Intelligent Search of Correlated Alarms from Database Containing Noise Data

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Abstract
Alarm correlation plays an important role in improving the service and reliability in modern telecommunication networks. Most previous research of alarm correlation didn’t consider the effects of noise data in the database. This paper focuses on the method of discovering alarm correlation rules from the database containing noise data. We firstly define two parameters Win_freq and Win_add as the measures of noise data and then present the Robust_search algorithm to solve the problem. At different size of Win_freq and Win_add, the experiments on alarm database containing noise data show that the Robust_search Algorithm can discover more rules with the bigger size of Win_add. We also compare two different interestingness measures of confidence and correlation by experiments.

Keywords
Alarm Correlation, Noise Data, Alarm Model, Network Management, Data Mining, Correlation Rules, Interestingness Measure

1. INTRODUCTION
Telecommunication networks are dynamic, hybrid, heterogeneous and distributed. As a result, it becomes more and more difficult for network administrators to maintain such networks, especially in the fault management, which needs seasoned engineers to do alarm correlation, determine which alarm indicates a fault and find the cause of the fault.

Alarm correlation is a conceptual interpretation of multiple alarms such that new meanings are assigned to these alarms [1]. In the past, the knowledge of alarm correlation was mainly obtained from network experts. But with the development of telecommunication networks, it is much more difficult for experts to keep up with the rapid change of networks. So more and more researchers adopt data mining methods to discover alarm correlation rules.

Data mining is a method of finding interesting patterns from data. It is a generalized inductive learning based on the past cases. The methods of mining

Accepted by IEEE/IFIP 2002 Network Operations and Management Symposium (NOMS’2002), Florence, Italy, April 2002. This research was supported by National 973 Project of China Grant No.G1999032709 and No.G1999032701.
alarm correlation rules are mostly based on the framework of mining association rule algorithm [5] that Agrawal et al. presented in 1993. Mannila and Toivonen et al. [2,3] presented the WINEPI algorithm to find frequent episode from large alarm database, which was applied to the TASA system [4]. Weiss and Hirsh [9] studied how to predict the rare event from alarm database by genetic algorithms and presented the timeweaver algorithm, which was applied to the ANSWER system [10].

Although many methods [1,2,9,20,21,22,23] have been proposed to analyze the alarm correlation, few methods took account of the effects of noise data contained in alarm database. In order to discover alarm correlation rules from alarm database containing noise data, we define two parameters Win_freq and Win_add as the measures of noise data and propose a new algorithm, called Robust_search, which can search the correlated alarms from alarm database containing noise data. At different size of Win_freq and Win_add, experiments on alarm database containing noise data show that the Robust_search Algorithm can discover more rules with the bigger size of Win_add. We also experimentally compare two different interestingness measures of confidence and correlation.

The organization of the paper is as follows. In Section 2, we survey related work and mainly compare our work with Mannila’s work. In Section 3, we introduce the problems currently facing alarm correlation and give a definition of noise data in this paper. In Section 4, we give a definition of alarm model. In Section 5, we mainly study discovering correlated alarms from the database containing noise and present a new algorithm, called Robust_search, which can discover correlated alarm sequences from alarm database containing noise data. In Section 6, we test the Robust_search algorithm and compare the interestingness measures of correlation and confidence by experiments. In Section 7, we summarize our work and discuss future work.

2. RELATED WORK

Agrawal and Srikant [6] first introduced mining sequential patterns from a set of market-basket data sequences, where each sequence element is a set of items purchased in the same transaction. They proposed and experimentally evaluated three algorithms in [6]. Subsequently, Agrawal and Srikant [7] proposed GSP (Generalized Sequential Patterns) Algorithm. The GSP algorithm allows for time-gape constraint, permits that the item of sequence can span a set of transactions within a user-specified window and also permits that the item can span the different item taxonomies.

Mannila et al. [2,3] proposed the WINEPI algorithms to discover the frequent episode from alarm database and classified episode into serial episode and parallel episode. Tuchs and Jobmann adopted Mannila’s method to analyze the alarms of GSM networks [13]. Gardner and Harle also adopted the Mannila’s method to analyze the alarms of SDH [14].
The differences between our methods and Mannila’s methods are explained below. Firstly, we consider the effect of noise data in alarm database and propose the Robust_search algorithm that can search the frequent alarm sequence from alarm database containing noise data, while Mannila et al. didn’t consider how to find the episode from alarm database containing noise data. Secondly, we use the number of the times of alarm occurring as the size of windows, while Mannila et al. used the time interval as the size of windows.

Yang and Wang et al. in [15,16] studied mining asynchronous periodic patterns in time series data with noise, proposed a flexible model of asynchronous periodic patterns and a two-phase algorithm. They only considered the serial model in time series data and didn’t consider the measure of the periodic patterns in the whole time series data.

3. ALARM CORRELATION

3.1 The Definition of Alarm Correlation

In network management, a fault is defined as the cause for malfunctioning. An alarm consists of a notification of the occurrence of a specific event, which may or not represent an error [19].

Alarm correlation is converting alarms and merging many alarms into one alarm containing more information. The alarm correlation gives the initial alarm more new meanings [1]. Alarm correlation rules can be used to discover the alarm representing the root cause of fault and exactly locate the fault.

3.2 The Problems of Analysis of Alarm Correlation and Definition of Noise Data

Alarms in telecommunication networks are massive, bursting and intermittent. When a fault occurs in the networks, a very large volume of alarms are generated. Network operators are swamped by the alarms, so that it is very difficult for them to discover the root cause of the fault very soon. Thus network operators need a new tool to analyze alarm correlation.

The feature of alarm bursting can be found from figure 1, where the X axis represents the time [mm/ddhh] and the Y axis represents the number of alarms per hour.

In fact, many alarms don’t contain the information about the root cause of fault. When a fault occurs in the networks, the fault may incur many alarms. So some alarms are redundant, which make it more difficult to process the fault. There are some reasons for generating more alarms [17,18].

1. A device may generate several alarms due to a single fault;
2. A fault may be intrinsically intermittent which implies in the sending of a notification at each new occurrence;
3. The fault of a component may result in the sending of an alarm notification
each time the service supplied by this component is invoked;
4. A single fault may be detected by multiple network components, each one of
them emitting an alarm notification;
5. The fault of a given component may affect several other components,
causing the fault’s propagation;
6. There may exist more than two faults at the same time;
7. There is no global network time (no synchronized clock) in the huge and
heterogeneous networks. As a result, the sending time stamps of two
messages are not exactly comparable.

Figure 1: The frequency of alarm occurring

In the analysis of the correlated alarms, we define that the noise data are
alarms that are contained in the correlated alarm sequence, but are not relevant to
the correlated alarm sequence. When making analysis of alarm correlation, we
must consider the effect of noise data. Otherwise, we can’t discover the correlated
alarm sequence. In Section 5.2, we will propose a new algorithm, called
Robust_search, which can search correlated alarm sequences from alarm database
containing noise data.

4. ALARM MODEL

An alarm consists of a notification of the occurrence of a specific event, which
may or not represent an error [19]. An alarm report is a kind of event report used in
the transportation of alarm information.

Definition 1. An alarm event
An alarm event is defined as $E_i = \langle e_i, t_n \rangle$, $i, n=1,2,3,...$, where $e_i$ is an alarm type
and $t_n$ is the time of alarm occurring.

Definition 2. An alarm type
An alarm type is defined as $e_i = \langle \text{object class}, \text{object instance}, \text{alarm num}, \text{desc} \rangle$, $i=1,2,3,...$, where \text{object class} is the serial NO. of \text{object class}, \text{object instance} is the serial NO. of \text{object instance}, \text{alarm number} is the NO. of alarm type and desc
is the alarm information consisting of alarm priority and alarm description.
Definition 3. An alarm tuple and its length
1.) An alarm tuple is defined as $Q_i = ((e_{k1}, e_{k2}, \ldots, e_{km}), t_i)$, $i, m = 1, 2, 3, \ldots$; $k1, k2, \ldots, km = 1, 2, 3, \ldots$, where $e_{k1}, e_{k2}, \ldots, e_{km}$ are the alarm types which concurrently occur at the time $t_i$. An alarm tuple can be represented by an alarm event $Q_i = (e_{k1}, t_i), (e_{k2}, t_i), \ldots, (e_{km}, t_i) = (E_{k1}, E_{k2}, \ldots, E_{km})$. If an alarm tuple $Q_i$ only contains one alarm type, then $Q_i = (e_{k1}, t_i) = E_{k1}$.

2.) The length of alarm tuple is $|Q_i| = |(e_{k1}, e_{k2}, \ldots, e_{km})| = m$, which is the number of the alarm types contained in the alarm tuple.

Definition 4. An alarm queue and its length
3.) An alarm queue is defined as $S_{ij} = <Q_i, Q_{i+1}, \ldots, Q_j>$ where $t_i < t_{i+1} < \ldots < t_j$. An alarm queue can be represented by an alarm event $S_{ij} = (Q_i, Q_{i+1}, \ldots, Q_j) = (E_{i1}, E_{i+1}, \ldots, E_{j1}, \ldots, E_{jm})$. The length of alarm queue is defined as $|S_{ij}| = |<Q_i, Q_{i+1}, \ldots, Q_j>| = j - i + 1$, which is equal to the number of alarm tuple contained in alarm queue.

Definition 5. A serial alarm queue and a parallel alarm queue
1.) If $\forall Q_k \in S_{ij}(i \leq k \leq j)$, we always have $|Q_i| = 1$, then the alarm queue $S_{ij}$ is called a serial alarm queue.

2.) If $\exists Q_k \in S_{ij}(i \leq k \leq j)$, we have $|Q_i| > 1$, then the alarm queue $S_{ij}$ is called a parallel alarm queue.

Definition 6. An alarm viewing window and its size
1.) An alarm viewing window is defined as $W_k = <Q_m, \ldots, Q_n|$ $d = n - m + 1>$, where $n \geq m$; $k, m, n = 1, 2, 3, \ldots$.

2.) The size of alarm viewing window is defined as $|W_k| = |<Q_m, \ldots, Q_n|d = n - m + 1| = d$, where $k, m, n = 1, 2, 3, \ldots$.

When making analysis of the correlated alarms, we would rather adopt the length of alarm queues as the size of alarm view windows than the time interval. If we adopt the time interval as the size of alarm view window, for the time intervals of the same length, some may contain a very large number of alarms, while others may contain a very small number of alarms, which will affect the correctness of alarm analysis. Therefore we adopt the times of alarm occurring as the size of alarm viewing window in this paper.

Definition 7. An alarm type sequence and its length
1.) An alarm type sequence is the m-tuple consisting of alarm types, which is denoted by $\text{Seq}_m = <e_{i1}, e_{i2}, \ldots, e_{im}>$, where $m = 1, 2, 3, \ldots; i1, \ldots, im = 1, 2, 3, \ldots$.

2.) Given alarm type sequence $\text{Seq}_m = <e_{i1}, e_{i2}, \ldots, e_{im}>$, The length of alarm type sequence is defined as $|\text{Seq}_m| = |<e_{i1}, e_{i2}, \ldots, e_{im}>| = m$.

Definition 8. The time weight of an alarm type sequence, a serial alarm type sequence, and a parallel alarm type sequence
1.) The time weight of an alarm type sequence is defined as follows. Given an
alarm type sequence \( Seq_m = \langle e_{i1}, e_{i2}, \ldots, e_{im} \rangle \), the average intervals among the occurring times of \( e_{i1}, e_{i2}, \ldots, e_{im} \) constitute the time weight of alarm type sequence, which is defined as weight(\( Seq_m \))\( = \langle \Delta t_1, \Delta t_2, \ldots, \Delta t_{m-1} \rangle \), \( m=1,2,3,\ldots; i1 \ldots im=1,2,3,\ldots \).

2.) A serial alarm type sequence is defined as follows. Given an alarm type sequence \( Seq_m = \langle e_{i1}, e_{i2}, \ldots, e_{im} \rangle \), \( m=1,2,3,\ldots; i1, i2, \ldots, im=1,2,3,\ldots \) and its time weight is weight(\( Seq_m \))\( = \langle \Delta t_1, \Delta t_2, \ldots, \Delta t_{m-1} \rangle \). If \( \forall \Delta t_k (1 \leq k \leq m-1) \), we always have \( \Delta t_k >0, k=1,2,3,\ldots \), then the alarm type sequence \( Seq_m \) is a serial alarm type sequence.

3.) A parallel alarm type sequence is defined as follows. Given an alarm type sequence \( Seq_m = \langle e_{i1}, e_{i2}, \ldots, e_{im} \rangle \), \( m=1,2,3,\ldots; i1, \ldots, im=1,2,3,\ldots \) and its time weight is weight(\( Seq_m \))\( = \langle \Delta t_1, \Delta t_2, \ldots, \Delta t_{m-1} \rangle \). If \( \exists \Delta t_k = 0 (1 \leq k \leq m-1) \), then an alarm type sequence \( Seq_m \) is a parallel alarm type sequence.

**Definition 9.** The relation of an alarm sequence \( \alpha \) is contained in an alarm sequence \( \beta \)

Given two alarm type sequences \( \alpha = \langle e_{i1}', e_{i2}', \ldots, e_{im}' \rangle \) and \( \beta = \langle e_{i1}, e_{i2}, \ldots, e_{in} \rangle \). If \( n \geq m, \exists e_{ik} \in \beta, \exists e_{ij} \in \beta (1 \leq ik < ij \leq n) \) and \( e_{i1}' = e_{ik} \cap e_{i2}' = e_{i(k+1)} \cap \ldots \cap e_{im}' = e_{ij} \), then \( \alpha \subseteq \beta \).

**Definition 10.** An alarm correlation rule

An alarm correlation rule is defined as

\[
\Delta t \quad e_{i1}, e_{i2}, \ldots, e_{ij} \Rightarrow e_{ik}, e_{ik+1}, \ldots, e_{im} \quad [\text{conf}=q\%, \text{supp}=p\%, W_k]
\]

After the alarm types \( e_{i1}, e_{i2}, \ldots, e_{ij} \) occur, in the interval of \( \Delta t \), the probability of alarm type sequence \( <e_{ik}, e_{ik+1}, \ldots, e_{im}> \) occurring is equal to \( q\% \).

5. MINING FREQUENT ALARM SEQUENCES

5.1 Main Algorithm

To solve the problem that noise data affect the analysis of alarm correlation, we present a new algorithm, called Robust_search (Algorithm 2 described in Section 5.2), which can discover the correlated alarm sequences from alarm database containing noise data.

In this paper, the main algorithm is Algorithm 1, which is based on the framework of mining association algorithm proposed by Agrawal etc al.[5,6,7]. Algorithm 1 is mainly composed of Algorithm 3 and Algorithm 2. Algorithm 3 generates the alarm type sequence candidates \( C_{m+1} \) from frequent alarm type sequence \( F_{ALARM_m} \) and Algorithm 2 counts the times that the alarm type sequence of \( C_{m+1} \) occurs in the alarm queue containing noise data.

In what follows, we will introduce the definitions used in Algorithm 1, Algorithm 2 and Algorithm 3.
Definition 11. \textit{Occur}(seq_m, W_k), \textit{Support}(seq_m, W_k), \textit{the confidence of the alarm correlation rule and a frequent alarm type sequence}

1.) Given an alarm type sequence \textit{seq}_m = \langle e_{i1}, e_{i2}, \ldots, e_{im} \rangle and an alarm viewing window \textit{W}_k, the times of the alarm type sequence \textit{seq}_m occurring in the alarm viewing window \textit{W}_k are defined as \textit{Occur}(seq_m, W_k) = \{\text{the times of seq}_m occurring in \textit{W}_k\}.

2.) Given an alarm type sequence \textit{seq}_m = \langle e_{i1}, e_{i2}, \ldots, e_{im} \rangle and an alarm viewing window \textit{W}_k, the support of \textit{seq}_m in \textit{W}_k is defined as \textit{Support}(seq_m, W_k) = \textit{Occur}(seq_m, W_k)/|\textit{W}_k|.

3.) Given two alarm type sequences: \textit{X}, \textit{Y} and an alarm viewing window \textit{W}_k, the confidence of the alarm correlation rule \textit{X} \Rightarrow \textit{Y} is defined as \textit{Conf}(X \Rightarrow Y, W_k) = [\textit{Support}(XY, W_k) / \textit{Support}(X, W_k) - \textit{Support}(Y, W_k)]

4.) A frequent alarm type sequence is defined as follows. In an alarm viewing window \textit{W}_k, given that the minimum support of alarm type sequence is \text{Mini support}, if the support of an alarm type sequence \textit{seq}_m is greater than \text{Mini support}, then the alarm type sequence \textit{seq}_m is a frequent alarm type sequence.

Alarm correlation algorithm (Algorithm 1) is composed of two main steps. In the first step, according to the minimum support (\text{Min support}), Algorithm 2 searches the frequent alarm type sequence from alarm queues and the discovered frequent alarm type sequences constitute the set of frequent alarm type sequences, denoted by \text{F_ALARM}_m. In the second step, according to the confidence of correlation rule, Algorithm 3 generates the alarm correlation rules from \text{F_ALARM}_m.

Algorithm 1

Input: alarm queue \text{S}_{ij}, W_k
Output: t frequent alarm sequence set: \text{F_ALARM}_m

1. compute \text{C}_1 := \{\alpha | \alpha \in \text{F_ALARM}_1\};
2. \text{m} := 1;
3. while \text{C}_m \neq \Phi do
4. begin
5. For all \alpha \in \text{C}_m, Search alarm queue \text{S}_{ij} to find support(\alpha, W_k); /*Algorithm 2*/
6. Obtain \text{F_ALARM}_m = \{\alpha | \text{C}_{id} \geq \text{min support}\} ;/*Algorithm 2*/
7. Generate Candidate \text{C}_{m+1} from \text{F_ALARM}_m ; /*Algorithm 3*/
8. \text{m} = \text{m} + 1;
9. end.
10. for all \text{m} , output \text{F_ALARM}_m;

5.2 Robust Search Algorithm

If a network facility has a fault, it may incur correlated alarms and other faults may also occur in the network facility and intricate many alarms. So the alarm event
sequence that we received will contain many alarms that have nothing to do with alarm correlation. Therefore, when searching the frequent alarm type sequence, we must consider the effects of noise data.

In the followings, we will introduce the definitions in Algorithm 2 and present a new algorithm, called Robust_search(Algorithm 2), which can search the frequent alarm type sequence from the alarm queue containing noise data.

Definition 12.  Win_seq, Win_freq and Win_add
1.) An alarm search window, denoted by Win_seq, is defined as the scope of the alarm type sequence being searched in the alarm queue.
2.) The size of alarm search window is defined as $|\text{Win}_\text{seq}|=|<E_m,…,E_n>|=n-m+1$, where $|\text{Win}_\text{seq}|=|\text{Win}_\text{freq}|+|\text{Win}_\text{add}|$.
3.) A frequent alarm window, denoted by Win_freq, is defined as the base window of the alarm type sequence of search.
4.) Given an alarm sequence $\alpha=<e_i1, e_i2,…,e_{im}>$ and $\alpha\in C_m$ where $C_m$ are composed of the alarm type sequence candidates of length m, The size of a frequent alarm window is defined as $|\text{Win}_\text{freq}|=|<e_{i1}, e_{i2},…,e_{im}>|=m$, which is equal to the length of the alarm type sequence of search.
5.) An additional alarm window, denoted by Win_add, is defined as the noise data tolerance window to search the alarm type sequence in an alarm search window Win_seq.
6.) The size of additional alarm window is defined as the maximum number of noise alarms included in the alarm search window Win_seq. We have a alarm sequence containing noise alarms $\beta=<e_i1, e_i2, e_i3,…,e_{im}>$ in Win_seq, where an alarm type sequence in $\beta$ is $<e_{i1}, e_{i2},…,e_{im}>$ and the noise alarm type sequence in $\beta$ is $<e_{i1}, e_{i2},…,e_{im}>$. The length of the additional alarm window is $|\text{Win}_\text{add}|=|<e_{i1}, e_{i2},…,e_{im}>|=k$, as well as $|\text{Win}_\text{freq}|=|<e_{i1}, e_{i2},…,e_{im}>|$, and $|\text{Win}_\text{seq}|=k+m$.

Robust_search(Algorithm 2.) is mainly described as follows. Given an alarm queue $S_{n1\text{eq}}=<Q_{n1}, Q_{n2},…,Q_{nq}>$ in the alarm viewing window $W_k$, in order to explain more clearly, we will adopt the alarm event to represent the alarm queue, i.e. $S_{n1\text{eq}}=<E_{n1\text{b}}, E_{n1\text{j}}),…, (E_{nq\text{b}}, E_{nq\text{j}})>$. Given an alarm type sequence $\alpha=<e_{i1}, e_{i2},…,e_{im}>$, the size of window i.e. Win_seq is equal to $m+|\text{Win}_\text{add}|$. At the
beginning, the pointer $Ptr_{seq}$ point to $E_{x1,y1}$ (x1, y1=1,2,3,...) (5th line in Algorithm 2.), which is the first alarm event containing the alarm type $e_{i1}$ in $W_k$. From $E_{x1,y1}$ to the end of the alarm search window $Win_{seq}$, Algorithm 2 looks for the alarm event containing the alarm type $e_{i2}$. If there exists $E_{x2,y2}$ (x2, y2=1,2,3,...) containing alarm type $e_{i2}$, then after the alarm event $E_{x2,y2}$, Algorithm 2 goes on to look for the alarm event containing alarm type $e_{i3}$, and so on. If $e_{i1}, e_{i2},...,e_{im}$ are all found in the scope of alarm search window $Win_{seq}$, then we say that the alarm type sequence $\alpha=<e_{i1}, e_{i2},...,e_{im}>$ occurs one time in $W_k$. After that the pointer $Ptr_{seq}$ is moved to the next alarm event containing $e_{i1}$. An example about the Robust_search algorithm is illustrated in figure 2.

Algorithm 2

Input: frequent alarm Candidate $C_m$, $W_k$, $win_add$
Output: Occur($C_m$, $W_k$)

1. $|Win_{seq}|:=m+|Win_add|$; /* $|Win_{freq}|=m$ */
2. for ($\alpha\in C_m$; ) /* $\alpha=<e_{i1}, e_{i2},...,e_{im}>$, $W_k=<Q_{n1}, Q_{n2},...,Q_{nk}|d=q>$ */
3. begin /* $C_count$ keeps the Occur($\alpha$, $W_k$) */
4. $C_count:=0$; /* $Ptr_{seq}$ is the start pointer of $Win_{seq}$ */
5. $Ptr_{seq}$ point to the first alarm event containing $e_{i1}$;
6. while($Ptr_{seq}$+$m$) is in $W_k$ )
7. begin
8. $Ptr_{temp}:=Ptr_{seq}$
9. for(p=1;p<=$m$;p++)
10. if(from $Ptr_{temp}$ to the end of $Win_{seq}$, $e_{ip}$ is not found) then break;
11. else $Ptr_{temp}$ point to the next alarm event in $Win_{seq}$;
12. end
13. if(p=$m+1$) begin
14. The $\alpha$ occurs one time in $Win_{seq}$, $C_count$++;
15. $Ptr_{seq}$ points to the first alarm event containing alarm type $e_{i1}$
16. after the alarm event that $Ptr_{temp}$ points to;
17. end
18. else $Ptr_{seq}$ points to the next alarm event containing $e_{i1}$;
19. end
20. Occur($\alpha$, $W_k$):=$C_count$;
end /* end of for loop */

5.3 The Complexity Analysis of Robust_search Algorithm

Given an alarm viewing window $W_k$ where $|W_k|=d$, we have an alarm event queue $S_{1d}=<Q_1, Q_2, ..., Q_d>$, an alarm type sequence $\alpha=<e_{i1}, e_{i2}, ..., e_{im}>$ and an alarm search window $Win_{seq}$ where $|Win_{seq}|=m+|Win_add|$. Let Supp=Support($<e_{i1}>$, $W_k$).
and \( M = \max \{ |Q_i|, 1 \leq i \leq d \} \). Then the worst time complexity of Robust_search algorithm on \( W_k \) is \( M \cdot d \cdot (1 + \text{Supp} \cdot |\text{Win}_\text{seq}|/M) \).

**Proof:**

In the Robust_search algorithm, the alarm search window slides \( (|Q_1| + |Q_2|, \ldots + |Q_d|) \) times on alarm queue \( S_{1d} \) in alarm viewing window \( W_k \). Note that \( \text{Supp} = \text{Support}(\langle e_{i1} \rangle, W_k) \), so there are at most \( d \cdot \text{Supp} \) alarm events containing \( 'e_{i1}' \). At each alarm event containing \( 'e_{i1}' \), the algorithm will do matching \( |\text{Win}_\text{seq}| \) times at most. Then the algorithm will do \( d \cdot \text{Supp} \cdot |\text{Win}_\text{seq}| \) times matching in the worst case. Therefore the worst time complexity of Robust_search algorithm is \( M \cdot d \cdot (1 + \text{Supp} \cdot |\text{Win}_\text{seq}|/M) \).

In the experiments of this paper, \( M \) is about 10, \( \text{Supp} \) is about 0.002 and \( |\text{Win}_\text{seq}| \) is about 10, then the time complexity of Robust_search algorithm mainly depends on the number of alarm events in \( W_k \). Since \( |\text{Win}_\text{seq}| = m + |\text{Win}_\text{add}| \) and the value of \( \text{Supp} \) is very small in general, the size of \( \text{Win}_\text{add} \) has little effect on the time complexity of Robust_search algorithm.

### 5.4 Generate Candidate Algorithm

Algorithm 3 is composed of two steps. In the first step, the algorithm generates alarm type sequence \( \gamma = \langle e_{i1}, e_{i2}, \ldots, e_{im}, e_{im}^{m} \rangle \) where \( |\gamma| = m+1 \), from \( F_{\text{ALARM}}_m \). In the second step, if all the subsets \( L \) of the alarm type sequence \( \gamma \), where \( |L| = m \), are contained in \( F_{\text{ALARM}}_m \), then \( \gamma \) belongs to \( C_{m+1} \).

**Algorithm 3**

*Input:* frequent alarm sequence set \( F_{\text{ALARM}}_m \).

*Output:* frequent alarm sequence Candidate set \( C_{m+1} \).

1. \( C_{m+1} := \varnothing \).
2. For \( \alpha, \beta \in F_{\text{ALARM}}_m \) and \( \alpha \neq \beta \) and \( \alpha = < e_{i1}, e_{i2}, \ldots, e_{im} > \) and \( \beta = < e_{i1}', e_{i2}', \ldots, e_{im}' > \) begin
3. 1. If \( (e_{i2} = e_{i1}', \cap e_{i3} = e_{i2}' \cap \cdots \cap e_{im} = e_{im-1}' ) \) then begin
4. 2. generate alarm sequence \( \gamma = < e_{i1}, e_{i2}, \ldots, e_{im}, e_{im}^{m} > \); /* Candidate generate */
5. 3. \( C_{m+1} := \{ \gamma \} \); /* For all \( L \subseteq \gamma \) and \( |L| = m \), we have \( L \in F_{\text{ALARM}}_m \) */
6. end
7. end
8. end

### 5.5 Generate Correlation Rules

There are various interestingness measurers of rules in the methods of data mining. R.Agrawal et al. in [5] first presented AIS association rules algorithm and its measure of association rule \( X \Rightarrow Y \), which is defined as \( \text{confidence}(X \Rightarrow Y) = \text{Support}(XY)/\text{Support}(X) \), where \( X \) and \( Y \) correspond to a set of attributes and \( X \) and \( Y \) are disjoint.

Brin et al. [11] studied generalizing Association Rules to Correlation as follows. The support and confidence of an association rule \( X \Rightarrow Y \) are defined as
Support=\text{P}[XY]$ and Confidence=$\text{P}[XY]/\text{P}[X]$. The confidence is the conditional probability of $Y$ given $X$. If $X$ and $Y$ are independent, then Confidence $=\text{P}[XY]/\text{P}[X]=\text{P}[Y]$. Therefore, if $\text{P}[Y]$ is high, then the confidence of the rules is high, which will make association rule meaningless. In order to solve the problem, S.Brin et al. [11] discussed measuring significance of association rules via the support and the chi-squared test for correlation and they also presented the interestingness measure $I=\text{P}(XY)/(\text{P}(X)\times\text{P}(Y))$. The interestingness measure is symmetrical, because the confidence of $X \Rightarrow Y$ is equal to the one of $Y \Rightarrow X$. However, Khailil M et al.[12] proved that the chi-squared test is correct for $2 \times 2$ continuous tables, but incorrect for the larger continuous table and they also presented the new interestingness measure $R(X \Rightarrow Y)=\text{P}(XY)/\text{P}(X)-\text{P}(Y)$. In this paper, we experimentally compare $R(X \Rightarrow Y)=\text{P}(XY)/\text{P}(X)-\text{P}(Y)$ with Confidence $=\text{P}[XY]/\text{P}[X]$, which is described in detail in experiment 2.

In [5] the association rules only have one single item of the consequent, then R. Agrawal and R. Srikant in [8] gave an algorithm of generating more than one item of the consequent. The Algorithm 4 is based on the algorithm generating association rules in [8] and the interestingness measure of the correlation rules adopts $R(X \Rightarrow Y)=\text{P}(XY)/\text{P}(X)-\text{P}(Y)$ in [11]. A rule holds if and only if the confidence of rule is greater than min_conf.

**Algorithm 4**

1. **Input:** Frequent alarm sequence set $F_{ALARM_m}$
2. **Output:** output the correlation rules $\beta \rightarrow (\alpha - \beta)$ and confidence $|\text{P}(\alpha)/\text{P}(\beta) - \text{P}(\alpha - \beta)|$
3. for all $\alpha \in F_{ALARM_m}$ do /* generate correlation rules */
4. for all $\beta \subseteq \alpha$ do
5. if $|\text{P}(\alpha)/\text{P}(\beta) - \text{P}(\alpha - \beta)| \geq \text{min_conf}$ then
6. begin
7. generate the rule $\beta \rightarrow (\alpha - \beta)$ with
8. confidence $|\text{P}(\alpha)/\text{P}(\beta) - \text{P}(\alpha - \beta)|$;
9. end

6. **EXPERIMENTS**

6.1 **The Results of Experiment 1**

The data in experiment 1 are the alarms in GSM Networks, which contain 181 alarm types and 91311 alarm events. The time of alarm events ranges from 2001-03-15-00 to 2001-03-19-23. In figure 3 the broken line graph is denoted by $win_{xy}$, where $x$ represents the size of additional alarm window i.e.$Win\_add$ and $y$ represents the size of frequent alarm window i.e. $Win\_freq$. In figure 3 the $Y$ axis is the number of alarm type sequences and the $X$ axis is $Mini\_support$ (using the minimum occurring times).
Figure 3: The number of frequent sequences changes with Win_add

Figure 4: Interestingness measure: Correlation and Confidence
The results of experiment 1 are illustrated in figure 3. From figure 3, it is also easy to see that as \(y\) increases, \(\text{win}_{0y}, \text{win}_{2y}\) and \(\text{win}_{4y}\) \((y=1,2,3,4,5)\) become close to each other more rapidly with the increment of \(\text{Mini}\_\text{support}\).

In sum, with the increment of the size of additional alarm windows, the number of frequent alarm type sequences increases and the number of alarm sequences will increase more slowly with the increment of the length of alarm sequence.

**6.2 The Results of Experiment 2**

The data in experiment 2 are the same as those in experiment 1. In figure 4 the X axis represents \(\text{Confidence}=P[XY]/P[X]\) and the Y axis represents \(\text{Correlation}=P(XY)/P(X)P(Y)\).

The results of experiment 2 are illustrated in figure 4. The interestingness measures of correlation rules are mainly distributed in \([0, 0.4]\), especially in \([0, 0.1]\). In figure 4, at the same support, with the increment of the additional alarm window i.e. \(\text{Win}\_\text{add}\), the number of correlation rules will increase. As \(\text{Win}\_\text{add}\) increases, the increment of high confidence rules is greater than that of lower ones. The relation between correlation and confidence is nearly linear and its slope is lower than 1.

**7. CONCLUSION**

Since the Robust_search algorithm can analyze alarm correlation from alarm database containing noise data, it will generate more alarm sequences, then the number of correlation rules increases. Although the correlation measure can reduce the rules, it still needs people to select the most useful ones from a large number of the rules. Therefore, it is necessary to study how to extract rules more correlated from alarm database containing noise in the future.

**ACKNOWLEDGMENTS**

This research was supported by National 973 Project of China Grant No.G1999032709 and No.G1999032701. Thanks Professor Wei Li for the choice of subject and guidance of methodology. Thanks for the suggestions from Professor Yuefei Sui of the Institute of Computing Technology, Chinese Academy of Sciences. Thanks for Nan Liu, Zhi Cui and Xinzhang Li of Beijing Mobile Telecom. The authors would also like to thank the other members of the NLSDE lab: Xin Gao, Peng Cheng, Gang Zhou, Lin Tian, and Dong Li.

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