Network Intrusion Detection

Intrusion detection is a new, retrofit approach for providing a sense of security in existing computers and data networks, while allowing them to operate in their current "open" mode.

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Intrusion detection is a new, retrofit approach for providing a sense of security in existing computers and data networks, while allowing them to operate in their current "open" mode. The goal of intrusion detection is to identify, preferably in real time, unauthorized use, misuse, and abuse of computer systems by both system insiders and external penetrators. The intrusion detection problem is becoming a challenging task due to the proliferation of heterogeneous computer networks since the increased connectivity of computer systems gives greater access to outsiders and makes it easier for intruders to avoid identification. Intrusion detection systems (IDSs) are based on the beliefs that an intruder's behavior will be noticeably different from that of a legitimate user and that many unauthorized actions are detectable. Typically, IDSs employ statistical anomaly and rule-based misuse models in order to detect intrusions.

A number of prototype IDSs have been developed at several institutions, and some of them have also been deployed on an experimental basis in operational systems. In this paper, several host-based and network-based IDSs are surveyed, and the characteristics of the corresponding systems are identified. The host-based systems employ the host operating system's audit trails as the main source of input to detect intrusive activity, while most of the network-based IDSs build their detection mechanism on monitored network traffic, and some employ host audit trails as well. An outline of a statistical anomaly detection algorithm employed in a typical IDS is also included.

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[1]*Authentication is the process of determining whether or not an activity is a genuine one. It is a very desirable security service and is an important property of a secure network or computer system. Data and communications integrity can be directly built on authentication mechanisms. Identification is the process of determining whether someone is truly the person who he says he is.*

Introduction

A secure computer or network system should provide the following services—*data confidentiality, data and communications integrity*, and assurance against *denial-of-service* [1, 2]. Data confidentiality service protects data against unauthorized disclosure. Release of a message's content to unauthorized users is a compromise which this service should protect. Data and communications integrity service is concerned with the accuracy, faithfulness, non-corruptibility, and believability of information transfer between peer entities (including computers connected by a network). This service must ensure correct operation of the system hardware and firmware, and it should protect against unauthorized modification of data and labels. Denial-of-service is a threat, and assurance against denial-of-service is an important security service [3]. A denial- of-service condition is said to exist whenever the system throughput falls below a pre-established threshold, or when access to a (remote) entity is unavailable. While such attacks are not completely preventable, it is often desirable to reduce the probability of such attacks below some threshold.

The conventional approach to secure a computer or network system is to build a "protective shield" around it. Outsiders who need to enter the system must identify and authenticate themselves — commonly known as the Identification & Authentication (I&A) problem.[1] Also, the shield should prevent leakage of information from the protected domain to the outside world. Mandatory access control techniques (e.g., cryptography-based) might be used in the design of such secure systems [1].

There are a number of limitations to this prevention-based approach for computer and network security, as outlined below.

- It is difficult, perhaps impossible, to build an useful system which is absolutely secure. That is, the possible existence of some design flaw in a system with a large number of components cannot be excluded. In addition, one cannot rule out the occurrence of administrative flaws such as misconfiguration of equipment when bought from vendor, errors due to backward compatibility of vendor equipment, and poor administrative policies and practices.
- It is impractical to assume that the vast existing infrastructure of (possibly insecure) computer and network systems will be scrapped in favor of new, secure systems since a tremendous investment into our current infrastructure has already been made.
- The prevention-based security philosophy constrains a user's activities; the current "open" mode

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of operation of most systems is regarded by many to be a highly-useful environment for promoting user productivity.
- Crypto-based systems cannot defend against lost or stolen keys, and against cracked passwords.
- Finally, a secure system can still be vulnerable to insiders misusing their privileges since it cannot fully guard against the insider threat, i.e., users who abuse their privileges. (Systems with mandatory access controls, however, can reduce the risks of some kinds of insider attacks.)

Around the mid-'80s, an alternative approach, called intrusion detection, for providing a different notion of security in computer systems was proposed [4]. The basic arguments in favor of this concept are those outlined in the previous paragraph, namely, that not only abandoning the existing and huge infrastructure of possibly-insecure computer and network systems is impossible, but also replacing them by totally-secure systems may not be feasible or cost effective. That is, our computers and networks may be under attack; but an intrusion detection system based on a retrofit technology should be able to detect such attacks, preferably in real time (i.e., when the attacks are in progress). Typically, an intrusion detection systems (IDS) alerts a system security officer (SSO) when it detects an attack. This approach is gaining increasing momentum and acceptance, and a number of prototype IDSs — some for a single host and others for several hosts connected by a network — have been built at several institutions.

Intrusion detection is defined to be the problem of identifying individuals[2] who are using a computer system without authorization (i.e., "crackers") and those who have legitimate access to the system but are abusing their privileges (i.e., the "insider threat"). Generally, an intrusion would cause loss of confidentiality, loss of integrity, denial of resources, or unauthorized use of resources. Some specific examples of intrusions that concern system administrators include:
- Unauthorized modifications of system files so as to permit unauthorized access to either system or user information.
- Unauthorized access or modifications of user files/information.
- Unauthorized modifications of tables or other system information in network components (e.g., modifications of router tables in an internet to deny use of the network).
- Unauthorized use of computing resources (perhaps through the creation of unauthorized accounts or perhaps through the unauthorized use of existing accounts).

An example intrusion scenario is included at the end of this section.

Detecting attacks requires the use of a model of intrusion, namely, what should the IDS look for? Currently, two types of models are employed in IDSs. The first model hypothesizes its detection upon the profile of a user's (or a group of users') normal behavior. It statistically analyzes parameters of the user's current session, compares them to the profile representing the user's normal behavior, and reports "significant" deviations to a SSO. Here, significant is defined as a threshold set by the specific model or by the SSO. A typical IDS may report the "Top Ten" most suspicious sessions to the SSO [5]. Because it catches sessions which are not normal, it is referred to as an "anomaly" detection model.

The second type of model bases its detection upon a comparison of parameters of the user's session and the user's commands to a rule-base of techniques used by attackers to penetrate a system. Attack signatures (i.e., known attack methods) are what this model looks for in the user's behavior. Since this model looks for patterns known to cause security problems, it is called a "misuse" detection model.

A number of IDSs base their design on analyzing the host operating system (OS)'s audit trails. Their examples include AT&T's ComputerWatch [6], TRW's Discovery [7, 8], Haystack Laboratory's HAYSTACK system [5], SRI International's Intrusion Detection Expert System (IDES) [9, 10, 11], Planning Research Corporation's Information Security Officer's Assistant (ISOA) [12, 13], National Security Agency's Multics Intrusion Detection and Alerting System (MIDAS) [14], and Los Alamos National Laboratory's Wisdom & Sense (W&S) [15] and Network Anomaly Detection and Intrusion Reporter (NADIR) [16]. Some of the basic algorithms employed in these systems include evaluation of a weighted multinomial function to detect deviations from normal behavior, a covariance-matrix-based approach for profiling normal behavior, and rule-based expert system approach to detect violations of security policy.

Early IDS models were designed to monitor a single host. However, more recent models accommodate the monitoring of a number of hosts interconnected by a network, e.g., ISOA, IDES, and UC Davis' Network Security Monitor (NSM) and Distributed Intrusion Detection System (DIDS). Some of these systems (ISOA and IDES) transfer the monitored information (host audit trails) from the monitored hosts to a central site for processing. Others (NSM, DIDS) monitor the network traffic flow as well, as part of their intrusion detection algorithms.

An Example Intrusion Scenario

A description of a real attack that occurred several months ago and was detected by our Network Security Monitor (NSM) [17] provides a good example of the types of attacks that occur regularly and must be detected. Pertinent facts include the following:
- At least ten different computers were involved.
- The computers were managed by eight sets of system administrators distributed over seven different sites, three states, and two countries.
- The attack exploited a number of different vulnerabilities in a number of different computer systems.

The attack took place in several stages over several days.

1) The initial phase of the attack included: a series of "doorknob-rattling" operations (namely, the use of common `account_name/password` combinations to break-in) from `COMPANY1.com`, resulting in a successful break-in into `shark.SCHOOL2.edu` by exploiting a flaw; importing a Trojan login program from `omen.SCHOOL3.edu` and installing it in shark; and followed (on the next day) by a login from `revir.SCHOOL1.edu` into `shark.SCHOOL2.edu` by the Trojan login program installed the previ-

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Detecting attacks requires the use of a model of intrusion: what should the IDS look for?

[2] *Typically, these individuals are users, but they may be hosts or programs (in case of machine attacks) as well.*

The ComputerWatch audit trail analysis tool provides a significant amount of audit data reduction and limited intrusion-detection capability.

ous day. Apparently this attempt is merely testing if the Trojan still existed, and the intruder quickly logs off.

2) The second element of the attack observed is another login to shark exploiting the Trojan login program; however, this login comes from bear.SCHOOL4.edu. Although this attack came from a different place, we are confident that this is the same person. This is based on two facts: the Trojan horse was installed only the night before; and the special password used was specific to shark, i.e., although other Trojan horses have been discovered, the password selected and set the night before is unique to shark. The intruder then uses shark as a platform from which to attack other computer systems.

3) The intruder exploits a hole in a .rhosts file on a computer at a well-known school on the east coast, next.SCHOOL6.edu, and logs in as uucp. Once on next, the intruder executes a program granting him root privileges.

4) As root, the intruder is able to exploit the fact that another computer's file system, kropotkin.SCHOOL7.edu, is mountable by next. Once the intruder is able to mount kropotkin, he is able to examine and manipulate the file system without having to login to kropotkin. The intruder installs another hole into kropotkin that allows anyone to login to the account tami from anywhere.

5) As it turns out, the home directory for user tami on kropotkin is the same on two other hosts at SCHOOL7, wombat.SCHOOL7.edu and SCHOOL7.edu. This fact gives the intruder access to these machines as well. After moving about the different SCHOOL7 computer systems, the intruder returns to shark at SCHOOL2.

6. The intruder next attacks a computer at SCHOOL5, called SCHOOL5.edu, by exploiting a Trojan login program previously installed.

7. Using SCHOOL5 as a platform, the intruder attacks a computer in Canada, polyv.COUNTRY2, by exploiting a Trojan login program there as well. The intruder notices the system administrator currently active, and he exits polyv.

8. After extensively examining SCHOOL5's file system, the intruder returns again to shark at SCHOOL2.

9. From shark, the intruder breaks into a computer at COMPANY2, previous.COMPANY2.com, by exploiting a "+ +" in the .rhosts file for the account me. The intruder, apparently satisfied that this hole is still intact, returns back to shark.

10. The intruder again breaks into polyv.COUNTRY2, and once again, his visit is short.

11. Finally, after more than six hours of attacking various computer systems, the intruder exits shark to return to bear.SCHOOL4.edu.

Host-Based Intrusion Detection Systems

An early abstract model of a typical IDS was proposed in [4]. Since then, a number of IDSs have been designed and deployed. A large number of IDSs employ their host OS's audit trail as the main source of input for detecting intrusions. Such systems are surveyed in this section. For each IDS surveyed, we provide an overview of the system, an outline of the system's organization, and a discussion on how the system operates.

ComputerWatch

Overview — The ComputerWatch audit trail analysis tool provides a significant amount of audit data reduction and limited intrusion-detection capability [6]. The amount of data viewed by an SSO is reduced while minimizing the loss of any informational content. Data reduction is performed by providing a mechanism for examining different views of the audit data based on information relationships.

ComputerWatch, designed for the System V/MLS operating system, was written to assist, but not replace, the SSO. The tool uses an expert system approach to summarize security sensitive events and to apply rules to detect anomalous behavior. It also provides a method for detailed analysis of user actions in order to track suspicious behavior.

System Organization — Audit trail records can be analyzed either by the SSO interactively, or in batch mode for later review, i.e., ComputerWatch does no real-time analysis of events. There are three levels of detection statistics, namely, system, group, and user. Statistical information for system-wide events is provided in a summary report. Statistical information for user-based events is provided by detection queries. Statistical information for group-based events will be a later enhancement [6].

System Operation — ComputerWatch provides a System Activity Summary Report for the SSO. This report contains summary information describing the security-relevant activities occurring on the system. The report can indicate what types of events need closer examination. The SSO can also perform his own analysis on the data. Expert system rules are used to detect anomalies or simple security breaches. The rules are fired when an equation is satisfied and when the rules in its predecessor list have been fired as well.

The detection queries that are provided have been designed to assist the SSO in detecting "simple" system security breaches. These security breaches may involve intrusion, disclosure, or integrity subversion. The detection queries display similar security-relevant system activities as those that are described in the summary report, but at a user level. A SQL-based query language is provided to allow the SSO the capability to design custom queries for intrusion detection.

Discovery

Overview — Discovery is an expert system tool developed by TRW for detecting unauthorized accesses to its credit database [7, 8]. The Discovery system itself is written in COBOL, while the expert system is written in an AI shell. Both run on IBM 3090s. Their goal is not to detect attacks on the operating system, but to detect abuses of the application, namely, the credit database.

System Organization — TRW runs a database that contains the credit histories of 133 million consumers. It is accessed more than 400,000 times a day using 150,000 different access codes,

many of which are used by more than one person [7, 8], but these numbers are expected to have increased by now. The database is accessed in three ways: on-line access by TRW customers who query consumers' credit information, monthly updates from accounts receivable data received on magnetic tape, and modifications to correct errors and inaccuracies. The Discovery system examines each of these processes for unauthorized activity.

Discovery is a statistical inference system which looks for patterns in the input data. Its targets include hackers, private investigators, and criminals. It is designed to detect three types of undesired activity, namely, accesses by unauthorized users, unauthorized activities by authorized users, and invalid transactions. Processing of the audit data is performed in daily batches.

System Operation — **1) Customer Inquiries.** Discovery's processing sequence is as follows. First, records with invalid formats are discarded. Valid records are then sorted and processed by a pattern recognition module. Inquiries are compared to both the standard inquiry profile and a model of illegitimate access. Access codes which are suspected of having been misused can also be flagged for tighter scrutiny.

The system produces a user profile for each customer by type-of-service and access method. These profiles are updated daily. The system generates statistical patterns based on the variables in each inquiry (e.g., presence or absence of a middle initial), access characteristics (e.g., time of day), and characteristics of a credit record (e.g., geographic area).

Each variable has a tolerance, established by accumulated patterns, within which the daily activity should fall. Three types of comparison are made: each inquiry with the global pattern, each subscriber's daily pattern with the global pattern, and a subscriber's pattern with an industry pattern. The system's output is an exception data file that lists the reasons for the exceptions, as well as a report module. Investigative data is also stored in a database and may be retrieved using a query language.

Initial production runs of the expert system produced large numbers of exceptions. Some of these were traced to variations due to time of day, etc. Heuristics based on analysis of actual cases are also being included in the expert system.

2) Database Update. Several factors in the incoming data from customers are measured by a COBOL program. Data is entered into the database only if statistical comparisons with previously reported data are within a pre-defined tolerance. Data that is rejected by the statistical analysis is submitted to an expert system for further validation, and is entered into the database if passed by the expert system.

3) Database Maintenance. The credit database may be modified by TRW operators to correct errors and inaccuracies. An expert system designed to monitor the maintenance process performs statistical analysis of maintenance transactions and analyzes each credit record's maintenance history.

Discovery has detected and isolated unauthorized accesses to the database, masqueraders, and invalid inquiries. It has also provided investigators with concise leads on illegitimate activity. Several of the deviations that have been discovered were found to be caused by customers changing their access methods and systems. The expert system allows TRW to apply a consistent security policy in the update process. A beneficial side-effect of the system is the compilation of purchasing patterns for each customer, which is useful for marketing purposes.

HAYSTACK

Overview — HAYSTACK was initially designed to be a system for helping Air Force Security Officers detect misuse of Unisys 1100/2200 mainframes used at Air Force Bases for routine "unclassified but sensitive" data processing [5]. HAYSTACK software reduces voluminous system audit trails to short summaries of user behaviors, anomalous events, and security incidents. This reduction enables detection and investigation of intrusions, particularly by insiders (authorized users).

In addition to providing audit trail data reduction, HAYSTACK attempts to detect several types of intrusions: attempted break-ins, masquerade attacks, penetration of the security system, leakage of information, denial of service, and malicious use. HAYSTACK's operation is based on behavioral constraints imposed by official security policies and on models of typical behavior for user groups and individual users.

System Organization — The initial HAYSTACK system consisted of two program clusters, one executing on the Unisys 1100/2200 mainframe, and the other executing on a 386-based PC running MS-DOS and the ORACLE database management system [5]. Data is transferred from the mainframe to the PC by magnetic tape or electronic file transfer over a communications line. Performancewise, it has been found that a typical day's worth of audit data can be processed within a few hours on the PC.

The preprocessor portion of HAYSTACK (which runs on the mainframe) is a straightforward COBOL application that selects appropriate audit trail records from the Unisys proprietary audit trail file as input, extracts the required information, and reformats it into a standardized format for processing on the PC. Software on the PC is written in C, embedded SQL, and ORACLE tools. It processes and analyzes the audit trail files, helps the SSO maintain the databases that underlie HAYSTACK, and gives the SSO additional support for his investigations.

System Operation — HAYSTACK helps an SSO detect intrusions (or misuse) in three different ways.

1) Notable Events. HAYSTACK highlights notable single events for review. Events that modify the security state of the system are reported, along with explanatory messages. This includes both "successful" and "unsuccessful" events that affect access controls, user-ids, and group-ids.

2) Special Monitoring. The SSO may "tag" particular security "subjects" and "objects" for special monitoring. This is analogous to setting an alarm to go off when a particular user-id is active, or when a particular file or program is accessed. This alarm may also increase the amount of reporting of the user's activity.

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3) Statistical Analysis. HAYSTACK performs two different kinds of statistical analysis. The first kind of statistical analysis yields a set of "suspicion quotients." These are measures of the degree to which the user's aggregate session behavior resembles one of the target intrusions which HAYSTACK is trying to detect.

About two dozen "features" (behavioral measures) of the user's session are monitored on the Unisys system, including time of work, number of files created, number of pages printed, etc. Given a list of the session features whose values were outside the expected ranges for the user's security group, plus the estimated significance of each feature violation for detecting a target intrusion, HAYSTACK computes a weighted multinomial "suspicion quotient" which signifies how closely that session resembles a target intrusion for the user's security group. The suspicion quotient is therefore a measure of the "anomalousness" of the session with respect to a particular weighting of features. HAYSTACK emphasizes that such suspicions are not "smoking guns," but are rather hints or hunches to the SSO that the session may warrant further investigation. Such a statistical anomaly detection algorithm is treated in greater detail in the section on an intrusion detection algorithm case study later in this article.

The second kind of statistical analysis detects variation within a user's behavior by looking for significant changes ("trends") in recent sessions compared to previous sessions.

Intrusion-Detection Expert System (IDES)

Overview — The Intrusion-Detection Expert System (IDES) developed at SRI International is a comprehensive system that uses complex statistical methods to detect atypical behavior, as well as an expert system that encodes known intrusion scenarios, known system vulnerabilities, and the site-specific security policy [9-11].

The overall goal of IDES is to provide a system-independent mechanism for the real-time detection of security violations. These violations can be initiated by outsiders who attempt to break into a system or by insiders who attempt to misuse their privileges. IDES runs independently on its own system (currently a Sun workstation) and processes the audit data received from the system being monitored.

System Organization — The IDES prototype uses a subject's historical profile of activity to determine whether its current behavior is normal with respect to past or acceptable behavior. Subjects are defined as users, remote hosts, or target systems. A profile is a description of a subject's normal (i.e., expected) behavior with respect to a set of intrusion-detection measures. IDES monitors target system activity as it is recorded in audit records generated by the target system. Due to the fact that these profiles are updated daily, IDES is able to adaptively learn a subject's behavior patterns; as users alter their behavior, the profiles change to reflect the most recent activity. Rather than storing the tremendous amount of audit data, the subject profiles keep only certain statistics such as frequency tables, means, and covariances.

IDES also includes an expert-system component that is able to describe suspicious behavior that is independent of whether a user is deviating from past behavior patterns. The expert system contains rules that describe suspicious behavior based on knowledge of past intrusions, known system vulnerabilities, or the site-specific security policy.

The IDES comprehensive system is considered to be loosely coupled in the sense that the decisions made by the two components are independent. While the two components share the same source of audit records and produce similar reports, their internal processing is done separately. The desired effect of combining these two separate components is a complementary system in which each approach will help to cover the limitations of the other.

System Operation — The system has two major components as discussed below.

1) The Statistical Anomaly Detector (IDES/STAT) [11]. In order to determine whether or not current activity is atypical, IDES/STAT uses a deductive process based on statistics. The process is controlled by dynamically-adjustable parameters that are specific to each subject. Audited activity is described by a vector of intrusion-detection variables that correspond to the measures recorded in the profiles. As each audit record arrives, the relevant profiles are retrieved from the knowledge base and compared with the vector of intrusion-detection variables. If the point defined by the vector of intrusion-detection variables is sufficiently far from the point defined by the expected values, with respect to the historical covariances for the variables stored in the profiles, then the record is considered anomalous. The covariance-matrix-based approach, however, has turned out to be compute-intensive, and recent versions of IDES have dropped the covariance-based computations [18].

The procedures are not only concerned with whether an audit variable is out of range, but also with whether an audit variable is out of range relative to the values of the other audit variables. IDES/STAT evaluates the total usage pattern, not just how the subject behaves with respect to each measure considered singly.

2) The Expert System. The IDES expert system will make attack decisions based on information contained in the rule-base regarding known attack scenarios, known system vulnerabilities, site-specific security information, and expected system behavior. It will, however, be vulnerable to intrusion scenarios that are not described in the knowledge base.

The expert system component is a rule-based, forward-chaining system. A production-based expert system tool (PBEST) has been used to produce a working system. The PBEST translator is used to translate the rule-base into C language code, which actually improves the performance of the system over using an interpreter. As the size of the rule-base increases, the processing time will also increase since the functions that implement the rules must search longer lists.

Information Security Officer's Assistant (ISOA)

Overview — The Information Security Officer's Assistant (ISOA) is a real-time security monitor implemented on a UNIX-based workstation that supports automated as well as interactive audit trail analysis [12, 13]. This monitor provides a sys-

tem for the timely correlation and merging of disjoint details into an assessment of the current security status of users and hosts on a network. The audit records, which are indicators of actual events, are correlated with known indicators (i.e., expected events) organized in hierarchies of concern, or security status.

ISOA's analysis capabilities include both statistical as well as expert system components. These components cooperate in the automated examination of various "concern levels" of data analysis. As recognized indicators (sets of indicators) are matched, concern levels increase and the system begins to analyze increasingly detailed classes of audit events for the user or host in question.

System Organization — The monitoring of events that do not constitute direct violation of the security policy requires a means to specify expected behavior on a user and host basis. The expected behavior can be represented in profiles that specify thresholds as well as associated reliability factors for discrete events. The observed events can then be compared to expected measures, and deviations can be identified by statistical checks of expected versus actual behavior. ISOA profiles also include a historical abstract of monitored behavior (e.g., a record of how often each threshold was violated in the past), and inferences that the expert system has made about the user. Hosts as well as individual users are monitored.

Events that cannot be monitored by examining thresholds make it necessary to effect a higher-order analysis that is geared towards correlating and resolving the meaning of diverse events. The expert system analysis component can specify the possible relationships and implied meaning of diverse events using its rule-base. Where statistical measures can quantify behavior, the rule-based analysis component can answer conditional questions based on sets of events.

System Operation — The underlying processing model of ISOA consists of a hierarchy of concern levels constructed from indicators. Analysis is structured around these indicators to build a global view of the security status for each monitored user and host. The indicators allow modeling and identification of various classes of suspicious behavior, such as aggregator, imposter, misfeasor, etc.

Two major classes of measures are defined: real-time and session. The real-time measures require immediate analysis, while session measures require (at minimum) start-of-session and end-of-session analysis.

ISOA supports two classes of anomaly detection: preliminary and secondary. Preliminary anomaly detection takes place during the collection of the audit data (i.e., in real time). Predetermined events trigger an investigation of the current indicator or event of interest. If further analysis is warranted, the current parameters are checked against the profiles for real-time violations or deviations from expected behavior.

Secondary anomaly detection is invoked at the end of a user login session or when required for resolution. The current session statistics are checked against the profiles, and session exceptions are determined.

When the expert system is notified that the state of indicators has changed significantly, it attempts to resolve the meaning of the current state of indicators. This is done by evaluating the appropriate subset of the overall rule-base, which consists of a number of individual rules that relate various indicator states with one another and with established threat profiles. The end result of anomaly resolution is presented to the SSO in the form of a graphical alert, an advice, and an explanation as to why the current security level is appropriate.

Multics Intrusion Detection and Alerting System (MIDAS)

Overview — The Multics Intrusion Detection and Alerting System (MIDAS) is an expert system which provides real-time intrusion and misuse detection for the National Computer Security Center's networked mainframe, Dockmaster, a Honeywell DPS-8/70 Multics computer system [14].

MIDAS has been developed to employ the basic concept that statistical analysis of computer system activities can be used to characterize normal system and user behavior. User or system activity that deviates beyond certain bounds should then be detectable.

System Organization — MIDAS consists of several distinct parts. Those implemented on Dockmaster itself include the command monitor, a preprocessor, and a network-interface daemon. Those that are installed on a separate Symbolics Lisp machine include a statistical database, a MIDAS knowledge base, and the user interface.

The command monitor captures command execution data that is not audited by the Multics system, the preprocessor transforms Dockmaster audit log entries into a canonical format, and the network-interface daemon controls communications. The statistical database records user and system statistics, the knowledge base consists of a representation of the current fact base and rule-base, and the user interface provides communication between MIDAS and the SSO.

An expert system utilizes a forward-chaining algorithm with four tiers (generations) of rules. The firing of some combination of rules in one tier can cause the firing of a rule in the next tier. The higher the tier, the more specific the rules become in regards to the possibility of attacks.

MIDAS keeps user and system-wide statistical profiles that record the aggregation of monitored system activity. The user's (system's) current session profile is compared to the historical profile to determine whether or not the current activity is outside two standard deviations.

System Operation — The logical structure of MIDAS revolves around the rules (heuristics) contained in the rule-base. There are currently three different types of rules which MIDAS employs to review audit data.

1) Immediate Attack. These rules examine a small number of data items without using any kind of statistical information. They are intended to find only those auditable events that are, by themselves, abnormal enough to raise suspicion.

2) User Anomaly. These rules use statistical profiles to detect when a user's behavior profile deviates from previously-observed behavior patterns. User profiles are updated at the end of a user's session if the behavior has changed significantly, and are maintained for each user throughout the life of the account.

MIDAS has been developed to employ the basic concept that statistical analysis of computer system activities can be used to characterize normal system and user behavior.

Wisdom and Sense is an anomaly detection system that operates on a Unix (IBM RT/PC) platform and analyzes audit trails from VAX/VMS hosts.

3) System State. These rules are similar to the user anomaly rules, but depict what is normal for the entire system, rather than for single users.

Wisdom and Sense

Overview — Wisdom and Sense (W&S) is an anomaly detection system developed at the Los Alamos National Laboratory [15]. It operates on a UNIX (IBM RT/PC) platform and analyzes audit trails from VAX/VMS hosts. It is an anomaly detection system which seeks to identify system usage patterns which are different from historical norms. It can process audit trail records in real time, although it is hampered by the fact that the operating system may delay writing the audit records.

The objectives of W&S are to detect intrusions, malicious or erroneous behavior by users, Trojan horses, and viruses. The system is based on the presumption that such behavior is anomalous and could be detected by comparing audit data produced by them with that of routine operation.

System Organization — W&S is a statistical, rule-based system. One of its major features is that it derives its own rule-base from audit data. It receives historical audit data from the operating system and processes it into rules. These rules are formed into a forest (i.e., a set of trees). The rules are human-readable, and thus the rule-base may be supplemented or modified by a human expert to correct deficiencies and inconsistencies. The rules define patterns of normal behavior in the system. A W&S rule-base may contain between 10^4 and 10^6 rules, which take 6 to 8 bytes each, and can be searched in about 50 ms. A typical generation of the rule-base takes less than an hour on an inexpensive workstation.

W&S views the universe as a collection of events, each represented by an audit record. Audit log records contain data about the execution of individual processes. Each record consists of a number of fields which contain information such as the invoker (user), the name of the process, its privileges, and system resources utilized.

Data is viewed primarily as categorical, i.e., any field in a record can take one of a number of values. Categorical data is represented as character strings. Continuous data, such as CPU time, is mapped into a set of closed ranges, and then treated as categorical data.

System Operation — **1) Rules.** Rules consist of a left-hand side (LHS), which specifies the conditions under which the rule applies; and a right-hand side (RHS) (also referred to as the rule's restriction), which defines what is considered normal under these conditions. The absence of a rule means that everything is considered normal.

The LHS could consist of field values or value ranges, values computed from a series of records (e.g, mean time between events), or subroutines returning a Boolean value. A given rule fires only if an audit record has fields whose values match the LHS and if any subroutines in the LHS return true.

The RHS may take the form of a list of acceptable categorical values for a record field, a list of acceptable ranges of a continuous field, and a list of user-defined functions. Each rule has a grade, which is a measure of its accuracy. Rules which are more specific, or which represent frequently-occurring patterns with less variability, are given better (i.e., higher) grades.

2) Constructing the Rule-Base. The historical data is first condensed, and then processed through the rule-base generator, which builds the forest of rule trees. At each level, the rule-base consists of nodes designating fields, and nodes designating acceptable values of each field. The rules are generated by repeatedly sorting the data and examining the frequency of field values. The tree is pruned as it is being built by using a number of pruning rules to limit its size.

3) Audit Data Analysis. The "Sense" part of W&S analyzes an activity file using the rule forest. It looks at a record, finds the applicable rules, and computes a figure of merit (FOM) for each field and each transaction. A transaction's FOM is the normalized sum of the grades of failed rules.

A number of transactions may be grouped to form a *thread*. Each thread belongs to a *thread class* that is defined by values of specific audit record fields. Some of the thread classes that are used include: each user-terminal combination, each program-user combination, and each privilege level. A set of operations may be defined for each thread class and carried out whenever a record in the class is processed. A FOM is computed for each thread as a time-decayed sum of the FOM's of its transactions. A transaction, or a thread, is considered anomalous if its FOM is above a predefined threshold.

The Sense module also provides an interactive interface to the configuration settings, rule-base maintenance routines, and analysis tools. W&S offers several aids to the task of explaining the meaning and cause of anomalous events. It has undergone operational testing and has detected interesting anomalies even in data originally thought to be free of such events.

Other Related Work

Additional related work can be found in the literature. Some are worth mentioning even though they may not fit in cleanly with our definition of an intrusion detection system. Recall that an IDS performs passive monitoring of computing resource usage, without changing the system's services per se.

The AT&T Dragons Approach — The AT&T Bell Labs work [19, 20] deviates from the above definition of an IDS because it replaces standard servers by a variety of trap programs that look for attacks. However, this approach is relevant because it can detect intruders; study the attackers' strategies, tools, and techniques; and alert the SSO accordingly. Specifically, these "proxy servers" are implemented on AT&T Bell Labs' Internet security gateway `research.att.com`. Except for some servers such as mail, FTP, and telnet, other services are replaced by "dummy servers." (This is partly justified by the widespread existence of security problems in current Internet software [21].) Some of these dummies are "packet suckers" while others are quite specialized. All such servers log the incoming request, attempt to trace it back (namely, employ counter-intelligence approaches to learn more about the source of the attack, e.g., via reverse fingers), and try to distinguish between legitimate users and outside attackers. These

tools have detected a variety of attacks from simple doorknob-rattling (such as guest login) to the more determined (e.g., forged NFS packets). Finally, an interesting chronicle on how an attacker is lured into the machine and how his actions are studied can be found in [20].

Signature Analysis — Some generic approaches for representing and detecting "attack signatures" have been reported [22-24]. One of these methods [22] employs sequential rules that characterize a user's behavior over time. A rulebase stores patterns of user activity, e.g., a rule can characterize the sequential relationship between security-relevant audit records. The rules can be static (based on security policy) or dynamic (based on time-based inductive learning techniques). Anomalies are detected whenever a user's activity deviates significantly from those specified in the rules. The main strength of this approach is that it allows adjacent security events to be correlated.

Clustering Techniques — Many of the IDSs discussed above rely on features of system and user behavior as inputs to their analysis algorithms which then determine the likelihood of an intrusion. The choice of these features is quite arbitrary and is based solely on the experience of an expert. A very relevant problem, called "clustering," is to determine important features to be used in an effective IDS design. This approach could be based upon an investigation of the experimentally-derived effectiveness of the features at classifying users as attackers and non-attackers [25, 26].

Network-Based Intrusion Detection Systems

ISOA and IDES

Early IDS models were designed to support a single host. However, more recent models accommodate the monitoring of a number of hosts interconnected by a network, e.g., ISOA and IDES. These systems (ISOA and IDES) transfer the monitored information (host audit trails) from multiple monitored hosts to a central site for processing. They employ the same algorithms as in the host-based systems. They do not monitor any network traffic.

Network Anomaly Detection and Intrusion Reporter (NADIR)

Overview — Network Anomaly Detection and Intrusion Reporter (NADIR) is a misuse detection system designed for Los Alamos National Laboratory (LANL)'s Integrated Computing Network (ICN) [16]. It is an automated expert system, which streamlines and supplements the manual audit record review performed by the SSO. NADIR compares weekly network activity of individual users and the ICN as a whole, against expert rules that define security policy and improper or suspicious behavior. It reports suspicious behavior to the SSO, and provides tools to allow the SSO to perform followup investigations.

System Organization — The ICN is LANL's main computer network. It serves nearly 9,000 users and includes computing equipment from supercomputers to terminals, each of which connect to an ICN port. An ICN port belongs to one of four partitions, each defined to operate at a certain security level. That is, a computer can access other computers in its partition or in partitions in lower (less secure) levels. The partitions are linked via a system of dedicated service nodes, namely, Network Security Controller (NSC) that provides user authentication and access control on ICN; Common File System (CFS) that stores data from each partition separately and guards against users in lower-partition machines accessing files stored in higher-partition machines; and Security Assurance Machine (SAM) that authenticates and records all attempts to down-partition files within CFS.

NSC, CFS, and SAM send raw audit records in "home-grown" format to NADIR, which is run on a SUN SPARCstation II. NADIR is implemented using the Sybase relational database management system.

System Operation — NADIR receives raw audit records from NSC, CFS, and SAM, and it generates weekly summaries of both individual user activity and aggregate ICN activity. (An example raw audit record from NSC would contain the partition and ICN number of the machine from which the authentication attempt is generated, plus the partition, classification level, and network component that the user wishes to access.) NADIR has a set of built-in expert rules for misuse detection; these rules are developed through audit analysis and consultation with security experts. NADIR compares weekly summaries with these rules, and assigns a "level-of-interest" to each rule that is triggered. A user's suspicion level is the sum of the level-of-interest of all rules it triggers. NADIR graphically shows its weekly reports on network usage, and it also highlights the most suspicious users. It can also provide more detailed reports on raw or profiled audit data to assist the SSO.

Network Security Monitor (NSM)

Overview (Advantages of Monitoring Network Traffic) — The Network Security Monitor (NSM) has been developed at the University of California, Davis. The NSM is different from the IDSs discussed earlier in that it does not analyze audit trails [17, 27-29]. The NSM analyzes traffic on a broadcast LAN to detect intrusive behavior. The reasons for this departure from the standard intrusion detection methods are outlined below.

First, although most IDSs are designed with the goal of supporting a number of different operating system platforms, all present audit-trail-based IDSs have only been used on a single operating system at any one time. These systems are usually designed to transform an audit log into a proprietary format used by the IDS [5, 9, 14]. In theory, audit logs from different operating systems need only to be transformed into this proprietary form for the IDS to perform its analysis. An IDS that can simultaneously support multiple operating systems is desirable. On the other hand, standard network protocols exist, e.g., TCP/IP and UDP/IP, which most major operating systems support and use. By using these network standards, the NSM can monitor a heterogeneous set of hosts and operating systems simultaneously.

Network Anomaly Detection and Intrusion Reporter is an automated expert system that streamlines and supplements the manual audit record review performed by the SSO.

Component	Description
Connection_ID	Unique integer used to reference this particular connection.
Initiator_address	The internet address of the host which initiated the connection.
Receiver_address	The internet address of the host to which the connection was made.
Service	An integer used to identify the particular service (i.e., telnet or mail) used for this connection.
Start_time	The time stamp on the first packet received for this connection.
Delta_time	The difference between the time stamp of the most recent packet of this connection and the Start_time.
Connection_state	The state of the connection. States for a connection include information such as: NEW-CONNECTION, CONNECTION-IN-PROGRESS, and CONNECTION-CLOSED.
Security_state	The current evaluation of the security state of this connection.
Initiator_pkts	The number of packets the host which initiated the connection has placed on the network.
Initiator-bytes	The number of bytes, excluding protocol headers, contained in the packets.
Reciever_pkts	The number of packets the host which received the connection has placed on the network.
Receiver_bytes	The number of bytes, excluding protocol headers contained in the packets.
Dimension	The dimension of the Initiator_X and the Receiver_X vectors. This value is the number of strings patterns being looked for in the data.
Initiator_X	A vector representing the number of strings matched in Initiator_bytes.
Receiver_X	A vector representing the number of strings matched in Receiver_bytes.

■ **Table 1.** *Connection vector.*

Second, audit trails are often not available in a timely fashion. Some IDSs are designed to perform their analysis on a separate host, so the audit logs must be transferred from the source host to a different machine for data analysis [5]. Furthermore, the operating system can often delay the writing of audit logs by several minutes [15]. The broadcast nature of a LAN, however, gives the NSM nearly-instant access to all data as soon as this data is transmitted on the network. It is then possible to immediately start the attack detection process.

Third, the audit trails are often vulnerable. In some past incidents, the intruders have turned off audit daemons or modified the audit trail. This action can either prevent the detection of the intrusion, or it can remove the capability to perform accountability (who turned off the audit daemons?) and damage control (what was seen, modified, or destroyed?) The NSM, on the other hand, passively listens to the network, and is therefore logically protected from subversion. Since the NSM is invisible to the intruder, it cannot be turned off (assuming it is physically secured), and the data it collects cannot be modified.

Fourth, the collection of audit trails degrades the performance of a machine being monitored (typically between 5 and 20 percent). Unless audit trails are being used for accounting purposes, system administrators often turn off auditing. If analysis of these audit logs is also to be performed on the host, added degradation will occur. If the audit logs are transferred across a network or a communication channel to a separate host for analysis, loss of network bandwidth as well as loss of timeliness of the data will occur. In many environments, the degradation of monitored hosts or the loss of network bandwidth may discourage administrators from using such an IDS. The alternative, namely, the NSM architecture, does not degrade the performance of the hosts being monitored. The monitored hosts are not aware of the NSM, so the effectiveness of the NSM is not dependent on the system administrator's configuration of the monitored hosts.

And, finally, many of the more seriously documented cases of computer intrusions have utilized a network at some point during the intrusion, i.e., the intruder was physically separated from the target. With the continued proliferation of networks and interconnectivity, the use of networks in attacks will only increase. Furthermore, the network itself, being an important component of a computing environment, can be the object of an attack. The NSM can take advantage of the increase of network usage to protect the hosts attached to the networks. It can monitor attacks launched against the network itself, an attack that host-based audit trail analyzers would probably miss.

System Organization (The NSM Model) — The NSM models the network and hosts being monitored in a hierarchically-structured Interconnected Computing Environment Model (ICEM). The ICEM is composed of six layers, the lowest being the bit stream on the network, and the highest being a representation for the state of the entire networked system.

The bottom-most, or first, layer is the packet layer. This layer accepts as input a bit stream from a broadcast LAN, e.g., Ethernet. The bit stream is divided up into complete Ethernet packets, and a time stamp is attached to the packet. This time-augmented packet is then passed up to the second layer. Application of the NSM to other LAN environments is straightforward.

The next layer, called the thread layer, accepts as input the time-augmented packets from the packet layer. These packets are then correlated into unidirectional data streams. Each stream consists of the data (with the different layers of protocol headers removed) being transferred from one host to another host by a particular protocol (e.g., TCP/IP or UDP/IP), through a unique set (for the particular set of hosts and protocol) of ports. This stream of data, called a thread, is mapped into a thread vector. All the thread vectors are passed up to the third layer.

The connection layer, which is the third layer, accepts as input the thread vectors generated by the thread layer. Each thread vector is paired, if possible, to another thread vector to represent a bidirectional stream of data (i.e., a host-to-host connection). These pairs of thread vectors are represented by a connection vector generated by the

combination of the individual thread vectors. Each connection vector is analyzed, and a reduced representation, a reduced connection vector, is passed up to the fourth layer.

Layer 4 is the host layer, which accepts as input the reduced connection vectors generated by the connection layer. The connection vectors are used to build host vectors. Each host vector represents the network activities of a single host. These host vectors are passed up to the fifth layer.

The connected-network layer is the next layer in the ICEM hierarchy. It accepts as input the host vectors generated by the host layer. The host vectors are transformed into a graph G by treating the `Data_path_tuples` of the host vectors as an adjacency list. If G(host1,host2,serv1) is not empty, then there is a connection, or path, from host1 to host2 by service serv1. The value for location G(host1,host2,serv1) is non-empty if the host vector for host1 has (host2,serv1) in its `Data_path_tuples`. This layer can build the connected sub-graphs of G, called a connected-network vector, and compare these sub-graphs against historical connected sub-graphs. This layer can also accept questions from the user about the graph. For example, the user may ask if there is some path between two hosts — through any number of intermediate hosts — by a specific service. This set of connected-network vectors is passed up to the sixth and final layer.

The top-most layer, called the system layer, accepts as input the set of connected-network vectors from the connected-network layer. The set of connected-network vectors is used to build a single system vector representing the behavior of the entire system.

System Operation (Detecting Intrusive Behavior) — The traffic on the network is analyzed by a simple expert system. The types of inputs to the expert system are described below.

The current traffic cast into the ICEM vectors as discussed above is the first type of input. Currently, only the connection vectors and the host vectors are used. The components for these vectors are presented in Tables I and II.

The profiles of expected traffic behavior are the second type of input. The profiles consist of expected data paths (namely, which systems are expected to establish communication paths to which other systems, and by which service?) and service profiles (namely, what is a typical telnet, mail, finger, etc., expected to look like?) Combining profiles and current network traffic gives the NSM the ability to detect anomalous behavior on the network.

The knowledge about capabilities of each of the network services is the third type of input (e.g., telnet provides the user with more capability than FTP does).

The level of authentication required for each of the services is the fourth type of input (e.g., finger requires no authentication, mail requests authentication but does not verify it, and telnet requires verified authentication).

The level of security for each of the machines is the fifth type of input. This can be based on the National Computer Security Center (NCSC) rating of machines, history of past abuses on different machines, rating received after running system evaluation software such as Security Profile Inspector (SPI) [30] or COPS, or simply which machines the SSO has some control over and which machines the SSO has no control over (e.g., a host from outside the monitored LAN environment would fall in the second category).

Component	Description
Host_ID	Unique integer used to reference this particular host.
Host_address	The internet address of this host.
Host_state	The state of the host. States include: ACTIVE, NOT_ACTIVE.
Security_state	The current evaluation of the security of this particular host.
Data_path_number	The number of data paths the currently connected to this host. It may be considered the number of arcs from a node in a graph.
Data_path_tuples	A list of four-tuple representing a data path from or to the host. The tuple consists of: Other_host_address, Service_ID, Initiator_tag, and Security_state (of the data path).

■ **Table 2.** *Host vector.*

The sixth type of input is signatures of past attacks.

The data from these sources is used to identify the likelihood that a particular connection represents intrusive behavior, or if a host has been compromised. The `security_state`, or suspicion level, of a particular connection is a function of four factors: the abnormality of the connection, the security level of the service being used for the connection, the direction of the connection sensitivity level, and the matched signatures of attacks in the data stream for that connection. We elaborate on these components of the `security_state` in the following paragraphs.

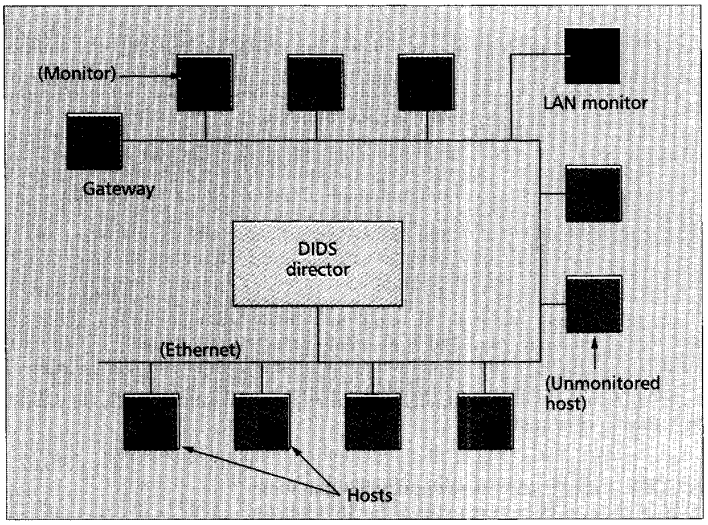
The abnormality of a connection is based on the probability of that particular connection occurring and the behavior of the connection itself. If a connection from host A to host B by service C is rare, then the abnormality of that connection is high. Furthermore, if the profile of that connection compared to a typical connection by the same type of service is unusual (e.g., the number of packets or bytes is unusually high in one direction for a FTP connection), the abnormality of that connection is high.

The security level of the service is based on the capabilities of that service and the authentication required by that service. The TFTP service, for example, has great capabilities with no authentication, so the security level for TFTP is high. The telnet service, on the other hand, also has great capabilities, but it also requires strong authentication. Therefore, the security level for telnet is lower than that of TFTP.

The direction of connection sensitivity level is based on the sensitivity levels of the two machines involved and on which host initiated the connection. If a low-sensitivity-level host connects to or attempts to connect to a high-sensitivity-level host, the direction of connection sensitivity level of that connection is high. On the other hand, if a high-sensitivity-level host connects to a low-level host, the direction of connection security level is low.

The matched signatures of attacks consist of the vectors `Initiator_X` and `Receiver_X`, which are simply lists of counts for the number of times some predetermined strings being searched for in the data is matched.

The connection vectors are essentially treated as



■ **Figure 1.** *DIDS target environment*

records in a database, and presentation of the information may be made as simple requests into the database. The default presentation format sorts the connections by suspicion level and presents the sorted list from highest suspicion level to the lowest. Presentations can also be made by specifying time windows for connection, connections from a specific host, connections with a particular string matched, etc.

The `security_state`, or suspicion level, of a host is simply the maximum `security_state` of its connection vectors over a particular window of time. The host vectors are also treated as records into a database, and they may be presented in a similar fashion as the connection vectors.

The NSM prototype has been deployed at UC Davis, Lawrence Livermore National Laboratory, and other DOE and Air Force sites. During a particular two-month test period, the NSM analyzed more than 111,000 connections on the Computer Science LAN segment at UC Davis, and it correctly identified more than 300 of these connections as intrusive. These security incidents spanned more than 40 different computers, at least four different hardware platforms, and at least six OS types. The majority of these incidents were associated with attempted break-ins, and some were successful as well. Additional incidents include stealing of password files, running of password crackers on password files, accessing of closed accounts by ex-students, reading of other people's mail, looking around in other people's directories, and using other people's accounts. It should be remarked that approximately only one percent of these security incidents were detected independently by the system administrators.

Distributed Intrusion Detection System (DIDS)

Overview — The Distributed Intrusion Detection System (DIDS) is a joint project between UC Davis, Lawrence Livermore National Laboratory, Haystack Laboratory, and the US Air Force [31, 32]. It is an outgrowth of the NSM project. DIDS is designed to guard against some of NSM's deficiencies, e.g., the NSM cannot monitor an attacker who enters a system via a dial-up line and hence may not generate any network activity and the NSM can be spoofed via encrypted traffic. Also, one would like to extend the network intrusion detection concept from the LAN environment to arbitrarily wider areas with the network topology being arbitrary as well.

In DIDS, each host in the monitored domain is also equipped with a host monitor. In the current DIDS design, these hosts are assumed to be connected via a LAN, which is monitored by a LAN monitor. Thus, network monitor data is augmented by data from monitored hosts. Generalization of the monitored environment beyond the local area is an open problem, and a preliminary design has been proposed [33].

In DIDS, the host and LAN monitors report any "interesting" events, which may possibly lead to intrusive activity, to a centrally-located DIDS director. The director employs an expert system to detect possible attacks. An initial prototype of DIDS has successfully demonstrated its ability to track users as they move around the network (possibly attempting to hide their true identities) and to identify doorknob rattling attacks [32, 34]. The DIDS architecture performs information aggregation so that even if the activity of a network-wide user may not be suspicious on a single host, the aggregate behavior may be suspect or unpermitted. One of the strengths of this architecture is that it performs "accountability" by tying users with their actions.

System Organization — The generalized distributed environment is heterogeneous, i.e., the network nodes can be hosts or servers from different vendors (Fig. 1). The DIDS architecture combines distributed monitoring and data reduction with centralized data analysis. This approach is unique among current IDSs. The components of DIDS are the DIDS director, a single host monitor per host, and a single LAN monitor for each broadcast LAN segment in the monitored network. DIDS can potentially handle hosts without monitors since the LAN monitor can report on the network activities of such hosts. The host and LAN monitors are primarily responsible for the collection of evidence of unauthorized or suspicious activity, while the DIDS director is primarily responsible for its evaluation. Reports are sent independently and asynchronously from the host and LAN monitors to the DIDS director through a communications infrastructure (Fig. 2). High-level communication protocols between the components are based on the ISO Common Management Information Protocol (CMIP) recommendations, allowing for future inclusion of CMIP management tools as they become useful. The architecture also provides for bidirectional communication between the DIDS director and any monitor in the configuration. This communication consists primarily of notable events and anomaly reports from the monitors. The director can also make requests for more detailed information from the distributed monitors via a `GET` directive, and issue commands to have the distributed monitors modify their monitoring capabilities via a `SET` directive. A large amount of low-level filtering and some analysis is performed by the host monitor to minimize the use of network bandwidth in passing evidence to the director.

The host monitor consists of a host event generator (HEG) and a host agent. The HEG collects and analyzes audit records from the host's operating system. The audit records are scanned for notable events,

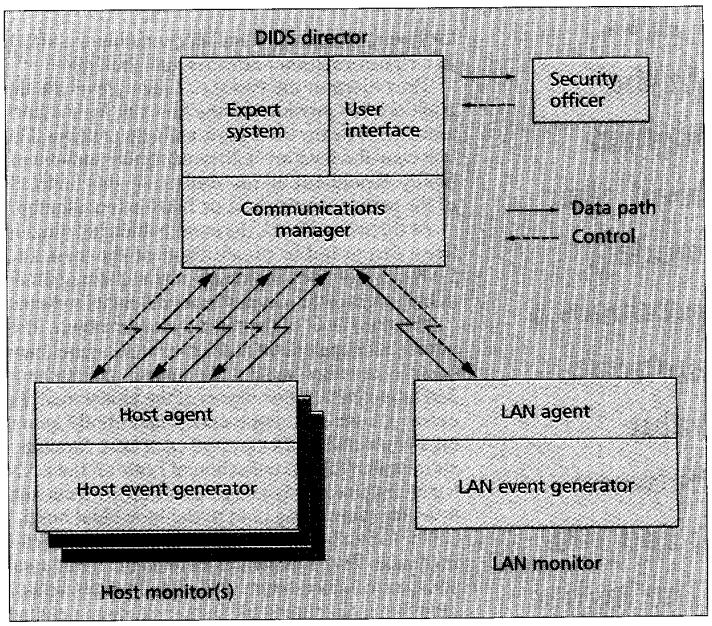
which are transactions that are of interest independent of any other records. These include, among others, failed events, user authentications, changes to the security state of the system, and any network access such as `rlogin` and `rsh`. These notable events are then sent to the director for further analysis. The HEG also tracks user sessions and report anomalous behavior aggregated over time through user and group profiles and the integration of the HAYSTACK intrusion detection algorithm [5] into DIDS. The host agent handles all communications between the host monitor and the DIDS director.

Like the host monitor, the LAN monitor consists of a LAN event generator (LEG) and a LAN agent. The LEG is currently a subset of the NSM [17, 27, 29]. Its main responsibility is to observe all of the traffic on its segment of the LAN in order to monitor host-to-host connections, services used, and volume of traffic. The LAN monitor reports on network activities such as `rlogin` and telnet connections, the use of security-related services, and changes in network traffic patterns.

The DIDS director consists of three major components that are all located on the same dedicated workstation — a communications manager, an expert system, and a user interface. Because the components are logically independent processes, they could be distributed as well. The communications manager is responsible for the transfer of data between the director and each of the host and the LAN monitors. It accepts the notable event records from each of the host and LAN monitors and sends them to the expert system. On behalf of the expert system or user interface, it is also able to send requests to the host and LAN monitors for more information regarding a particular user. The expert system is responsible for evaluating and reporting on the security state of the monitored system. It receives the reports from the host and the LAN monitors, and, based on these reports, it makes inferences about the security of each individual host, as well as the system as a whole. The expert system is a rule-based system with simple learning capabilities. The director's user interface allows the SSO interactive access to the entire system. The SSO can watch activities on each host, watch network traffic (by setting "wiretaps"), and request more specific types of information from the monitors.

It is anticipated that a growing set of tools, including incident-handling tools and network-management tools, will be used in conjunction with the intrusion-detection functions of DIDS. This will give the SSO the ability to actively respond to attacks against the system in real time. Incident-handling tools may consist of possible courses of action to take against an attacker, such as cutting off network access, a directed investigation of a particular user, removal of system access, etc. Network-management tools that are able to perform network mapping would also be useful.

System Operation — **1) The Network-user Identification (NID)** One of the challenges for intrusion detection in a networked environment is to track users and objects (e.g., files) as they move across the network. For example, an intruder may use several different accounts on different machines during the course of an attack. Correlating data from several independent sources, including the network itself, can aid in recognizing this type of behavior and in tracking an intruder to his source. In a networked



■ **Figure 2.** *Communications architecture.*

environment, an intruder may often choose to employ the interconnectivity of the computers to hide his true identity and location. It may be that a single intruder uses multiple accounts to launch an attack, and that the behavior can be recognized as suspicious only if one knows that all of the activity emanates from a single source. For example, it is not particularly noteworthy if a user inquires about who is using a particular computer (e.g., using the UNIX `who` or `finger` command). However, it may be indicative of an attack (or a preparation of an attack) if a user inquires about who is using each of the computers on a LAN and then subsequently logs into one of the hosts. Detecting this type of behavior requires attributing multiple sessions, perhaps with different account names, to a single source.

This problem is unique to the network environment and has not been dealt with before in this context. The solution to the multiple user identity problem is to create a network-user identification (NID) the first time a user enters the monitored environment, and then to apply that NID to any further instances of the user [34]. All evidence about the behavior of any instance of the user is then accountable to the single NID. In particular, we must be able to determine that `smith@host1` is the same user as `jones@host2`, if in fact they are. Since the NID problem involves the collection and evaluation of data from both the host and LAN monitors, examining it is a useful method to understand the operation of DIDS.

2) The Expert System. DIDS utilizes a rule-based (or production) expert system written in CLIPS. The expert system uses rules derived from a hierarchical Intrusion Detection Model (IDM). The IDM describes the transformation from the distributed raw audit data to high-level hypotheses about intrusions and about the overall security of the monitored environment. This unified view of the distributed system simplifies the recognition of intrusive behavior that spans individual hosts. The model is the basis of the rule-base. The IDM consists of

At the highest level, the model produces a numeric value between 1 and 100. The higher the number, the less secure is the network.

six layers, with each layer representing the result of a transformation performed on the data.

The objects at the first (i.e., lowest) level are the audit records provided by the host OS, by the LAN monitor, or by any third-party auditing package. The objects at this level are both syntactically and semantically dependent on the source. At this level, all of the activity on the host or LAN is represented.

At the second level, the *event* (which has already been discussed in the context of the host and LAN monitor) is both syntactically and semantically independent of the source standard format for events.

The third layer of the IDM creates a subject. This introduces a single identification for a user across many hosts on the network. It is the subject who is identified by the NID. Upper layers of the model treat the network-user as a single entity, essentially ignoring the local identification on each host. Similarly, above this level, the collection of hosts on the LAN is generally treated as a single distributed system with little attention being paid to the individual hosts.

The fourth layer of the model introduces the event in context. There are two kinds of context: temporal and spatial. As an example of temporal context, behavior which is unremarkable during standard working hours may be suspicious during off-hours [35]. The IDM, therefore, allows for the application of information about wall-clock time to the events it is considering. Wall-clock time refers to information about the time of day, weekdays versus weekends and holidays, as well as periods when an increase in activity is expected. In addition to the consideration of external temporal context, the expert system uses time windows to correlate events occurring in temporal proximity. This notion of temporal proximity implements the heuristic that a call to the UNIX `who` command followed closely by a `login` or `logout` is more likely to be related to an intrusion than either of those events occurring alone. Such related patterns of behavior are also referred to as attack signatures [23, 24]. Spatial context implies the relative importance of the source of events. That is, events related to a particular user, or events from a particular host, may be more likely to represent an intrusion than similar events from a different source. For instance, a user moving from a low-security machine to a high-security machine may be of greater concern than a user moving in the opposite direction. The model also allows for the correlation of multiple events from the same user or source. In both of these cases, multiple events are more noteworthy when they have a common element than when they do not.

The fifth layer of the model considers the *threats* to the network and the hosts connected to it. Events in context are combined to create threats. The threats are partitioned by the nature of the abuse and the nature of the target. In other words, what is the intruder doing, and what is he doing it to? Abuses are divided into *attacks*, *misuses*, and *suspicious acts*. Attacks represent abuses in which the state of the machine is changed. That is, the file system or process state is different after the attack than it was prior to the attack. Misuses represent out-of-policy behavior in which the state of the machine is not affected. Suspicious acts are events which, while not a violation of policy, are of interest to an IDS. For example, commands which provide information about the state of the system may be suspicious. The targets of abuse are characterized as being either system objects or user objects and as being either passive or active. User objects are owned by non-privileged users and/or reside within a non-privileged user's directory hierarchy. System objects are the complement of user objects. Passive objects are files, including executable binaries, while active objects are essentially running processes.

At the highest level, the model produces a numeric value between one and 100 which represents the overall security state of the network. The higher the number, the less secure is the network. This value is a function of all the threats for all the subjects on the system. Here again we treat the collection of hosts as a single distributed system. Although representing the security level of the system as a single value seems to imply some loss of information, it provides a quick reference point for the SSO. In fact, in the current implementation, no information is lost since the expert system maintains all the evidence used in calculating the security state in its internal database, and the SSO has access to that database.

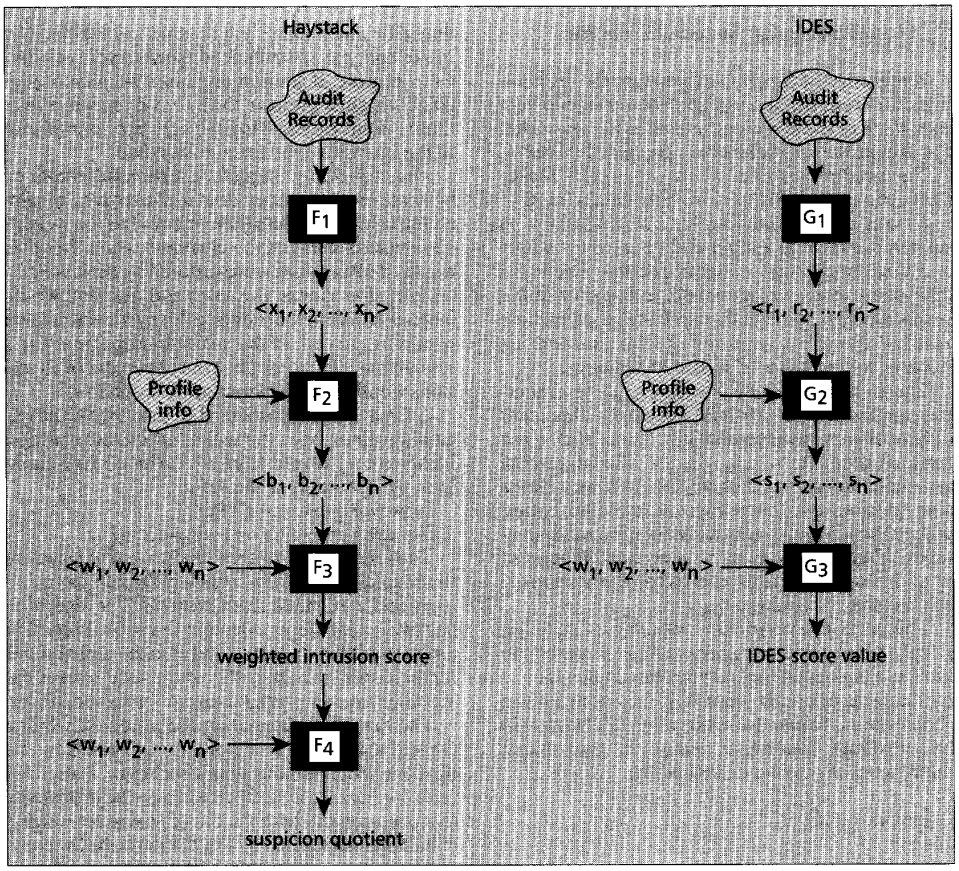
In the context of the NID problem, we are concerned primarily with the lowest three levels of the model: the audit data, the event, and the subject. The generation of the first two of these have already been discussed; the creation of the subject is the focus of the following subsection.

3) Building the NID. With respect to UNIX, the only legitimate ways to create an instance of a user are for the user to login from a terminal, a console, or an off-LAN source, to change the user-id in an existing instance, or to create additional instances (local or remote) from an existing instance. In each case, there is only one initial login (system-wide) from an external device. When this original login is detected, a new unique NID is created. This NID is applied to every subsequent action generated by that user. When a user with a NID creates a new login session, that new session is associated with his original NID. Thus, the system maintains a single identification for each physical user.

We consider an instance of a user to be the 4-tuple `<session_start, user-id, host-id, time>`. Thus each login creates a new instance of a user. In associating a NID with an instance of a user, the expert system first tries to use an existing NID. If no NID can be found which applies to the instance, a new one is created. Trying to find an applicable existing NID consists of several steps. If a user changes identity (e.g., using UNIX's `su` command) on a host, the new instance is assigned the same NID as the previous identity. If a user performs a remote login from one host to another host, the new instance gets the same NID as the source instance. When no applicable NID is found, a new unique NID is created.

The actual association of a NID with a user instance is through the hypothesis net_user. A new hypothesis is created for every event reported by the distributed monitors. This new hypothesis, called a subject, is formed by another rule. The rule creates a subject, getting the NID from the net_user and the remaining fields from the host audit record, if and only if both the user-id and the host-id match. It is through the use of the subject that the expert system correlates a user's actions regardless of the login name or host-id.

There is still some uncertainty involved with the NID problem. If a user leaves the monitored domain and then comes back in with a different user-id, it is not possible to connect the two instances. Similarly, if a user passes through an unmonitored



■ **Figure 3.** *Statistical intrusion detection algorithms.*

host, there is still uncertainty that any connection leaving the host is attributable to any connection entering the host. Multiple connections originating from the same host at approximately the same time also allow uncertainty if the user names do not provide any helpful information. The expert system can make a final decision with additional information from the host and LAN monitors that can (with high probability) disambiguate the connections. To deal with such situations, a new concept, called "thumbprinting," which is a mechanism for identifying identical network connections, is being developed [33].

Case Study: An Intrusion Detection Algorithm

The intrusion detection algorithm used in the HAYSTACK system is also the core of the host monitor used in DIDS. This algorithm is employed here as an example to demonstrate how a statistical anomaly detection algorithm typically operates.

The HAYSTACK algorithm (hereafter referred to as the algorithm) assumes that the audit trail generated from a host has been converted to a canonical audit trail (CAT) format. Even though different machines may generate audit data in different formats, they can still be served by the same intrusion detection algorithm by having their generated audit information converted to the CAT format. The algorithm examines a CAT file to generate session vectors representing the activities of the users' sessions (where a user session includes all activities between a login and a logout). These session vectors are then analyzed against specific types of intrusive activity, and "anomaly scores" for the sessions are calculated. When the scores cross some specific thresholds, warnings reports are generated. The analysis of the session vectors is the specific focus of our discussion here.

A user's activities are analyzed according to a four-step process. The first step is to generate a session vector representing the activities of the user for a particular session. The second step is the generation of a bernoulli vector representing the attributes which are out of range for a particular session. The third step is the generation of a weighted intrusion score, for a particular intrusion type, from the bernoulli vector and a weighted feature vector. The fourth step is the generation of the suspicion quotient representing how suspicious the algorithm believes this session to be when compared to all other sessions.

This four-step process is shown in Fig. 3. Boxes F_1 through F_4 represent the functions for each of the above processes. Fig. 3 also shows the steps G_1 through G_3 followed by the IDES statistically anomaly detection algorithm [11], and it indicates how the steps in the Haystack and the IDES algorithms parallel each other. We restrict our attention to the Haystack algorithm here. F_1, the generation of the session vector, is not covered. Functions F_2 through F_4 are discussed below.

■ ■ ■ ■ ■

The HAYSTACK algorithm assumes that the audit trail generated from a host has been converted to a canonical audit trail (CAT) format.

Intrusion detection is a viable and practical approach for providing a different notion of security in our huge and existing infrastructure of computer and network systems.

F_2: Generating the Bernoulli Vector

F_2 represents the function to generate the bernoulli vector from the session and the threshold vectors. Each of these vectors, as well as the algorithm to calculate the bernoulli vector, are described below.

The session vector $X = <x_1, x_2, \cdots, x_n>$ represents the counts for various attributes used to represent a user's activities for a single session. A session begins with a login audit record for a user and terminates with a logout record. The login and logout times are also included as part of the session vector. Some of the attributes used include session duration, number of files opened for reading, and number of secure I/O failures.

The threshold vector $T = <t_1, t_2, \cdots, t_n>$ represents the ranges for each attribute i in which 90 percent of historical measurements fall. Thus, each t_i is a tuple of the form $<t_{i,min}, t_{i,max}>$. The algorithm assumes that each of the t_i vectors follows a Gaussian distribution. In the current implementation of the algorithm, all measurements are actually one-tailed. That is, $t_{i,min}$ is set to 0, so that 90 percent of all historical measurements for the attribute i are less than or equal to $t_{i,max}$.

The bernoulli vector $B = <b_1, b_2, \cdots, b_n>$ is a simple binary vector representing which of the attribute counts fall outside the thresholds for the particular user group. That is, if the count for the i^{th} attribute x_i falls outside the range t_i, then b_i will be set to one; otherwise, b_i is set to zero. Thus, the function F_2 can be described by:

for $i \leftarrow 1$ n *do*

$$b_i = \begin{cases} 0 & t_{i,min} \le x_i \le t_{i,max} \\ 1 & otherwise \end{cases}$$

F_3: Generating the Weighted Intrusion Score

F_3 represents the function to generate the weighted intrusion score for a particular session and for a particular intrusion type. By itself, the weighted intrusion score is meaningless; however, with the knowledge of the distribution of the weighted intrusion scores for all sessions, this weighted intrusion score can be used to assign a suspicion value to the session. The weighted feature vector and the algorithm to calculate the weighted intrusion score are described below.

A weighted intrusion vector $W = <w_1, w_2, \cdots, w_n>$ exists for each group and intrusion type pair. Each w_i relates the importance of the i^{th} attribute to detecting the particular intrusion type. Therefore, if $w_i > w_j$, then the fact that the i^{th} attribute exceeds the threshold t_i is more useful in detecting the particular intrusion than the fact that the j^{th} attribute exceeds the threshold t_j.

The weighted intrusion score is simply the sum of all weights, w_i, where the i^{th} attribute exceeded its threshold t_i. Its value is given by:

$$\textit{weighted intrusion score} = \sum_{i=1}^{n} b_i * w_i$$

F_4: Generating the Suspicion Quotient

F_4 represents the function to calculate the suspicion quotient, or suspicion value, for a particular session and intrusion type. The suspicion quotient describes how closely a session resembles the intrusion type as compared to all other sessions. For example, if session one has a suspicion quotient which is greater than that of session two, then session one is said to have a greater resemblance to the intrusion type than session two.

The suspicion quotient for a session is determined by what percentage of random sessions have a weighted intrusion score less than or equal to the weighted intrusion score of the current session. In other words, if all sessions were ordered by their weighted intrusion scores, the suspicion quotient would indicate where in the ordering this particular session would be placed. If the suspicion quotient for a session was 97 percent, then only 3 percent of all sessions would be considered more suspicious.

A table can be generated to provide the suspicion quotient from the weighted intrusion score. Function F_4 would then be reduced to a table look-up operation of the form:

suspicion quotient = *TABLE*
[`weighted_intrusion_score`]

The following algorithm can be used to calculate the suspicion quotient from a weighted intrusion score and a weighted feature vector. The algorithm has two major steps: calculate the probability that a session will have a score j, and sum the probabilities for all scores $j \le$ *max_score*, where *max_score* is the maximum score any weighted intrusion score can have.

The first step, calculating the probability that a session will have a score of j, is performed by the dynamic programming algorithm below. It uses the table P where $P_{i,j}$ is interpreted to be the probability that a session will have a score of j using the weights of the first i attributes. $Pr_i(0)$ is defined to be the probability that the i^{th} attribute will be within its threshold (and thus $b_i * w_i = 0$). Similarly, $Pr_i(1)$ is the probability that the i^{th} attribute will be outside its threshold (and thus $b_i * w_i = w_i$), i.e., $Pr_i(1) = 1 - Pr_i(0)$. The parameters $\{Pr_i(0), i = 0, 1, \cdots, n\}$ are user selectable, and in the HAYSTACK system, they are all set to 0.9. The first step of the algorithm follows.

```
/* initialize the probability table */
P0,0 = 1.0
for j ← 1 to max_score do
    P0,j = 0.0
/* fill in the probability table */
for i ← 1 to n do
    for j ← 0 to max_score do
```

$$P_{i,j} = P_{i-1,j} * Pr_i(0) + P_{i-1,j-w_i} * Pr_i(1)$$

After the algorithm terminates, the table $P_{n,j}$ describes the probability that a random session will have a weighted intrusion score $= j$.

The second step of the algorithm calculates the probability that a random session's weighted intrusion score is less than or equal to the weighted intrusion score given. This is given by the equation

$$\textit{suspicion quotient} = \sum_{j=0}^{score} P_{n,j}$$

In summary, the intrusion detection algorithm outlined above analyzes a session vector in three steps: 1) it calculates a bernoulli vector, 2) it calculates the weighted intrusion score, and 3) it calculates the suspicion quotient.

Conclusion

Intrusion detection is a viable and practical approach for providing a different notion of security in our huge and existing infrastructure of (possible insecure) computer and network systems. Intrusion detection systems are based on host-audit-trail and network traffic analysis, and their goal is to detect attacks, preferably in real time. A number of prototype intrusion detection systems have been built, and this concept has been proven to be extremely promising.

In the future, it is expected that the current prototypes will be developed further in order to turn them into production-quality systems. Benchmarking mechanisms in order to test the effectiveness of IDSs should be developed. Accurate approaches for representing attacks and misuse (including development of models for new attack methods) as well as new and more-effective detection strategies must be investigated. In addition, much more research is expected to be conducted, e.g., how can the intrusion-detection concept be extended to arbitrarily large networks (e.g., the worldwide Internet), how can the IDS itself be protected from attackers, etc.

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Accurate approaches for representing attacks and misuse as well as new and more effective detection strategies must be investigated.