Network Security Situation Awareness Based on Spatio-temporal Correlation of Alarms

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***Abstract*—Traditional intrusion detection systems often deal with massive alarms based on specific filtering rules, which is complex and inexplicable. In this demo, we developed a network security situation awareness (NSSA) system based on the spatio-temporal correlation of alarms. It can monitor the security situation from the temporal dimension and discover abnormal events based on the time series of alarms. Also, it can analyze alarms from the spatial dimension on the heterogeneous alarm graph and handle alarms in batches of events. With this system, system operators can filter most irrelevant alarms quickly and efficiently. The rich visualization of alarm data could also help find hidden high-risk attack behaviors.**

***Index Terms*—Situation Awareness, Spatio-temporal Correlation, Community Discovery, Subgraph Mining, Pattern Matching.**

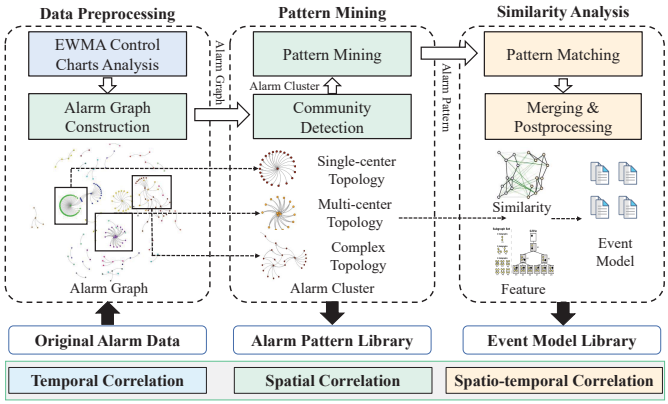


Fig. 1: Overall framework of the NSSA system.

I. Introduction

Intrusion detection systems (IDSs) have been widely deployed to identify malicious network traffic based on predefined signatures in recent years. However, an IDS would generate huge amounts of false alarms, which prevents system operators from comprehending the network security situation. In the real case, these false alarms are usually eliminated by specific filtering rules, which are manually designed according to the characteristics of each false alarm. This approach is time-consuming and unsuitable for large-scale networks with millions of heterogeneous alarms. Also, it is difficult to migrate these specific rules to other networks.

In this demo, we design a network security situation awareness (NSSA) system based on the spatio-temporal correlation of alarms. First, we use the Exponential Weighted Moving-Average (EWMA [1]) model to locate abnormal events via monitoring multiple temporal statistical indicators of alarms in real-time. Then, we construct alarm graphs within each hour, and deal with alarms in batches based on the spatial correlation of alarms on the graph. With the NSSA system, system operators could handle alarms from IDS in an explainable and efficient approach semi-automatically.

II. System Architecture

As shown in Fig. 1, the NSSA system mainly consists of three parts: data preprocessing, pattern mining, and similarity analysis. The details of each part are as follows.

A. Data Preprocessing

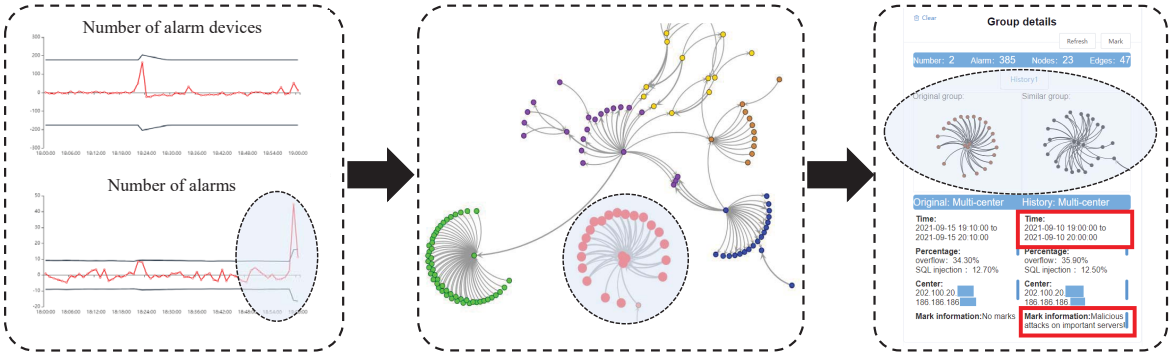
The alarms triggered by the same event would be closely distributed in both temporal and spatial dimensions. First, we use the EWMA control charts to quickly capture the occurred moment of abnormal traffic or access behaviors.

As one event may trigger a series of alarms, it would be cost-effective to aggregate the alarms related to the same event into a group, and handle the alarms in batches of events. Moreover, it could further ease the burden of alarm analysis if we can recommend the historical decision of similar events to system operators. With this idea, we split the alarms by time and construct an alarm graph for each slice, where each node denotes an IP address, and each directed edge denotes an alarm from the source IP address to the destination IP address. The time window is dynamically set according to the current security situation.

The alarm graphs could be filtered by vendors of alarm devices and rendered with different colors based on clusters, vendors, number of alarms, and customized threat indicators in the NSSA system. With the alarm graph, system operators could master the overall network security situation in a visual and friendly way.

B. Pattern Mining

We can find alarm patterns in alarm graphs using improved community discovery algorithms. First, alarms in the graph are roughly clustered into different clusters via the Louvain



(1) Anomaly detection via EWMA control charts.

(2) Event Localization by analyzing alarm patterns in the alarm graph.

(3) Classification based on historical alarm patterns.

Fig. 2: Demonstration of intrusion detection, localization, and automatic classification.

[2] algorithm based on community modularity. Then, the clustering results are amended to obtain the final alarm pattern. Specifically, alarms with rare attack types are picked out and handled separately. Clusters with complex topologies are further split into simple clusters (i.e., single-centered, multi-centered, and other simple topologies) by eliminating a few infrequent connections. Finally, frequent clusters are picked out as alarm patterns and stored in the alarm pattern library.

C. Similarity Analysis

We group alarm patterns with high similarities together into the same event model. The main properties for similarity matching are as follows.

1) *Subgraph motifs* [3]: Topological attributes extracted from alarm patterns by the G-tries algorithm [4].
2) *Alarm types*: Proportion vectors of different attack types for each alarm pattern.
3) *Node homogeneity*: The similarity of central nodes' attributes and the overlap ratio of surrounding nodes for two alarm patterns.

With event models, alarms could be handled conveniently and efficiently in batches. The system also provides a calibration function to revise the automatically generated event models, and the input from system operators will be saved as expert knowledge. After labeling some event models based on specialist knowledge, system operators could handle new alarm patterns in an explainable way semi-automatically.

III. Demo Setup

We have developed an NSSA system based on the above framework. The detailed operations are illustrated in a demo video at **https://bit.ly/NSSA-ST**, where the alarm data are from the IDS of a power grid company. As shown in Fig. 2, after a consecutive attack is launched on three important servers in the network, the NSSA system can detect, locate and classify abnormal events efficiently. **First**, the system presents the overall security situation in the time dimension. Specifically, it monitors the number of alarms and alarm devices in EWMA control charts. Once an indicator crosses the detection boundary, the system will generate an alert indicating some possible abnormal events. As shown in Fig. 2-1, the window of EWMA control charts pops up and alerts, indicating that the number of the alarm exceeds the limit. **Next**, the system can help locate the event in the spatial dimension, i.e., find the corresponding alarm pattern on the alarm graph. As shown in Fig. 2-2, a three-centered alarm pattern can be found in the alarm graph at this moment. **Finally**, the system will automatically match similar historical patterns and sort them according to their similarity. As shown in Fig. 2-3, the most similar pattern in history are displayed in the right column of the "group details". From the figure, these two alarm patterns are extremely similar in both topology structure and alarm type proportion. From the historical data, the previous alarm pattern is automatically labeled as "malicious attacks on important servers". The result is manually verified, and the processing information is "banned attacking IP". Then, all the alarms in the new alarm pattern could be handled in the same way by a simple click in the system.

In addition, for common false positives and low-threat patterns, the system will automatically process them and generate report logs silently. For undecidable patterns, the system will push them to system operators for further investigation. In this way, we can greatly reduce the workload of system operators.

IV. Conclusion

We developed an NSSA system with rich data visualization based on spatio-temporal correlation of alarms. It can discover abnormal events using EWMA control charts, and handle alarms in batches of abnormal events based on the alarm graph semi-automatically. Moreover, it can automatically deal with false and low-risk alarms based on historical operations. These functions could help system operators filter useless alarms and focus on hidden high-risk attack behaviors.

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