = [T_0 ,...,T_{n-1}], $f_0...f_{k-1}$ are the mappings from object-types to object-types , $e_0...e_{n-1}$ indicate the existence of co-occurrence instances between two instance types over time on the edges.

For example, we generate instance type level graph (Fig.4) using the data set given in Fig. 2a. In Fig.4, we use time-series [1 1 1 0] to show that A1 and C1 are co-located at time slot 0, time slot 1, time slot 2 and disappear at time slot 3. Therefore, we can easily capture the existence of co-occurrence instances over time by traversing instance type level graph.

Definition 3.2 Given a set of candidate co-occurrence patterns (CP), object type level graph (OG) is used to indicate the participation count of particular object-types contributing to particular co-occurrence patterns. We define object type level graph as follows.

$$OG = (E, CP, TF, f_0...f_{k-1}, p_0...p_{n-1}, |f_i : E\epsilon CP^{TF}; p_i : E\epsilon CP^{TF}) \qquad (5)$$

Where E is the set of spatiotemporal mixed object-types, CP is the set of co-occurrence patterns, TF is the length of the entire time interval, $f_0...f_{k-1}$ are the mappings from particular object-types to the particular co-occurrence patterns , $p_0...p_{n-1}$ indicate the participation count of particular object-types contributing to particular co-occurrence patterns over time on the edges.

For example, we generate object type level graph (Fig.5) using the data set given in Fig. 2a. In Fig.2a, the co-occurrence pattern AC has co-occurrence instances sets A1, C1, A3, C2 at time slot 0, time slot 1 and time slot 2. At time slot 3, AC has no co-location instances. In Fig.5, since A1 and A3 are different instances of A, we used time-series [2 2 2 0] to show the participation count of object-type A contributing to co-location pattern AC. By using object type level graph, we can get the spatial prevalence index values and time prevalence index values.

Definition 3.3 Given instance type level graph and object type level graph, MDCOP Graph is composed of two parts: instance type level graph and object type graph. The instance type level and object type graphs are connected through links. We define MDCOP Graph as follows.

$$MDCOPGragh = (IG, OG, TF, E, I, l_0...l_{k-1}, |l_i : I \rightarrow E^{TF}) \qquad (6)$$

Where IG is instance type level graph, OG is object type level graph. TF is the length of the entire time interval, E is the set of spatiotemporal mixed object-types, I is the set of instances of all object-types. $l_0 ... l_{k-1}$ are the mappings from object-types to their own instances.

For example, we generate MDCOP graph (Fig.6) using the data set given in Fig. 2a. In Fig.6, both the instance type level and object type graphs are connected through links for easy traversal.

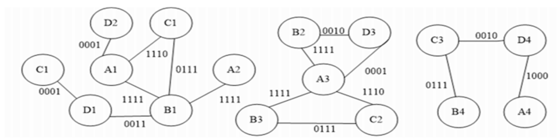


Fig. 4. Instance type level graph

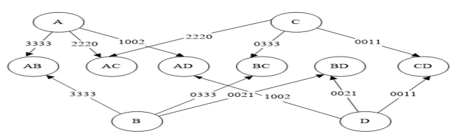


Fig. 5. Object type level graph

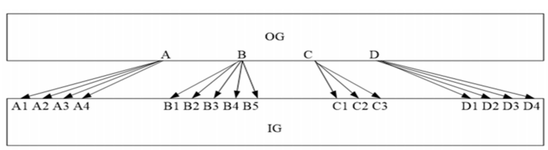


Fig. 6. Object type level graph

3.3. Problem Statement

Given:

A set E of spatiotemporal object types over a common spatiotemporal framework.
A neighbor relation R over locations.
A multiple set of user defined spatial and temporal prevalence thresholds.
Find:

Minimize cost of generate the MDCOP graph.

A set of frequent MDCOPs whose mixed-drove prevalence satisfies spatial and temporal prevalence thresholds.

Objective:

Capture and represent the temporal variation of MDCOPs.

Minimize cost of candidate generation.

Minimize cost of generate the MDCOP graph.

Constraints:

To build the MDCOP graph that stores all the MDCOPs.

To find the correct and complete set of MDCOPs for any threshold value specified.

4. Mining MDCOPS

In this section, we discuss fastMDCOP-Miner and then propose two novel MDCOP mining algorithms: MDCOP Graph Miner and LDMDCOP Graph Miner to mine MDCOPs. We also give the execution trace of these algorithms.

4.1. Fast MDCOP-Miner

FastMDCOP-Miner [3] uses a spatial co-location mining algorithm for each time slots to find spatial prevalent co-locations and prune time non-prevalent patterns as early as possible between the time slots to discover MDCOPs. To mine co-locations, Huang et al. proposed a join-based approach, Yoo et al. proposed a partial join-based approach and a join-less approach [16][18][11], this approach is based on the join-based collocation algorithm proposed by Huang et al., but it is also possible to use other approaches. Fast MDCOP-Miner [3] will first discover all size k spatial prevalent MDCOPs and prune time non-prevalent patterns as early as possible between the time slots to discover MDCOPs. Then the algorithm will generate size k +1 candidate MDCOPs using size k MDCOPs until there are no more candidates. However, this approach is Apriori like and involves candidate generation which is costly as it enumerates all possible cliques over all time instants.

4.2. MDCOP Graph Miner

To eliminate the drawbacks of fast MDCOP-Miner, we propose a MDCOP mining algorithm (MDCOP Graph Miner) to discover MDCOPs by storing all the MDCOPs in the MDCOP Graph.

This data structure is motivated by Time Aggregated Graphs (TAG) [7], which models time varying road conditions as time series on the edges of a road network. In our case, we use two different types of series over the edges. One of the series captures the existence of co-occurrence patterns between two instances over time. Based on the existence time series of co-occurrence patterns between pairs of instances, we aggregate the information to object types. At the object type graph, each time series contains the participation count of a particular object contributing to a particular co-location pattern. Both the instance type level and object type graphs are connected through links for efficient traversal.

Firstly, MDCOP Graph Miner will establish spatial temporal network MDCOP Graph, initialize the spatial relationship between each time slot; then it generates k+1 candidate spatiotemporal co-occurrence patterns; It obtains instance sets of candidate spatiotemporal co-occurrence patterns through querying MDCOP Graph and calculates time and space frequent degrees, generate k+1 spatiotemporal co-occurrence patterns; Iteratively, it repeatedly generating candidate co-occurrence patterns until there is no new candidate co-occurrence pattern and algorithm terminate. Eventually, we get all the co-occurrence patterns meeting temporal and spatial thresholds.

We give the pseudo code of the algorithm and provide an execution trace of it using the data set in Fig. 2a. Algorithm1 shows the pseudo code of the MDCOP Graph Miner algorithm. This pseudo code is used to explain two algorithms: MDCOP Graph Miner and LDMDCOP Graph Miner which will be discussed in the next section. The choice of the algorithm is provided by the user. In the algorithm, steps 1-14 create the MDCOP Graph. Steps 15-21 give an iterative process to mine MDCOPs, steps 15-21 continue until there is no candidate MDCOP to be generated. Step 22 gives a union of the results. The execution traces of MDCOP Graph Miner are explained below.

```
Algorithm 1 pseudo code for the MDCOP Graph Miner
Inputs:
E: a set of spatial object types
ST: a spatiotemporal data set < object_type, object_id,
 x, y, timeslot >
R: spatial neighborhood relationship
TF: a time slot frame t_0,...,t_{n-1}
θ p:a spatial prevalence
θ time: a time prevalence threshold
Output: MDCOPs whose spatial prevalence indices, i.e.,
participation indices, are no less than θ p,
for time prevalence indices are no less than θ time.
Variables:
t : time slots(t_0,...,t_{n-1})
k:co-occurrences size
Tk: set of instances of size k co-occurrences
SPk: set of spatial prevalent size k co-occurrences
TPk: set of time prevalent size k co-occurrences
Ck: set of candidate size k co-occurrences
MDPk: set of mixed-drove size k co-occurrences
MDG: graph stores all the MDCOPs
Address: address for storing time series to the file
Method:
   k = 2
   Ck (0) = gen_candidate_co_occ(E)
   for each time slot t in TF
       Tk (t) = gen_co_occ_inst(Ck (t),ST, R)
       set timeSeries [t] =1 for Tk (t)
       SPk (t) = find_spatial_prev_co_occ(Tk (t), θ p)
       TPk (t) = find_time_index(SPk (t))
      MDPk (t) = find_time_prev_co_occ(TPk (t), θ  time)
       Ck (t) = MDPk (t)
 if(alg_choice  "LDMDCOP Graph Miner")
        Address = gen_co_occ_address (Tk (t) )
       access the MDG file by the addresses
       set timeSeries [t] =1 for Tk (t) if required
   if(alg_choice == "MDCOP Graph Miner")
       MDG = gen_MDCOP_Graph(MDPk)
```

```
while (not empty MDPk)
   Ck +1 = gen _candidate_co_occ ( MDPk)
    Tk +1= gen _instancesTree (Ck +1,MDG)
   SPk+1 = find_spatial_prev_co_occ(Tk+1, θ p)
   TPk +1 = find_time_index(SPk+1 )
    MDPk+1 = find_time_prev_co_occ(TPk+1, θ time)
       k = k+1
 return union( MDP2 ,..., MDPk)
```

The execution trace of the MDCOP Graph Miner is given in Fig.7. This data set in Fig.2a. Contains four object-types A, B, C, and D and their instances in four time slots (i.e., A has four instances). The instances of each object-type have a unique identifier, such as A1. To discover MDCOPs, we use a monotonic composite interest measure which is a combination of the spatial prevalence and time prevalence measure. The spatial prevalence measure shows the strength of the spatial co-location when the index is greater than or equal to a given threshold [3][18].The time prevalence measure shows the frequency of the pattern over time.

In step1, by dividing each entry in Fig. 7a with the corresponding number of instances for an object, we get the participation ratio of an object type in co-location. For example, the participation index of collocation AB is [3/5 3/5 3/5 3/5], which is the minimum participation ratio of type A and B in all time slots. We prune time non-prevalent patterns whose participation indices are less than a given threshold as early as possible. For example, there are four time slots and the time prevalence threshold is 0.5.In this case, a size k pattern should be present for at least two time slots to satisfy the threshold. If the time prevalence index of a pattern is 0 for the first (or any) three time slots, there is no need to generate it and check its prevalence for the rest of the time slots even if it is time persistent for the remaining time slots. Spatial prevalent patterns AB, AC, and BC are selected as MDCOPs since they are time prevalent (their time prevalence indices satisfy the given time prevalence threshold 0.5). In contrast, spatial prevalent patterns AD, BD and CD are pruned since they are time non-prevalent.

In step2, three sub-graphs on the bottom of Fig. 7b are created. It also creates links from the instance types to the object type, for example, Link between A3 and A if A3 is part of at least one co-occurrence. The links between the object and the instance type help in traversing the data set efficiently to calculate the spatial prevalence index values. Connections between the object type graph and the instance type graph are missing to reduce clutter and the series in the object graph has not been represented for the same reason. After the algorithm has been executed, the series on edge A and AB would be [3/4 3/4 3/4 3/4] because of co-locations A1B1, A2B1, A3B2 andA3B3. Note that A3 is counted only once at each time interval though it appears in two co-locations at every time instant.

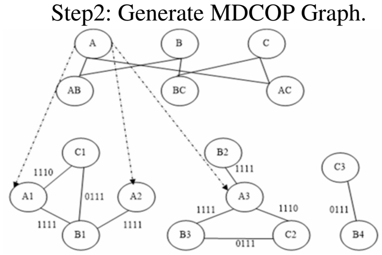
In step3, the candidate MDCOP ABC is generated through AB, AC and BC. Generally, the number of candidate patterns is large. Then if we generate temporal time prevalence index for every candidate pattern, candidate pattern whose temporal time prevalence index is less than a given threshold can be pruned. For example, ABC is a candidate pattern, the temporal time series of ABC is [0 1 1 0] equals to time series of AB [1 1 1 1] & AC [1 1 1 0] & BC [0 1 1 1], the time prevalence index is 0.5 which is no less than the given threshold. Thus, we generate instances of candidate pattern ABC. By modeling the instances-trees for candidate patterns, the instances of candidate pattern ABC can be generated.

Step1: Generate size 2 co-occurrence patterns.

Object Type	Candidate MDCOP	Paticipation Count	Paticipation Rations	Paticipation Index	Time Series	Time prevalence index
A	AB	3 3 3 3	3/4 3/4 3/4 3/4	3/5 3/5 3/5 3/5	1 1 1 1	4/4
B	AB	3 3 3 3	3/5 3/5 3/5 3/5			
A	AC	2 2 2 0	2/4 2/4 2/4 0	2/4 2/4 2/4 0	1 1 1 0	3/4
C	AC	2 2 2 0	2/3 2/3 2/3 0			
A	AD	1 0 0 2	1/4 0 0 2/4	1/4 0 0 2/4	0 0 0 1	1/4(prune)
D	AD	1 0 0 2	1/4 0 0 2/4			
B	BC	0 3 3 3	0 3/5 3/5 3/5	0 3/5 3/5 3/5	0 1 1 1	3/4
C	BC	0 3 3 3	0 3/3 3/3 3/3			
B	BD	0 0 2 1	0 0 2/5 1/5	0 0 2/5 1/5	0 0 1 0	1/4(prune)
D	BD	0 0 2 1	0 0 2/4 1/4			
C	CD	0 0 1 -	0 0 1/3 -	0 0 1/4 -	0 0 0 -	(prune)
D	CD	0 0 1 -	0 0 1/4 -			

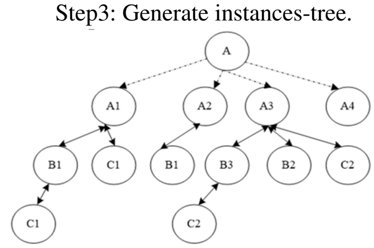
(a)

Step2: Generate MDCOP Graph.



(b)

Step3: Generate instances-tree.



(c)

Step 4: Generate size 3 co-occurrence patterns

Object Type	Candidate MDCOP	Paticipation Count	Paticipation Rations	Paticipation Index	Time Series	Time prevalence index
A	ABC	0 2 2 0	0 2/4 2/4 0	0 2/5 2/5 0	0 1 1	2/4
B	ABC	0 2 2 0	0 2/5 2/5 0			
C	ABC	0 2 2 0	0 2/3 2/3 0		0	

(d)

Fig. 7. Execution trace of the MDCOP Graph Miner algorithm. (a) Step 1. (b) Steps 2. (c) Steps 3. (d) Steps 4

In step4, the participation indices of pattern ABC are 2/5 in time slots 1 and 2 and its time prevalence index 0.5 equals to the threshold. Since there are not enough subsets to generate the next superset patterns, the algorithm stops at this stage and outputs the union of all size MDCOPs, i.e., A B, AC, BC, and ABC.

4.3. LDMDCOP Graph Miner

Most of existing spatiotemporal co-occurrence patterns mining algorithms are only work on memory. Due to the advance of geo-sensor technology, spatiotemporal data increased dramatically. The demand of mining spatiotemporal co-occurrence patterns in large datasets is now gradually urgent.

In practical applications, such as now have 300MB armed vehicles date, when a vehicle moves, its co-occurrence pattern also present movement in a similar trajectory. By mining spatiotemporal co-occurrence patterns of moving vehicle data, we can infer military strategy through co-occurrence patterns. As another example, the public security bureau of Zhejiang province has 2GB of crime data, we can identify many interesting co-occurrence patterns from the data, such as fraud and gambling is a co-occurrence pattern, then the police can infer the offender's whereabouts. However, in the above practical application, the amount of spatiotemporal data is huge, existing mining algorithms cannot obtain useful co-occurrence patterns efficiently.

For solving the above problems, we use MOCOP Graph to store the data sets of instances; the instance set is stored in the hard disk file. In the calculation process, we only load the necessary data to memory in order to save the space. Meanwhile, we establish index for the instances in document to improve data query efficiency.

In this section, we propose a new algorithm, called LDMDCOP Graph Miner, which can handle large data sets by using file index. MDCOP Graph is an efficient storage method, which can capture the information required to mine MDCOPs from the data sets. When the volume of the data sets is large, it consumes a lot of space to store MDCOP Graph. Since the capacity of memory is limited, there may be no enough space to store large amount of data sets or big MDCOP Graph. As a result, we use file index to store big MDCOP Graph. This approach will still have two problems. One is how to store the big MDCOP Graph in the file; the other is how to capture the information required for mining MDCOPs from the MDCOP Graph in the file.

In order to solve these problems, we use adjacency matrix to store the MDCOP Graph. The advantage of adjacency matrix is the ability to determine the existence of a particular edge in constant time, and access the storage media only once. According to this method, we can calculate the address for a particular edge to store its time series in the file and also access the time series by the same address, there is no need to store the address of the time-series, we calculate the address according to the same expression which used to calculate the address for storing. The expression is as follows.

$$address(R_i, C_j) = R_i \times N + C_j - E(R_i, C_j) \tag{7}$$

Where R_i is the row number, C_j is the column number, N is the total number of instance, E (R_i , C_j) is the number of patterns whose instances are of the same type.

Physical address can be obtained according to this formula. So long as we can get the required time sequence through visiting the file only once. By indexing methods to achieve the storage of MDCOP Graph in file, while efficiently obtaining the required information.

Firstly, LDMDCOP Graph Miner will establish spatial temporal network MDCOP Graph, initialize the spatial relationship between each time slot; then generate k+1 candidate spatiotemporal co-occurrence patterns, calculate Pi and TPi, prune the patterns which don't meet spatial and temporal thresholds, then generate k+1 spatiotemporal co-occurrence patterns; It repeats the above operate until there is no new candidate co-occurrence pattern; Eventually we get all the co-occurrence patterns meeting temporal and spatial thresholds.

The difference between LDMDCOP Graph Miner and MDCOP Graph Miner is that MDCOP Graph Miner has the different storage structure and storage media. LDMDCOP Graph Miner storage MDCOP Graph as adjacency matrix in document, while MDCOP Graph Miner storage MDCOP Graph as adjacent table in memory. Other steps are basically the same.

The pseudo code of the LDMDCOP Graph Miner is given in Algorithm 1. When the LDMDCOP Graph Miner is chosen, the algorithm will activate steps 10, 11, 12 and deactivate steps 13 and 14. We use adjacency matrix to store the MDCOP Graph. At the same time, the addresses for storing time series of co-occurrence instances could be calculated and the addresses also are used to access the file for getting the information required to mine MDCOPs.

The execution trace of gen_MDCOP_Graph in LDMDCOP Graph Miner is explained as algorithm 2.

```
Algorithm 2 pseudo for gen_MDCOP_ Graph in
 LDMDCOP Graph Miner
    Inputs:
ST: a spatiotemporal data set < object_type, object_id,
x, y, timeslot >
TF: a time slot frame t0,...,tn-1
t:time slot number
MDPk: set of mixed-drove size k co-occurrences
Output:
MDG File: MDCOP Graph file
Variables:
Address:index table
eofAdress:end address of the current file
logAddress:logical address
phyAddress:physical address
Method:
BEGIN
  FOR each co-occurrence patterns Pi of MDP2(t)
                FOR each co-located instances (Ai,Bj)
 of Pi
                     logAddress = gen_Address ( Ai , Bj )
                  IF (Address[logAddress] == 0)
                 Address[logAddress] = eofAddress
                        eofAddress += TF
                     END IF
                        phyAddress = Address[logAddress]
                     set timeSeries[t] = 1 for AiBj
                       update timeSeries in MDG File
       END FOR
```

```
  END FOR
END
```

The method to store MDCOP Graph in LDMDCOP Graph Miner is described as algorithm 2. It stores the nearest relationships between instances of co-occurrence patterns in each timeslot. It generates the logical address logAddress between time series of instances through gen_Address and lookup index table. Then, it obtain physical address phyAddress according to logical address logAddress; finally the time series of instances are instored in the files.

As described in algorithm 2, for each co-location pattern of each co-occurrence pattern, firstly generate its logical address (algorithm 3); if this co-location pattern doesn't have physical address, then generate physical address; update the end address of current file; once this co-location pattern has physical address, then obtain its physical address through index table and update its time series; finally store the updated time series in MDG file.

The difference between LDMDCOP Graph Miner and MDCOP Miner is the storage structure for MDCOP Graph. This chapter below will focus on the description of the process storing MDCOP Graph by adjacency matrix and index storage, as to mine spatial-temporal co-occurrence patterns from data sets in figure 2. (a).

According to table 1, we can create index for the adjacency matrix, which has been shown in table 2. The logical address is generated by the former formula, while physical address is the storage address of time series. We can efficiently obtain physical address by indexing table, so as to achieve quick indexing for required information.

```
Algorithm 3 pseudo for gen_Address
Inputs:
ST: a spatiotemporal data set < object_type, object_id,
 x, y, timeslot >
TF: a time slot frame t0,...,tn-1
type1:type1
type2:type2
ins1:instance 1
ins2:instance 2
Output:
Address: storage address between instance 1 and 2
Variables:
N:types of different instances
typeIns:instance set of each type
typeInsNum: instance number of each type
insNum:instance number
deleteIns:the number of instances of patterns
with same type
BEGIN
WHILE(!ST.eof())
  typeIns[typeId].push(insId)
END WHILE
FOR each type i in E
                N += typeIns[i].size()
END FOR
FOR each type i in E
                FOR each instance j of i
                        IF( i== 0)
                         insNum[i][j] = j
```

```
         ELSE
                               insNum[i][j] = insNum [i-1]
                [ typeIns[i-1].size() -1] +j+1
         END IF
                END FOR
END FOR
FOR each type i in E
                FOR each instance j of i
                        deleteIns[i][j] += insNum[i+1][0]
     END FOR
END FOR
Address = insNum[type1][ins1] * N
+ insNum[type2][ins2]- deleteIns[type1][ ins1]
END
```

Table 1. MDCOP Graph adjacency matrix

	B1	B2	B3	B4	B5	C1	C2	C3	D1	D2	D3	D4
A1	1111	0000	0000	0000	0000	1110	0000	0000	0000	0000	0000	0000
A2	1111	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000
A3	0000	1111	1111	0000	0000	0000	1110	0000	0000	0000	0000	0000
A4	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000	0000
B1	×	×	×	×	×	0111	0000	0000	0000	0000	0000	0000
B2	×	×	×	×	×	0000	0000	0000	0000	0000	0000	0000
B3	×	×	×	×	×	0000	0111	0000	0000	0000	0000	0000
B4	×	×	×	×	×	0000	0000	0111	0000	0000	0000	0000
B5	×	×	×	×	×	0000	0000	0000	0000	0000	0000	0000
C1	×	×	×	×	×	×	×	×	0000	0000	0000	0000
C2	×	×	×	×	×	×	×	×	0000	0000	0000	0000
C3	×	×	×	×	×	×	×	×	0000	0000	0000	0000

Table 2. Index Table

Instances	A1B1	A1C1	A2B1	A3B2	A3B3	A3C2	B1C1	B3C2	B4C3
Logical Address	0	5	12	25	26	30	48	63	71
Physical Address	0	4	8	12	16	20	24	28	32

5. Analytical Evaluation

This section gives the analysis of correctness and completeness for the MDCOP mining algorithms.

5.1. Correctness

LEMMA 1: MDCOP Graph Miner and LDMDCOP Graph Miner are complete.

Proof: The MDCOP Graph Miner and LDMDCOP Graph Miner are complete if they find all MDCOPs that satisfy a given participation index threshold and time prevalence threshold. We can show this by proving that none of the functions in the algorithm miss any patterns.

The $gen\_candidate\_co\_occ$ function does not miss any patterns. The input of this function is size k MDCOPs, and the output is candidate size $k+1$ MDCOPs. The gen_InstancesTree function does not miss any patterns. This function generates instances of candidate size $k+1$ MDCOPs if they are in the neighborhood distance and forming a clique.We can prove this with the completeness of the Breadth First Search algorithm which enumerates all connected edges of a given instance level sub-graph. Further, the links from the object type nodes to the instance level nodes are visited. This guarantees that no instance level sub-graph is missed by the algorithm. Further, using the time series on the instance level sub-graphs, the participation ratios of object types in their respective co-occurrences are updated for every object instance visited by the BFS.

5.2. Completeness

LEMMA 2: MDCOP Graph Miner and LDMDCOP Graph Miner are correct.

Proof: MDCOP graph is correct if the participation indices of each co-occurrence is calculated according to [17][9][14]for all time instances. First, all edges in the instance level sub-graph are traversed only once by the BFS and hence are accounted only once for the participation index of the co-location. Second, if there is a case where an instance B_i co-occurrences with A_j and A_k where A_j and A_k are of the same object type A, then the existence series of B in AB has to be considered only once for calculating participation ratio of B in AB. We use these participation indices weed out candidates not meeting the given thresholds.

Hence, the MDCOP Graph Miner and LDMDCOP Graph Miner are correct.

5.3. Complexity

LEMMA 3: MDCOP Graph Miner Graph Miner is more effective than fastMDCOP-Miner.

Proof: For fastMDCOP-Miner, we just assume that T_f is the cost time of fastMDCOP-Miner. Just as shown in the following formula.

$$T_f = T_{neighbor\_pairs}(ST) + T_f(2) + \sum_{k>2} T_f(k) \tag{8}$$

Where ST is spatiotemporal data set, $T_f(2)$ is the time for calculating co-occurrence patterns under k=2; $T_f(k)$ is the time for calculating these patterns when k >2, we can calculate $T_f(k)$ by the following formula.

$$\begin{aligned} T_f(k) &= T_{gen\_candidate}(P_{k-1}) + T_{gen\_co\_occ\_inst}(C_k) \\ &\quad + T_{find\_spatial\_prev}(T_k) + T_{find\_spatial\_prev}(SP_k) \\ &\approx T_{gen\_co\_occ\_inst}(C_k) \end{aligned} \tag{9}$$

Where P_{k-1} represents co-occurrence patterns under $(k-1)$ size; C_k represents candidate co-occurrence patterns under size; T_k represents candidate co-occurrences pattern instances under k size; SP_k indicates co-location patterns under k size.

For MDCOP Graph Miner, as the same, we assume T_g indicates the total cost time. T_g can be calculated by the following formula.

$$T_g = T_{MDCOP\_Graph}(ST) + T_g(2) + \sum_{k>2} T_g(k) \tag{10}$$

Where ST is spatiotemporal data set, $T_g(2)$ is the time for calculating co-occurrence patterns under k=2; $T_g(k)$ is the time for calculating these patterns when k>2.As the same, $T_g(k)$ just can be calculated by this formula.

$$\begin{aligned} T_g(k) &= T_{gen\_candidate}(P_{k-1}) + T_{gen\_instanceTree}(C_k) \\ &\quad + T_{find\_spatial\_prev}(T_k) + T_{find\_spatial\_prev}(SP_k) \\ &\approx T_{gen\_instancesTree}(C_k) \end{aligned} \tag{11}$$

P_{k-1} represents co-occurrence patterns under $(k-1)$ size; C_k represents candidate co-occurrence patterns under k size; T_k represents candidate co-occurrences pattern instances under k size; SP_k indicates co-location patterns under k size.

To compare the total cost time advantage between fastMDCOP-Miner and MDCOP Graph Miner, firstly, we can aim at the cost time for initializing the neighboring relationships and generating co-occurrence patterns when k=2. Obviously, MDCOP Graph Miner is more costly than fastMDCOP-Miner as the former needs more extra time to generate MDCOP Graph. The results appear as shown below.

$$T_{neighbor\_pairs}(ST) + T_f(2) < T_{MDCOP\_Graph}(ST) + T_g(2) \tag{12}$$

It's worth nothing that Tgen_candidate, Tfind_spatial_prev and Tfin_time_prev are equal in formulas Tf(k) and Tg(k). And these three costs just can be ignored comparing to Tgen_co_occ_inst.

Then, the comparison of the cost for generating co-occurrence patterns is under k>2. The ratio is as follows.

$$\frac{T_f(k)}{T_g(k)} \approx \frac{T_{gen\_co\_occ\_inst}(C_k)}{T_{gen\_instancesTree}(C_k)} \approx \frac{|C_k| \times t_join}{|C_k| \times t_scan} \approx \frac{t_join}{t_scan} \tag{13}$$

Where t_{join} indicates the cost of join operation to generate candidate co-occurrence patterns; t_{scan} indicates the cost of generating candidate co-occurrence patterns through searching MDCOP Graph.

If the spatial temporal data sets we input is intensive, $t_{scan} \ll t_{join}$. And with the growth of spatial frequency threshold or temporal frequency threshold, this ratio tends to be bigger, there are more spatialtemporal co-occurrence patterns required to be generated.

Through the above analysis, assuming the average count of instances in each time slot is N, the total number of co-location patterns under k=2 is Nco-lo; average number of co-occurrence patterns is Nins; the maximum length of candidate co-occurrence patterns is I; TF represents the total number of time slots.

For fast MDCOP-Miner, the time complexity of $Tneibor\_pairs(ST)$ is $O(N * N * TF)$; and time complexity respectively of $T_f(2)$ and $T_f(k)$ are $O(Nco-lo)$

(which can be ignored) and $O(NinsI)$. Therefore, the total time complexity of fastMDCOP-Miner is [$O(N*N*TF)$+ $O(Nco-lo)$+$O(NinsI)$].

For MDCOP Graph Miner, the time complexity of $TMDCOP\_Graph(ST)$ is $O(N*N*TF+Nco-lo)$. And time complexity of $T_g(2)$ and $T_g(k)$ respectively are $O(Nco-lo)$ and $O(NinsI-1)$. The total time complexity of MDCOP Graph Miner is [$O(N*N*TF+Nco-lo)$+$O(Nco-lo)$+$O(NinsI-1)$].

By comparing these two total time complexity, we can come to a conclusion that the latter is smaller than the former. In other word, MDCOP Graph Miner is more effective than fastMDCOP-Miner.

As shown in the methods, we can get conclusion that LDMDCOP Graph Miner Graph Miner is effective in mining MDCOP patterns under big data sets. For this miner method, let T_l represents the total time LDMPCOP Graph Miner costs. So T_l can be described by this formula.

$$T_l = T_{MDCOP\_Graph}(ST) + T_l(2) + \sum_{k>2} T_l(k) \tag{14}$$

Where ST indicates the data set; $T_l(2)$ is the cost time for calculating spatialtemporal co-occurrence patterns when k=2; $T_l(k)$ just represents the total time for generating co-occurrence patterns when $k > 2$.

$$\begin{aligned} T_l(k) &= T_{gen\_candidate}(P_{k-1}) + T_{gen\_co\_occ\_inst}(C_k) \\ &\quad + T_{find\_spatial\_prev}(T_k) + T_{find\_time\_prev}(SP_k) \\ &\quad \approx T_{gen\_co\_occ\_inst}(C_k) \end{aligned} \tag{15}$$

Also, P_{k-1} represents co-occurrence patterns under $(k-1)$ size; C_k represents candidate co-occurrence patterns under k size; T_k represents candidate co-occurrences pattern instances under k size; SP_k indicates co-location patterns under k size. And comparing to $T_{gen\_co\_occ\_inst}$, we can just ignore $T_{gen\_candidate}$, $T_{find\_spatial\_prev}$ and $T_{fin\_time\_prev}$.

Assume that hard disk I/O time-consuming is M-fold to memory I/O time-consuming. The time complexity of TMDCOP_Graph(ST) is $O(N*N*M*TF)$; for $T_l(2)$ is $O(Nco-lo)$; for $T_l(k)$ is $O(Ninsk-l*M)$. The total time complexity for LDMDCOP Graph Miner is $O(N*N*M*TF)$+ $O(Nco-lo)$+ $O(Ninsk-l*M)$.

LDMDCOP Graph Miner can effectively mine spatialtemporal co-occurrence patterns from big spatial and temporal data sets, which can't be reached by MDCOP Graph Miner and na?ve method. Meanwhile, we can get correct and complete sets of spatial-temporal co-occurrence patterns.

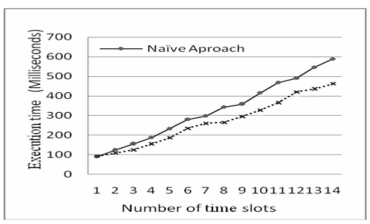
6. Experimental Results

We use Real Data Sets and Synthetic to evaluate the proposed algorithm. The real data includes 15 time snapshots and 21 distinct vehicle types and their instances. The minimum instance number is 2, the maximum instance number is 78, and the average number of instances is 19. To evaluate the performance of the algorithms, spatiotemporal data sets were generated based on the spatial data generator proposed by Huang et al. [3]. Synthetic data sets were generated for spatial frame size $D \times D$.For simplicity,the data sets were divided into regular grids whose side lengths had neighborhood relationship R.

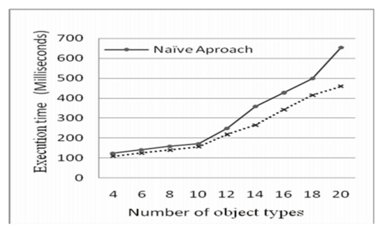
6.1. Experimental Results for Real Data Sets

We evaluated the effect of the number of time slots on the execution time of the MDCOP algorithms using the real data set. The participation index, time prevalence index, and distance were set at 0.2, 0.8, and 100 m respectively. Experiments were run for a minimum of 1 time slot and a maximum of 14 time slots. Results show that the MDCOP Graph Miner requires less execution time than the fast MDCOP-Miner (Fig. 8a). As the number of time slots increases, the ratio of the increase in execution time is smaller for MDCOP Graph Miner than for the fast MDCOP-Miner. It shows that MDCOP Graph Miner has time cost advantage to fast MDCOP-Miner.

The participation index, time prevalence index, number of time slots, and distance were set at 0.2, 0.8,15, and 100 m, respectively. Results show that the MDCOP Graph Miner outperforms the fast MDCOP-Miner when the number of object-types increases (Fig. 8b). It is observed that the increase in execution time for the fast MDCOP-Miner is bigger than that of the MDCOP Graph Miner as the number of object-types increases for the real data set.



(a)



(b)

Fig. 8. (a) Effect of number of time slots and object types using real data set

6.2. Experimental Results for Synthetic Datasets

Effect of the Spatial Prevalence Threshold. We evaluated the effect of the spatial prevalence threshold on the execution times of MDCOP mining algorithms. The fixed parameters were time participation index, distance, and number of time slots, and their values were 0.8, 20 m, and 100, respectively. Experimental results show that the MDCOP Graph Miner this paper proposed is more computationally efficient than the fast MDCOP-Miner (Fig. 9a). The execution time of the MDCOP Graph Miner decreases as the spatial prevalence threshold increases, and obviously MDCOP Graph Miner is running less time than fast MDCOP-Miner with all spatial prevalence.

We also evaluated the effect of the spatial prevalence threshold on the execution time of the LDMDCOP Graph Miner using synthetic data sets. The participation index, distance and number of time slots, were set at 0.8, 20 m, 100, respectively. The results showed that the execution time of the LDMDCOP Graph Miner decreases as the time prevalence threshold increases (Fig. 9b).

Effect of the Time Prevalence Threshold We evaluated the effect of the time prevalence threshold on the execution times of MDCOP mining algorithms. The fixed parameters

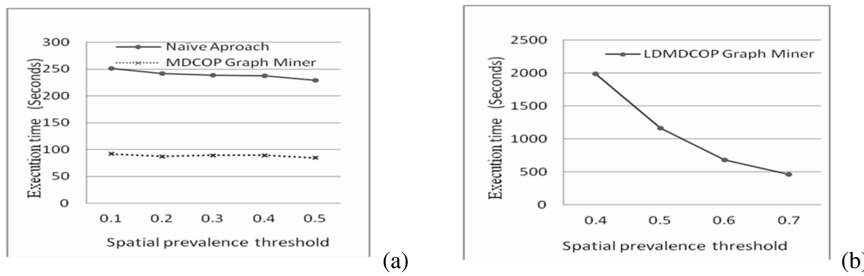


Fig. 9. (a), (b) Effect of the spatial prevalence threshold using synthetic data sets

were spatial participation index, distance, and number of time slots, and their values were 0.4, 20 m, and 100, respectively. Experimental results show that the MDCOP Graph Miner this paper proposed is more computationally efficient than the fast MDCOP-Miner (Fig. 10a). The execution time of the MDCOP Graph Miner decreases more than fast MDCOP-Miner as the spatial prevalence threshold increases.

We also evaluated the effect of the time prevalence threshold on the execution time of the LDMDCOP Graph Miner using synthetic data sets. The participation index, distance and number of time slots, were set at 0.5, 20 m, 100, respectively. The results showed that the execution time of the LDMDCOP Graph Miner decreases as the time prevalence threshold increases (Fig. 10b).

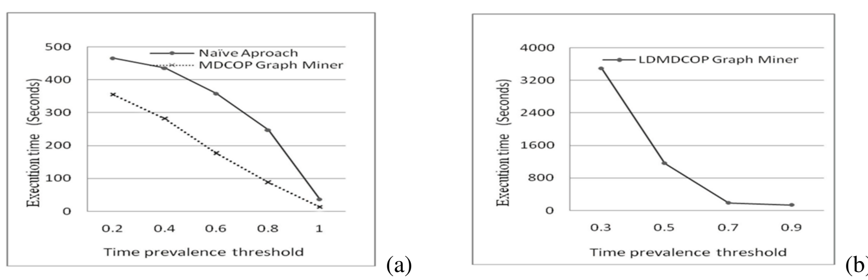


Fig. 10. ((a), (b) Effect of the time prevalence threshold using synthetic data sets

7. Conclusions and Future Work

In the exception detection, there are many data attributes in the data packet captured in the network. There are a lot of useless and redundant attributes, As the dimension of data object increases, the cost of intrusion detection system increases exponentially. It will not only consume a large amount of storage space, but also greatly increase the time and space complexity of the intrusion detection program. Excessive dimensions will not only increase the resource consumption of the system, but also reduce the accuracy of detection.

In order to improve the traditional spatiotemporal co-occurrence pattern mining techniques in mixed-drove spatiotemporal co-occurrence patterns detection. We designed the method to improve calculation efficiency. In this paper, we presented a novel and computationally efficient algorithm (the MDCOP Graph Miner) for mining MDCOPs with large attack dataset. MDCOP Graph Miner represents the close relationship between the instances with MDCOP Graph structure; obtain information for mining co-occurrence patterns efficiently through accessing MDCOP Graph and design an effective pruning strategy simultaneously. Experiments show that MDCOP Graph Miner algorithm can not only get the complete and correct spatiotemporal co-occurrence patterns, but also improve computational efficiency.

Although MDCOP Graph Miner algorithm improves the efficiency in mixed-drove spatiotemporal co-occurrence patterns detection, but for large spatial and temporal attack data processing and analysis capabilities, or lack of. In order to solve this problem, on the basic of MDCOP Graph Miner, we presented an improved MDCOP Graph Miner algorithm (the LDMDCOP Graph Miner) which can deal with large spatiotemporal attack data sets. LDMDCOP Graph Miner takes MDCOP Graph as the storage structure for close relationships between instances, and storage MDCOP Graph on the hard disk. In the process of calculation, only the necessary attack data is loaded into memory, so as to solve attack data storage problems. Meanwhile, LDMDCOP Graph Miner makes index for MDCOP Graph, which improves the data query efficiency. Experiments show that LDMDCOP Graph Miner algorithm can not only get the complete and correct mixed-drove spatiotemporal co-occurrence patterns detection, as well as have high computational efficiency.

In the future, we will extend the MDCOP graph and the subsequent mining algorithm for insertions of object attack types at arbitrary time interval. We hope to investigate the idea of multi-scale relationship for different co-occurrence patterns detection.

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Zhanquan Wang is an associate professor at Department of Computer Science and Engineering of East China University of Science and Technology in Shanghai, China. He received his Ph.D. in computer science from Zhejiang University in China in 2005. His current research interests include Spatial Datamining, GIS, Educational technology. Contact him at zhqwang@ecust.edu.cn.

Taoli Han is currently a Master candidate at East China University of Science and Technology in Shanghai, China. He received his bachelor's degree in Computer science and technology from Hainan University in Haikou, China in 2017. Her current research interests include datamining, spatial datamining. Contact him at 2730023187@qq.com.

Huiqun Yu (Corresponding Author) is professor and PhD supervisor, received the PhD degree from the department of computer science, ShangHai JiaoTong University, in 1995. He is the senior member of IEEE and China Computer Federation and ACM members. His main research interests include trusted computing, cloud computing, software engineering and service oriented software in cloud. Contact him at yhq@ecust.edu.cn

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