Visualization and Clustering for SNMP Intrusion Detection

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Abstract. Accurate intrusion detection still is an open challenge. Present work aims at being one step towards that purpose by studying the combination of clustering and visualization techniques. To do that, MOVICAB-IDS, previously proposed as a hybrid intelligent Intrusion Detection System (IDS) based on visualization techniques, is upgraded by adding automatic response thanks to clustering methods. To check the validity of the proposed clustering extension, it has been applied to the identification of different anomalous situations related to the SNMP network protocol by using real-life data sets. Different ways of applying neural projection and clustering techniques are studied in present work. Through the experimental validation it is shown that the proposed techniques could be compatible and consequently applied to a continuous network flow for intrusion detection.

Keywords: Network Intrusion Detection, Computational Intelligence, Exploratory Projection Pursuit, Clustering, k-means, Automatic Response.

1 Introduction

One of the most harmful issues of attacks and intrusions is the ever-changing nature of attack technologies and strategies, which increases the difficulty of protecting computer systems. For that reason, among others, Intrusion Detection Systems (IDSs) (Di Pietro and Mancini 2008) have become an essential asset in addition to the computer security infrastructure of most organizations. An IDS can roughly be defined as a tool designed to detect suspicious patterns that may be related to a network or system attack, in the context of computer networks. Intrusion Detection (ID) is therefore a field that focuses on the identification of attempted or ongoing attacks.

MOVICAB-IDS (MObile VIsualisation Connectionist Agent-Based IDS) was proposed (Herrero and Corchado 2009; Corchado and Herrero 2011) as a novel IDS comprising a Hybrid Artificial Intelligent System (HAIS). It monitored the network activity to identify intrusive events. This hybrid intelligent IDS combined different AI paradigms to visualize network traffic for ID at packet level. Its main goal was to provide security personnel with an intuitive and informative visualization of network traffic to ease intrusion detection. The proposed MOVICAB-IDS applied an unsupervised neural projection model to extract interesting traffic dataset projections and to display them through a mobile visualization interface. One of its main drawbacks was its dependence on human processing; MOVICAB-IDS could not automatically raise an alarm to warn about attacks. Hence, human supervision was required to identify the anomalous situations. Additionally, human users could fail to detect an intrusion even when visualized as an anomalous one.

In a computer network context, a protocol is a specification that describes low-level details of host-to-host interfaces or high-level exchanges between application programs. Among all the implemented network protocols, several can be considered highly dangerous in terms of network security. That is the case of SNMP (Simple Network Management Protocol) (Case et al. 1990; Davin, Galvin, and McCloghrie 1992), which was ranked as one of the top five most vulnerable services by CISCO (Vulnerability Statistics Report 2000). Specially the two first versions (Case et al. 1990; Case et al. 1993) of this protocol that still are the most widely used at present time. SNMP attacks were also listed by the SANS Institute as one of the top 10 most critical internet security threats (The Top 10 Most Critical Internet Security Threats (2000-2001 Archive) 2001; Northcutt et al. 2001). Those were the reasons for MOVICAB-IDS to be focused on the anomalous situations related to this protocol.

SNMP was oriented to manage nodes in the Internet community (Case et al. 1990). It is an application layer protocol that supports the exchange of management information (operating system, version, routing tables, default TTL, and so on) between network devices. This protocol enables network administrators to manage network performance and is used to control network elements such as routers, bridges, and switches. As a result, SNMP data are quite sensitive and liable to potential attacks. Indeed, an attack based on this protocol may severely compromise system security (Myerson 2002).

To overcome the limitations of MOVICAB-IDS, present work proposes the application of clustering techniques in conjunction with other mechanisms previously applied in MOVICAB-IDS. Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters). The clustering problem has been addressed in many contexts and by researchers in many disciplines; this reflects its broad appeal and usefulness as one of the steps in exploratory data analysis. The experimental study tries to know whether clustering could be more informative applied over the projected data rather than the original data captured from the network.

1.1 Related Previous Work

This section discusses previous work and the main contribution of the proposed system. Present work aims to provide automatic response to MOVICAB-IDS applying clustering methods. Clustering methods have been previously applied to intrusion detection: (Zheng, Xuan, and Hu 2011) proposes an alert aggregation method, clustering similar alerts into a hyper alert based on category and feature similarity. From a similar perspective, (Qiao et al. 2012) proposes a two-stage clustering algorithm to analyze the spatial and temporal relation of the network intrusion behaviors' alert sequence. (Jiang et al. 2006) describes a classification of network traces through an improved nearest neighbor method, while (Cui and Ieee 2012) applies data mining algorithms for the same purpose and the results of preformatted data are visually displayed. (Ge and Zhang 2012) discusses on how the clustering algorithm is applied to intrusion detection and analyses intrusion detection algorithm based on clustering problems.

The above mentioned studies apply clustering methods directly to raw network data whereas the proposed system applies clustering to previously projected data (processed by neural models). Present work focuses on the upgrading of MOVICAB-IDS, to incorporate new facilities. It is now required an enhanced visualization by combining projection and clustering results to ease traffic analysis by security personnel. That is, both simple and accumulated segments are now processed by neural projection and clustering techniques. By doing so, further information on the nature of the packets travelling along the network could be compressed in the visualization. Additionally, automatic response could be incorporated in MOVICAB-IDS to quickly abort intrusive actions while happening.

The remaining sections of this study are structured as follows: section 2 discusses the combination of visualization and clustering techniques and describes the applied ones. Experimental setting and results are presented in section 3 while the conclusions of this study are discussed in section 4.

2 Combining Visualization and Clustering

MOVICAB-IDS was based on the application of different AI paradigms to process the continuous data flow of network traffic. In order to do so, MOVICAB-IDS splits massive traffic data into limited datasets and visualizes them, thereby providing security personnel with an intuitive snapshot to monitor the events taking place in the observed computer network. The following paradigms were combined within MOVICAB-IDS:

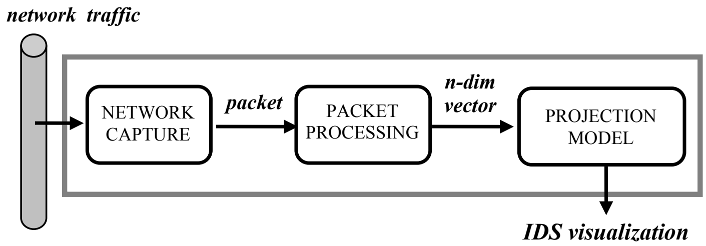
– **Multiagent System (MAS)**: some of the components are wrapped as deliberative agents capable of learning and evolving with the environment (Herrero, Corchado, Pellicer et al. 2009).

– **Case-based Reasoning (CBR)**: some of the agents contained in the MAS are known as CBR-BDI agents (Carrascosa et al. 2008) because they integrate the BDI (Beliefs, Desires and Intentions) (Bratman 1987) model and the CBR (Case-Based Reasoning) paradigm.

– **Artificial Neural Network (ANN)s**: the connectionist approach fits the intrusion-detection problem mainly because it allows a system to learn, in an empirical way, the input-output relationship between traffic data and its subsequent interpretation (Herrero, Corchado, Gastaldo et al. 2009). The previously described CBR-BDI agents incorporate the CMLHL neural model (described in section 2.1) to generate projections of network traffic.

The combination of these paradigms allowed the user to benefit from certain properties of ANN (generalization that allows the identification of previously unseen attacks), CBR (learning from past experiences), and agents (reactivity, proactivity, sociability, and intelligence), which greatly facilitates the ID task.

Fig. 1**.** MOVICAB-IDS general architecture.



The general framework for MOVICAB-IDS is depicted in Fig. 1. This framework could be described as follows:

- packets traveling through the network are intercepted by a **capture device**;
- traffic is **coded by a set of features** spanning a multidimensional vector space;
- a **projection model** operates on feature vectors and yields as output a suitable representation of the network traffic. The projection model clearly is the actual core of the overall IDS. That module is designed to yield an effective and intuitive representation of network traffic, thus providing a powerful tool for the security staff to visualize network traffic.

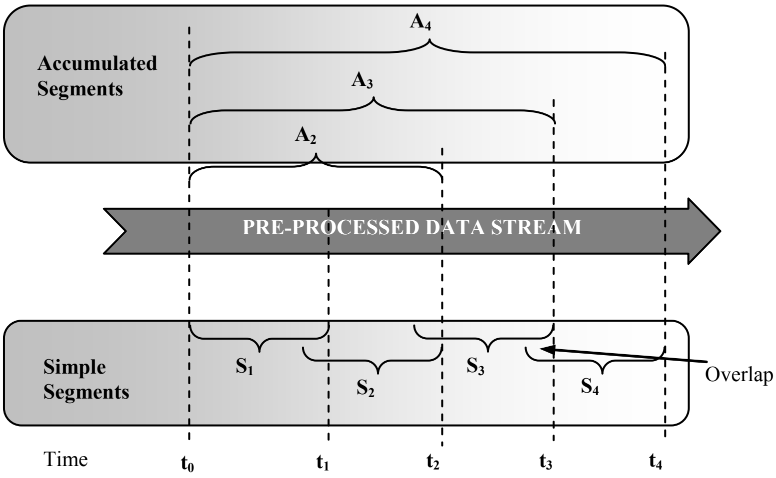
To process the continuous flow of network traffic, MOVICAB-IDS split the pre-processed data stream into simple and accumulated segments as depicted in Fig. 2. These segments are defined as follows:

– **Equal simple segments (S_x)**: each simple segment contains all the packets with timestamps between the initial and final time limits of the segment. There must be a time overlap between each pair of consecutive simple segments because anomalous situations could conceivably take place between simple segment S_x and S_{x+1} (where S_{x+1} is the next segment following S_x).

– **Accumulated segments (A_x)**: each one of these segments contains several consecutive simple ones. To avoid duplicated packets, time overlap is removed in accumulated segments.

One of the main reasons for such a partitioning was to present a long-term picture of the evolution of network traffic to the network administrator, as it allows the visualization of attacks lasting longer than the length of a simple segment. To avoid confusion on the part of the analyst, accumulated segments were visualized at the same time. This prompted the network administrator to realize that there is only one anomalous situation being visualized twice.

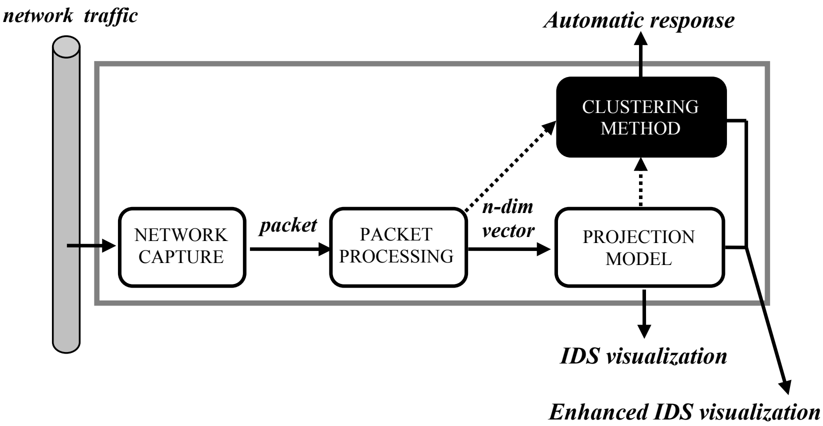
Fig. 2. MOVICAB-IDS segmentation of pre-processed data.



2.1 Proposed System

Present work focuses on the upgrading of the previously introduced framework, to incorporate new facilities, as described below. The initial architecture of MOVICAB-IDS is extended to combine clustering methods and projection models, as depicted in Fig. 3.

Fig. 3**.** Clustering extension for the proposed system.



As automatic response is a desirable feature for an IDS, MOVICAB-IDS is extended in order to do that. For this purpose, human supervision is not enough so an autonomous way of analysing network traffic is proposed in present work. Clustering methods are proposed and compared in this study to work in unison with the neural projection model that was previously validated.

The following subsections describe the different techniques that take part in the proposed solution. For the dimensionality reduction as a projection method, Cooperative Maximum Likelihood Hebbian Learning (Corchado and Fyfe 2003) is explained as it proved to be the most informative one among many considered (Corchado and Herrero 2011). It is described in section 2.2. On the other hand, to test clustering performance some of the standard methods have been tested, namely: *k*-means and agglomerative clustering, described in section 2.3.

2.2 Cooperative Maximum Likelihood Hebbian Learning

The standard statistical method of Exploratory Projection Pursuit (EPP) (Friedman and Tukey 1974) provides a linear projection of a data set, but it projects the data onto a set of basis vectors which best reveal the interesting structure in data; interestingness is usually defined in terms of how far the distribution is from the Gaussian distribution.

One neural implementation of EPP is Maximum Likelihood Hebbian Learning (MLHL) (Corchado et al. 2004), (Fyfe and Corchado 2002). It identifies interestingness by maximising the probability of the residuals under specific probability density functions which are non-Gaussian.

One extended version of this model is the Cooperative Maximum Likelihood Hebbian Learning (CMLHL) (Corchado and Fyfe 2003) model. CMLHL is based on MLHL (Corchado et al. 2004), (Fyfe and Corchado 2002) adding lateral connections (Corchado and Fyfe 2003), (Corchado, Han, and Fyfe 2003) which have been derived from the Rectified Gaussian Distribution (Seung, Socci, and Lee 1998). The resultant net can find the independent factors of a data set but does so in a way that captures some type of global ordering in the data set.

Considering an N-dimensional input vector (x), and an M-dimensional output vector (y), with W_{ij} being the weight (linking input j to output i), then CMLHL can be expressed (Corchado and Fyfe 2003), (Corchado, Han, and Fyfe 2003) as:

1. Feed-forward step:

$$y_i = \sum_{j=1}^{N} W_{ij} x_j, \forall i \ . \qquad \textbf{(1)}$$

2. Lateral activation passing:

$$y_i(t+1) = \left[y_i(t) + \tau(b - Ay)\right]^+ \ . \qquad \textbf{(2)}$$

3. Feedback step:

$$e_j = x_j - \sum_{i=1}^{M} W_{ij} y_i, \forall j \ . \qquad \textbf{(3)}$$

4. Weight change:

$$\Delta W_{ij} = \eta . y_i . sign(e_j) | e_j |^{p-1} \ . \qquad \textbf{(4)}$$

Where: η is the learning rate, τ is the "strength" of the lateral connections, b the bias parameter, p a parameter related to the energy function (Corchado et al. 2004), (Fyfe and Corchado 2002), (Corchado and Fyfe 2003) and A a symmetric matrix used to modify the response to the data (Corchado and Fyfe 2003). The effect of this matrix is based on the relation between the distances separating the output neurons.

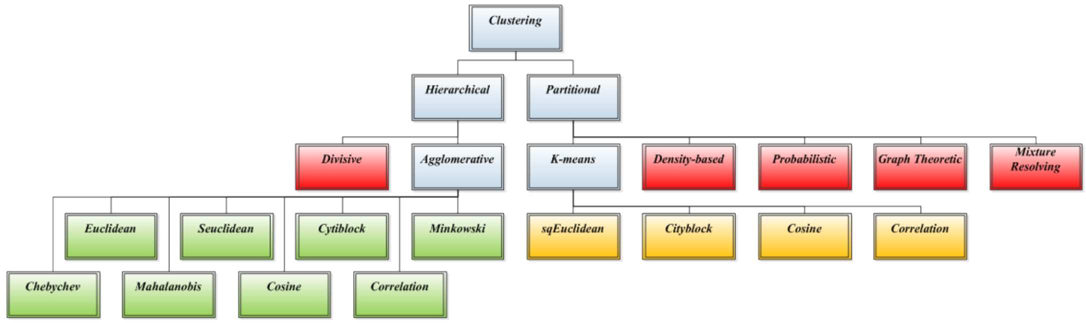
2.3 Clustering

Cluster analysis (Xu and Wunsch 2009), is the organization of a collection of data items or patterns (usually represented as a vector of measurements, or a point in a multidimensional space) into clusters based on similarity. Hence, patterns within a valid cluster are more similar to each other than they are to a pattern belonging to a different cluster.

Pattern proximity is usually measured by a distance function defined on pairs of patterns. A variety of distance measures are in use in the various communities (Andreopoulos et al. 2009), (Zhuang et al. 2012). The clustering output can be hard (allocates each pattern to a single cluster) or fuzzy (where each pattern has a variable degree of membership in each of the output clusters). A fuzzy clustering can be converted to a hard clustering by assigning each pattern to the cluster with the largest measure of membership.

There are different approaches to clustering data, but given the high number and the strong diversity of the existent clustering methods, we have focused on the ones shown in Figure 4.

Fig. 4. Clustering methods used on this paper: one hierarchical (Agglomerative) and other partitional method (K-means).



At the top level, there is a distinction between hierarchical and partitional approaches. Hierarchical methods produce a nested series of partitions (illustrated on a dendrogram which is a tree diagram) based on a similarity for merging or splitting clusters, while partitional methods identify the partition that optimizes (usually locally) a clustering criterion. Hence, obtaining a hierarchy of clusters can provide more flexibility than other methods. A partition of the data can be obtained from a hierarchy by cutting the tree of clusters at certain level.

Hierarchical methods generally fall into two types:

1. Agglomerative: an agglomerative approach begins with each pattern in a distinct cluster, and successively joins clusters together until a stopping criterion is satisfied or until a single cluster is formed.
2. Divisive: a divisive method begins with all patterns in a single cluster and performs splitting until a stopping criterion is met or every pattern is in a different cluster. This method is neither applied nor discussed in this paper.

Partitional clustering aims to directly obtain a single partition of the data instead of a clustering structure, such as the dendrogram produced by a hierarchical technique. Many of these methods are based on the iterative optimization of a criterion function that reflects the similarity between a new data and the each of the initial patterns selected for a specific iteration. Partitional methods have advantages in applications involving large data sets for which the construction of a dendrogram is computationally prohibitive. The problem of these algorithms is the need of the number of desired output clusters. Exhaustive search over all the set of possible initial labeling for an optimum output is clearly computationally prohibitive. Therefore, in practice, the algorithm is typically run a number of times with different starting states, and the best configuration obtained from all of the runs is used as the output clustering. Hence, we can meet different results depending on the initial labeling chosen (usually random). Additional techniques for the grouping operation include density-based (Tu et al. 2012), probabilistic (Brailovsky 1991), graph-theoretic (Argyrou 2009) and mixture-resolving clustering methods, but they are not used on this paper.

3 Experiments and Results

The main idea behind this experimental study is two-fold: on the one hand it is aimed at discovering whish simple clustering techniques can be successfully applied to the SNMP intrusion detection problem. On the other hand, it tries to check whether clustering and projection could work in unison to ease intrusion detection. Additionally, as previously stated, the experimental study tries to show whether clustering could be more informative applied over the projected data rather than the original data captured from the network. That is, the same data have been analyzed for intrusion detection, in two different ways, according to what is depicted in Fig. 3. The two considered alternatives are: clustering on projected (dimensionality-reduced) data, and clustering on original (five-dimensional) data.

This section describes the dataset used for evaluating the proposed clustering methods and how they were generated. The experimental settings and the obtained results are also detailed.

3.1 Datasets

Five features were extracted from the headers of packets travelling along the network to form the data set:

- **Packet ID**: sequential integer nonlinear.
- **Timestamp**: the time difference in relation to the first captured packet. Sequential integer nonlinear.
- **Source Port**: the port of the source host from where the packet is sent. Discrete integer values.
- **Destination Port**: the port of the destination host to where the packet is sent. Discrete integer values.
- **Size**: total packet size (in Bytes).
- **Protocol ID**: we have used values between 1 and 35 to identify the packet protocol. Discrete integer values.

After initial experiments, it was decided to apply MOVICAB-IDS to the anomalous situations related to SNMP. The Management Information Base (MIB) can be defined in broad terms as the database used by SNMP to store information about the elements that it controls. Like a dictionary, an MIB defines a textual name for a managed object and explains its meaning.

As previously stated, consideration should be given to SNMP from a security standpoint, due to its very limited security mechanisms and the security sensitive data that is stored in the MIB. Attackers can exploit these vulnerabilities in the SNMP for network reconnaissance and remote reconfiguration or shut down of SNMP devices. Thus, MOVICAB-IDS focuses on the most commonly reported types of attacks that target SNMP:

- **SNMP network scan**: three types of scans (or sweeps) have been defined: network scans, port scans, and their hybrid block scans (Staniford, Hoagland, and McAlerney 2002). Unlike other attacks, scans must use a real source IP address, because the results of the scan (open ports or responding IP addresses) must be returned to the attacker (Ren et al. 2006). A port scan (or sweep) may be defined as series of messages sent to different port numbers to gain information on its activity status. These messages can be sent by an external agent attempting to access a host to find out more about the network services that this host is providing. So, a scan is an attempt to count the services running on a machine (or a set of machines) by probing each port for a response, providing information on where to probe for weaknesses. Thus, scanning generally precedes any further intrusive activity. This work focuses on the identification of network scans, in which the same port (the SNMP port) is the target for a number of computers in an IP address range. A network scan is one of the most common techniques used to identify services that might then be accessed without permission (Abdullah et al. 2005).
- **MIB information transfer**: this situation involves a transfer of some (or all the) information contained in the SNMP MIB, generally through the *Get* command or similar primitives such as *GetBulk* (Malowidzki 2002; Sprenkels and Martin-Flatin 1999). This kind of transfer is potentially quite a dangerous situation because anybody possessing some free tools, some basic SNMP knowledge and the community string (in SNMP versions 1 and 2), will be able to access all sorts of interesting and sometimes useful information. As specified by the Internet Activities Board, the SNMP is used to access MIB objects. Thus, protecting a network from malicious MIB information transfer is crucial. However, the "normal" behavior of a network may include queries to the MIB. This is a situation in which visualization-based IDSs are quite useful; these situations may be visualized as anomalous by an IDS but it is the responsibility of the network administrator to decide whether or not it constitutes an intrusion.

In addition to the previously mentioned SNMP situations, the analysed datasets contain a great background of network traffic that may be considered as “normal”. Information about the packets was gathered from a middle-size university network. As used in previous experiments, further details on the data can be found in (Corchado and Herrero 2011; Herrero and Corchado 2009). The datasets studied in present work contain each one of the anomalous situations on their one, and additionally, another dataset was generated combining both of them. They can be described as follows:

- Dataset 1: contains three network scans (anomalous situations) that target port numbers 161, 162 and 3750 of all the machines within an IP address range. The two first ones are the SNMP default port numbers and the third one is introduced as a different case of study.
- Dataset 2: contains "normal" traffic and an MIB information transfer generated by the get-bulk SNMP command.
- Dataset 3: contains three network scans as those in Dataset 1 and an MIB information transfer.

3.2 Details of Applied Clustering Techniques

As similarity is fundamental to the definition of a cluster, a measure of the similarity is essential to most clustering methods and it must be carefully chosen. Present study applies well-known distance criteria used for examples whose features are all continuous, as described below.

Table 1. Some of the well-known distance measures that are usually employed in clustering methods.

Metric	Description
Euclidean	Euclidean distance: $$D_{ab} = \sqrt{\sum_{j=1}^{p} \left(x_{aj} - x_{bj}\right)^2}$$ Where: • x_{aj} , x_{bj} values taken by the jth variable for the objects *a* and *b*, respectively in the multi-variable space. • *p* number of dimensions.
sEuclidean	Standardized Euclidean distance. Each coordinate difference between rows in *X* is scaled by dividing by the corresponding element of the standard deviation.
Cityblock	City block metric also known as Manhattan distance: $$D_{ab} = \sum_{j=1}^{p} \left| x_{aj} - x_{bj} \right|$$ Where: • x_{aj} , x_{bj} values taken by the j^{th} variable for the objects *a* and *b*, respectively in the multi-variable space. • *p* number of dimensions.
Minkowski	Minkowski distance: $$D_{ab} = \sqrt[\lambda]{\sum_{j=1}^{p} \left| x_{aj} - x_{bj} \right|^{\lambda}}$$ • x_{aj} , x_{bj} values taken by the j^{th} variable for the objects *a* and *b*, respectively in the multi-variable space. • *p* number of dimensions. • λ=1 Cityblock distance. • λ=2 Euclidean distance.
Chebychev	Chebychev distance (maximum coordinate difference).

Mahalanobis	Mahalanobis distance, using the sample covariance of X: $D_{ab} = \sqrt{(x_a - x_b)^T S^{-1} (x_a - x_b)}$ • x_a , x_b values of the objects a and b, respectively in the multi-variable space. • S covariance matrix.
Cosine	One minus the cosine of the included angle between points (treated as vectors).
Correlation	One minus the sample correlation between points (treated as sequences of values).

The most popular metric for continuous features is the Euclidean distance which is a special case of the Minkowski metric (p =2). It works well when a data set has compact or isolated clusters (J. Mao 1996). The problem of using directly the Minkowski metrics is the tendency of the largest-scaled feature to dominate the others. Solutions to this problem include normalization of the continuous features (sEuclidean distance).

Linear correlation among features can also distort distance measures, it can be relieved by using the squared Mahalanobis distance that assigns different weights to different features based on their variances and pairwise linear correlations. The regularized Mahalanobis distance was used in (J. Mao 1996) to extract hyperellipsoidal clusters.

3.2.1 *K*-means Algorithm

Four different distance measures are applied in present study for *K*-means algorithm, as described in Table 2. The proposed solution has been tested on all of them and the best result can be seen on section 3.3.

Table 2. Distance measures employed for K-means in this study.

Metric	Description
sqEuclidean	Squared Euclidean distance. Each centroid is the mean of the points in that cluster.
Cityblock	Sum of absolute differences. Each centroid is the component-wise median of the points in that cluster.
Cosine	One minus the cosine of the included angle between points (treated as vectors). Each centroid is the mean of the points in that cluster, after normalizing those points to unit Euclidean length.
Correlation	One minus the sample correlation between points (treated as sequences of values). Each centroid is the component-wise mean of the points in that cluster, after centering and normalizing those points to zero mean and unit standard deviation.

3.2.2 Agglomerative Clustering

Based on the way the proximity matrix is updated in the second phase, a variety of linking methods can be designed (this study has been developed with the linking methods shown in Table 3).

Table 3. Linkage functions employed for agglomerative clustering in this study.

Method	Description
Single	Shortest distance. $d'(k,\{i,j\}) = \min\{d(k,i), d(k,j)\}$

Complete	Furthest distance. $d'(k,\{i,j\}) = \max\{d(k,i), d(k,j)\}$
Ward	Inner squared distance (minimum variance algorithm), appropriate for Euclidean distances only.
Median	Weighted center of mass distance (WPGMC: Weighted Pair Group Method with Centroid Averaging), appropriate for Euclidean distances only.
Average	Unweighted average distance (UPGMA: Unweighted Pair Group Method with Arithmetic Averaging).
Centroid	Centroid distance (UPGMC: Unweighted Pair Group Method with Centroid Averaging), appropriate for Euclidean distances only.
Weighted	Weighted average distance (WPGMA: Weighted Pair Group Method with Arithmetic Averaging).

Most hierarchical clustering algorithms are based on the single-link and complete-link. These two algorithms differ in the way they characterize the similarity between a pair of clusters:

1. *Single-link algorithm:* the distance between two clusters is the minimum of the distances between all pairs of patterns drawn from each of the clusters.
2. *Complete-link algorithm:* the distance between two clusters is the maximum of all pairwise distances between patterns in each of the clusters.

In either case, two clusters are merged to form a larger cluster based on minimum distance criteria. The complete-link algorithm produces compact clusters (Baeza-Yates 1992). The single-link algorithm, by contrast, suffers from a chaining effect. It has a tendency to produce clusters that are straggly or elongated. The clusters obtained by the complete-link algorithm are more compact than those obtained by the single-link algorithm. The single-link algorithm is more versatile than the complete-link algorithm. However, it has been observed that the complete-link algorithm produces more useful hierarchies in many applications than the single-link algorithm.

3.3 Results

The best results obtained by applying the previously introduced techniques to the described datasets are shown in this section. The results are projected through CMLHL and further information about the clustering results is added to the projections, mainly by the glyph metaphor (colors and symbols). The projections comprise a legend that states the color and symbol used to depict each packet, according to the original category of the data.

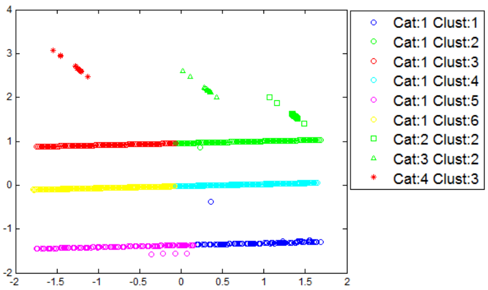
The clustering methods have been applied several times to the analyzed datasets by combining different values for the algorithm options. The following sections show the best results, whose parameter settings and performance are also detailed. The following subsections comprise the results obtained by the projection and clustering technique for each one of the datasets.

Dataset 1

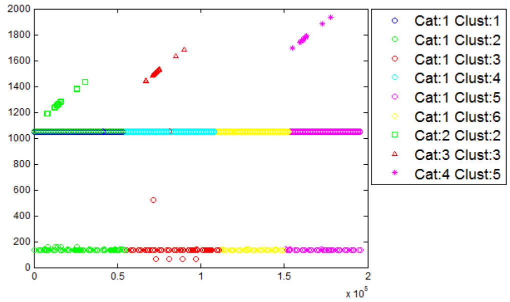
Fig. 5 shows the results obtained by k-means over this dataset. The data has been labeled as follows: normal (Cat. 1), scan to port 161 (Cat. 2), scan to port 162 (Cat. 3) and scan to port 3750 (Cat. 4).

Fig. 5. Best clustering result under the frame of MOVICAB-IDS through *k*-means for Dataset 1.

5.a K-means on projected data: *k*=6, sqEuclidean distance.



5.b K-means on original data: *k*=6, sqEuclidean distance.



From Fig. 5 it can be seen that all the packets from the scans (represented as non-horizontal small bars) are clustered in the same group. However, some other packets, regarded as normal, have been also included in those clusters. Apart from these two projections, a comprehensive set of experiments has been carried out, whose results can be seen in Table 4. For this experimental study, different values of *k* parameter were tested; the best of them (in terms of false positive and negative rates) are the ones in the following table.

Table 4. K-means experiments with different conditions for Dataset 1.

Data	k	Distance Criteria	False Positive	False Negative	Replicates/ Iterations	Sum of Distances
Projected	2	sqEuclidean	48.0186 %	0 %	5/4	1705.77
Original	2	sqEuclidean	46.6200 %	2.0979 %	5/5	9.75E+11
Projected	4	sqEuclidean	22.9604 %	0 %	5/8	643.352
Original	4	sqEuclidean	69.1143 %	0 %	5/8	4.38E+11
Projected	6	sqEuclidean	22.9604 %	0 %	5/8	301.218
Original	6	sqEuclidean	45.4545 %	0 %	5/24	2.91E+11
Projected	2	Cityblock	46.2704 %	0 %	5/7	1380.1
Original	2	Cityblock	49.6503 %	2.0979 %	5/9	3.50E+07
Projected	4	Cityblock	22.9604 %	0 %	5/8	710.545
Original	4	Cityblock	72.0249 %	0 %	5/15	2.15E+07
Projected	6	Cityblock	22.9604 %	0 %	5/14	526.885
Original	6	Cityblock	48.0187 %	0 %	5/10	1.41E+07
Projected	2	Cosine	47.9021 %	0 %	5/3	316.193
Original	2	Cosine	78.5548 %	0 %	5/5	15.4214
Projected	4	Cosine	22.9604 %	0 %	5/7	86.2315
Original	4	Cosine	46.8531 %	0 %	5/12	3.79324
Projected	6	Cosine	22.9604 %	0 %	5/5	35.9083
Original	6	Cosine	47.2028 %	0 %	5/24	2.51022
Projected	2	Correlation	52.0979 %	0 %	5/3	273.91
Original	2	Correlation	80.0699 %	0 %	5/6	20.6143
Projected	4	Correlation	51.8648 %	0 %	5/7	46.7877
Original	4	Correlation	47.2028 %	0 %	5/16	5.53442
Projected	6	Correlation	27.4876 %	0.3497 %	5/12	16.9416
Original	6	Correlation	47.3193 %	0 %	5/29	3.69279

To ease the analysis of the k-means experiments on dataset 1, some statistics have been calculated and are shown in Table 5.

Table 5. Statistics about K-means experiments on Dataset 1.

	Original			**Projected**		
	False Positive	False Negative	Sum of Distances	False Positive	False Negative	Sum of Distances
Mean	56.5071167	0.34965	1.4201E+11	34.28365	0.02914167	503.653508
Typical error	4.01775318	0.23573398	8.6391E+10	3.85309772	0.02914167	156.758045

Median	47.669	0	7050010.31	25.224	0	308.7055
Standard Deviation	13.9179053	0.81660647	2.9927E+11	13.347522	0.10094969	543.025798
Variance	193.708088	0.66684612	8.956E+22	178.156344	0.01019084	294877.017
Kurtosis	-1.13370381	2.64	5.65763708	-2.10880135	12	1.15711245
Skew	0.93079135	2.05523721	2.36669772	0.40838197	3.46410162	1.36888005
Range	34.6154	2.0979	9.75E+11	29.1375	0.3497	1688.8284
Min	45.4545	0	2.51022	22.9604	0	16.9416
Max	80.0699	2.0979	9.75E+11	52.0979	0.3497	1705.77

The high false negative rate (FNR) is one of the main problems that most IDS have to face. It can be seen in Tables 4 and 5 that the proposed system achieves an almost zero FNR for dataset 1 in most cases, with very low deviation. For the remaining cases, it keeps as a very low value as the number of packets in the network scans is much lower than those from normal traffic.

On the other hand, there is not a clear difference (in terms of clustering error) between the experiments on original and projected data, although for a certain number of clusters, the results on projected data are better. Regarding original and projected data, the false negative rate is almost similar (0.34965 vs. 0.02914167), being slightly lower in the case of projected data. Additionally, the number of needed iterations is lower for the projected data, as the dimensionality of the data has been previously reduced through CMLHL. By looking at the sum of distances (sum of point-to-centroid distances, summed over all *k* clusters), a clear conclusion cannot be drawn as it depends on the distance method.

Agglomerative clustering has been also applied and the details of the run experiments (with no clustering error) are shown in Table 6. Two of the best results, with different values for distance criteria, linkage and number of clusters, are depicted in Fig. 5.

Table 6. Experimental setting of the agglomerative method for Dataset 1.

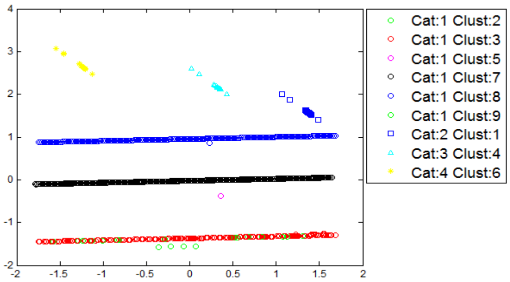
Data	Distance	Linkage	Cutoff	Range	Cluster
Projected	Euclidean	Single	0.37	0.307 - 0.3803	9
Projected	sEuclidean	Single	0.37	0.3087 - 0.3824	9
Projected	Cityblock	Single	0.42	0.4125 - 0.443	9
Projected	Minkowski	Single	0.38	0.307 - 0.3803	9
Projected	Chebychev	Single	0.35	0.2902 - 0.366	9
Projected	Mahalanobis	Single	0.35	0.3084 - 0.3824	9
Original	sEuclidean	Single	1.80	1.533 - 1.813	5
Original	sEuclidean	Complete	4.62	4.62 - 4.628	4
Original	sEuclidean	Average	3.00	2.696 -3.271	4
Original	sEuclidean	Weighted	3.20	3 - 3.261	4
Original	Mahalanobis	Single	2.40	2.289 - 2.438	4
Original	Mahalanobis	Complete	6.00	5.35 - 6.553	3
Original	Mahalanobis	Average	4.00	3.141 - 4.624	3
Original	Mahalanobis	Weighted	4.00	3.504 - 4.536	3

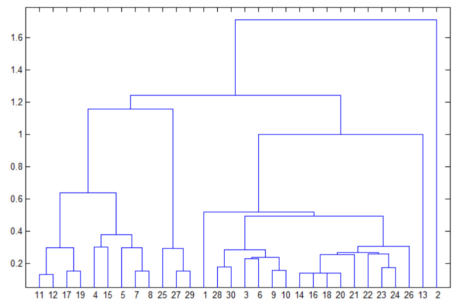
It can be seen in Table 6 that in the case of projected data, the minimum number of clusters without error is 9, while in the case of original data, it could be lowered to 3 with appropriate distance method. From the intrusion detection point of view, a higher number of clusters does not mean a higher error rate because more than one cluster can be assigned to both normal and attack traffic. In the case of original data, the sEuclidean and Mahalanobis distances are minimizing the number of clusters without error. On the contrary, some other distance criteria are applicable for the projected data with same performance regarding clustering error.

Results from one of the best experiments described in Table 6 are depicted in Fig. 6: traffic visualization and the dendrogram associated to agglomerative clustering. The following sample has been chosen: Euclidean distance, linkage single, cutoff: 0.37, 9 groups without error. It is shown that clusters 1, 4 and 6 are associated to the three network scans and the remaining ones are associated to normal traffic.

Fig. 6. Best results of agglomerative clustering under the frame of MOVICAB-IDS for Dataset 1.

6.a Agglomerative clustering on projected data. **6.b** Corresponding dendrogram.



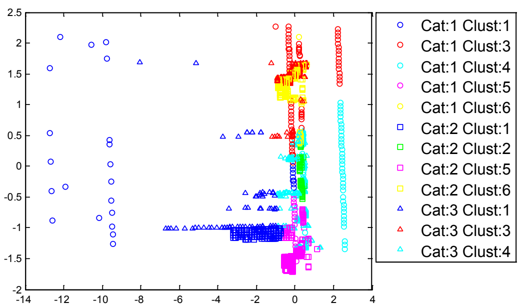


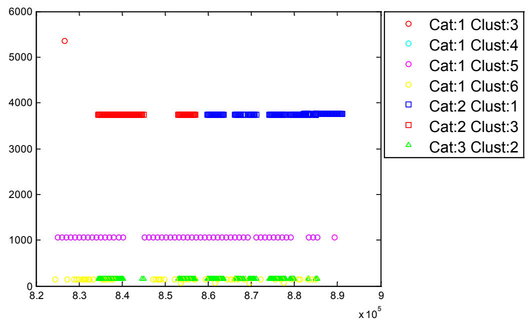
Dataset 2

Fig. 7 shows the results obtained by k-means on this data. The data has been labeled as follows: normal (Cat. 1), source-to-destination MIB transfer (Cat. 2), and destination-to-source MIB transfer (Cat. 3).

Fig. 7. Best clustering result under the frame of MOVICAB-IDS through *k*-means for Dataset 2.

7.a K-means on projected data: *k*=6, cosine distance. **7.b** K-means on original data: *k*=6, cosine distance.





For the MIB information transfer (dataset 2 in Fig. 7), the clustering does not group data without mistakes as it mixes packets from different categories (two MIB transfer classes and normal traffic). For the original, data, although the number of clusters (k parameter) is the same, data are more precisely separated. Apart from these two projections, some more experiments have been conducted, whose details (performance, true positive and false positive rates, values of *k* parameter, etc.) can be seen in Table 7.

Table 7. K-means experiments with different conditions for Dataset 2.

Data	k	Distance Criteria	False Positive	False Negative	Replicates/ Iterations	Sum of Distances
Projected	2	sqEuclidean	2.1600 %	38.3800 %	5/5	10061
Original	2	sqEuclidean	1.8000 %	35.1200 %	5/4	5.39394e+011
Projected	4	sqEuclidean	4.1200 %	0.6200 %	5/14	4927.44
Original	4	sqEuclidean	2.3800 %	0 %	5/9	1.78131e+011
Projected	6	sqEuclidean	4.1200 %	0.3600%	5/20	2909.3
Original	6	sqEuclidean	2.3800 %	0 %	5/15	9.53914e+010
Projected	2	Cityblock	1.9200 %	38.3800 %	5/4	7031.35
Original	2	Cityblock	1.9000 %	35.1200 %	5/5	5.55984e+007
Projected	4	Cityblock	2.9600 %	9.5800 %	5/11	4490.81
Original	4	Cityblock	3.1400 %	17.3800 %	5/5	3.14953e+007

Projected	6	Cityblock	3.4400 %	9.5800 %	5/10	3355.85
Original	6	Cityblock	2.8200%	8.7400 %	5/10	2.34431e+007
Projected	2	Cosine	0.0200 %	38.3800 %	5/3	1499.24
Original	2	Cosine	2.3600 %	38.3800 %	5/3	0.0756523
Projected	4	Cosine	1.8400 %	9.9600 %	5/13	567.405
Original	4	Cosine	0.0200 %	0 %	5/3	0.000122694
Projected	6	Cosine	4.1200 %	5.6200 %	5/15	313.959
Original	6	Cosine	0.0200 %	0 %	5/5	7.23926e-005
Projected	2	Correlation	2.3400 %	47.6600 %	5/7	1540.27
Original	2	Correlation	2.3800 %	0 %	5/3	0.0252179
Projected	4	Correlation	2.7600 %	13.1200 %	5/6	380.787
Original	4	Correlation	0.0200 %	0 %	5/4	0.000101501
Projected	6	Correlation	3.1800 %	9.9200 %	5/11	157.413
Original	6	Correlation	0.0200 %	0 %	5/4	9.21847e-005

To ease the analysis of the k-means experiments on dataset 2, some statistics have been calculated and are shown in Table 8.

Table 8. Statistics about K-means experiments on Dataset 2.

	Original			**Projected**		
	False Positive	False Negative	Sum of Distances	False Positive	False Negative	Sum of Distances
Mean	1.60333333	11.2283333	6.7752E+10	2.74833333	18.4633333	3102.902
Typical error	0.35224676	4.61010054	4.5784E+10	0.34621292	4.91226531	889.802658
Median	2.13	0	11721550	2.86	9.94	2224.785
Standard Deviation	1.22021856	15.9698567	1.586E+11	1.19931672	17.0165862	3082.36682
Variance	1.48893333	255.036324	2.5154E+22	1.43836061	289.564206	9500985.24
Kurtosis	-1.59285712	-0.86485947	8.37440612	1.11499896	-1.29230795	0.92700337
Skew	-0.51490173	1.00709953	2.82978313	-0.86863118	0.70989152	1.17191648
Range	3.12	38.38	5.3939E+11	4.1	47.3	9903.587
Min	0.02	0	7.2393E-05	0.02	0.36	157.413
Max	3.14	38.38	5.3939E+11	4.12	47.66	10061

For the MIB transfer, and differentiating from network scans (dataset 1), most experiments got a FNR higher than zero. As can be seen in table 8, the FNR is once again slightly higher in the case of projected data. For most of those cases, the rates are very low in percentage, and as the number of packets in the MIB transfer is much higher than those from normal traffic, it means that very few packets of anomalous traffic are clustered as normal. On the other hand, there is a clear difference (in terms of clustering error) between the experiments on original and projected data; the results on original data are better in terms or error rates. Additionally, the number of needed iterations is lower for the projected data, as the dimensionality of the data has been previously reduced through CMLHL. As in previous experiments for dataset 1, the sum of distances (sum of point-to-centroid distances, summed over all *k* clusters) does not support a clear conclusion as it strongly depends on the distance method.

The run experiments for the agglomerative method with very little FPR or no clustering error are shown in Table 9.

Table 9. Experimental setting of the agglomerative method for Dataset 2.

Data	**Distance**	**Linkage**	**Cutoff**	**False Positive**	**Cluster**
Projected	Euclidean	Single	0.9	0,9000 %	11
Projected	sEuclidean	Single	0.4	0 %	25
Projected	Cityblock	Single	1	0,9000 %	12
Projected	Minkowski p=3	Single	0.9	0,9000 %	11
Projected	Chebychev	Single	0.8	0,9000 %	11
Projected	Mahalanobis	Single	0.9	0,9000 %	11
Original	Euclidean	Single	2600	0 %	17
Original	sEuclidean	Single	0.7	0 %	18

Original	sEuclidean	Average	0.8	0 %	40
Original	sEuclidean	Weighted	1	0 %	34

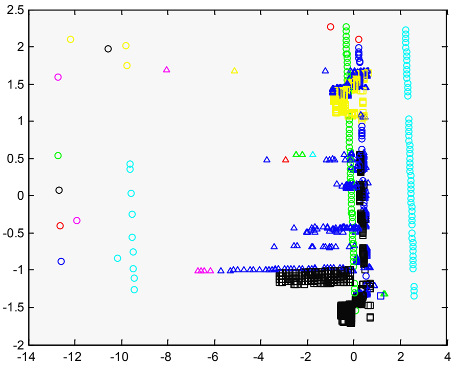
It can be seen that in the case of projected data, that the minimum number of clusters without error is 25, while in the case of original data, it could be lowered to 17 with appropriate distance method. In both cases the sEuclidean distance minimizes the number of clusters with no error. Some other distance criteria are applicable, providing a non-zero value of FPR.

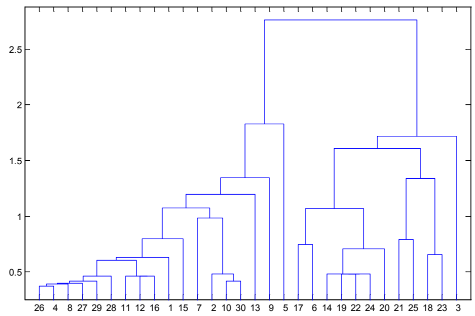
Results from one of the best experiments described in Table 9 are depicted in Fig. 8, including traffic visualization and the associated dendrogram on projected data. The chosen experiment details are: sEuclidean distance, single linkage, cutoff: 0.4 and 25 groups without error.

Fig. 8**.** Best results of agglomerative clustering under the frame of MOVICAB-IDS for Dataset 2.

8.a Agglomerative clustering on projected data: sEuclidean, linkage: single, cutoff: 0.4

8.b Corresponding dendrogram.





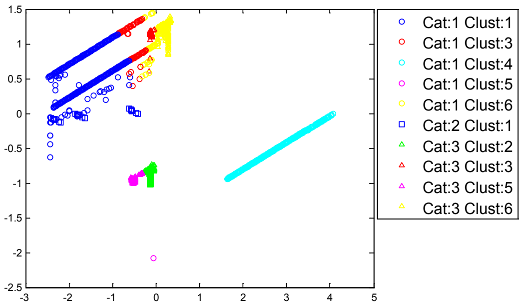
Dataset 3

Fig. 9 shows the results obtained by k-means on dataset 3, which includes samples of network scans and MIB information transfer, as it has been previously described. The data have been labeled as follows: normal (Cat. 1), network scans (Cat. 2), and MIB information transfer (Cat. 3).

From Fig. 9.b. it can be seen that all the packets in each one of the scans (represented as non-horizontal small bars) are clustered in the same group. However, some other packets, regarded as normal, have been also included in those clusters. In the selected result, some of the defined clusters do only gather data of one class (rather normal or anomalous traffic) but some other groups do mix traffic from different classes. Apart from these two projections, some more experiments have been conducted, whose details (performance, true positive and false positive rates, values of *k* parameter, etc.) can be seen in Table 10.

Fig. 9. Best clustering result under the frame of MOVICAB-IDS through *k*-means for Dataset 3.

9.a K-means on projected data: *k*=6, cosine distance.



9.b K-means on original data: *k*=6, cosine distance.

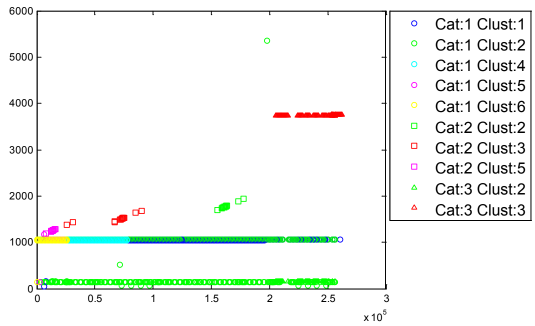


Table 10. K-means experiments with different conditions for Dataset 3.

Data	k	Distance Criteria	False Positive	False Negative	Replicates/ Iterations	Sum of Distances
Projected	4	sqEuclidean	9.1885 %	0 %	5/7	2164.04
Original	4	sqEuclidean	7.8758 %	0.6137 %	5/7	2.04074e+012
Projected	6	sqEuclidean	9.1885 %	0 %	5/19	1095.92
Original	6	sqEuclidean	13.6379 %	0.3069 %	5/19	1.07906e+012
Projected	12	sqEuclidean	9.1885 %	0 %	5/12	519.748
Original	12	sqEuclidean	10.5353 %	0 %	5/66	4.4814e+011
Projected	4	Cityblock	9.1886 %	0 %	5/6	4588.48
Original	4	Cityblock	7.6202 %	0.6137 %	5/7	8.45902e+007
Projected	6	Cityblock	9.1885 %	0 %	5/5	2883.24
Original	6	Cityblock	11.5410 %	0 %	5/20	6.41156e+007
Projected	12	Cityblock	9.1884 %	0 %	5/10	2707.28
Original	12	Cityblock	15.2915 %	0 %	5/17	3.94205e+007
Projected	4	Cosine	9.1885 %	0 %	5/5	276.139
Original	4	Cosine	10.3136 %	0 %	5/10	8.25662
Projected	6	Cosine	9.1885 %	0 %	5/20	108.304
Original	6	Cosine	2.1650 %	0 %	5/22	4.40786
Projected	12	Cosine	7.2963 %	0 %	5/24	34.7098
Original	12	Cosine	2.1650 %	0 %	5/51	2.06836
Projected	4	Correlation	10.4501 %	0.9206 %	5/6	201.623
Original	4	Correlation	12.0014 %	0 %	5/23	11.3542
Projected	6	Correlation	11.0296 %	0.9206 %	5/9	77.0721
Original	6	Correlation	9.0181 %	0 %	5/26	6.24039
Projected	12	Correlation	15.8371 %	0 %	5/11	19.4603
Original	12	Correlation	8.4778 %	0 %	5/42	2.83514

To ease the analysis of the k-means experiments on dataset 3, some statistics have been calculated and are shown in Table 11.

Table 11. Statistics about K-means experiments on Dataset 3.

	Original			Projected		
	False Positive	False Negative	Sum of Distances	False Positive	False Negative	Sum of Distances
Mean	9.22021667	0.12785833	2.9734E+11	9.843425	0.15343333	1223.00135
Typical error	1.15776058	0.07024146	1.84E+11	0.6006213	0.10344473	435.526542
Median	9.66585	0	19710255.7	9.1885	0	397.9435
Standard Devia-	4.0106003	0.24332357	6.3739E+11	2.08061323	0.35834306	1508.7082

tion						
Variance	16.0849147	0.05920636	4.0626E+23	4.32895141	0.12840975	2276200.42
Kurtosis	0.10714212	1.13010355	5.21076751	7.20243839	2.64	0.55976979
Skew	-0.61166909	1.63781177	2.33542803	2.40346377	2.05523721	1.21422466
Range	13.1265	0.6137	2.0407E+12	8.5408	0.9206	4569.0197
Min	2.165	0	2.06836	7.2963	0	19.4603
Max	15.2915	0.6137	2.0407E+12	15.8371	0.9206	4588.48

Only few of the experiments on dataset 3 through *k*-means got a FNR equal to zero. For those cases, a very low value was obtained and, as the number of anomalous packets is much higher than those from normal traffic, it means that very few anomalous packets are clustered as normal. On the other hand, as can be seen in table 11, there is not a clear difference (in terms of clustering error) between the experiments on original and projected data, although for a certain number of clusters, the results on projected data are better. Additionally, the number of needed iterations is lower for the projected data, as the dimensionality of the data is lower. By looking at the sum of distances (sum of point-to-centroid distances, summed over all *k* clusters), a clear conclusion cannot be drawn as it depends on the distance method.

Comprehensive details of the run experiments with very little FPR or no clustering error are shown in Table 12, for the case of agglomerative clustering.

Table 12. Experimental setting of the agglomerative method for Dataset 3.

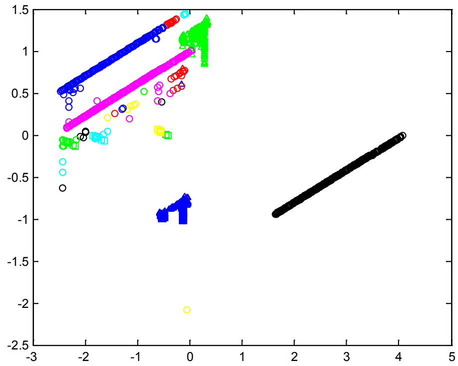
Data	Distance	Linkage	Cutoff	False Positive	Cluster
Projected	Euclidean	Single	0.15	0.1363 %	31
Projected	sEuclidean	Single	0.15	0.1363 %	31
Projected	Cityblock	Single	0.2	0.2216 %	28
Projected	Minkowski p=3	Single	0.15	0.1534 %	26
Projected	Chebychev	Single	0.12	0.1363 %	32
Projected	Mahalanobis	Single	0.16	0.1363 %	29
Original	sEuclidean	Single	0.4	0 %	33
Original	Cityblock	Single	1200	0 %	58
Original	Mahalanobis	Single	0.6	0 %	32

From Table 12 we can conclude that in the case of projected data, a non-error clustering is not obtained by agglomerative method, but the FPR can be greatly reduced. To do so, around 30 clusters are obtained, depending on the clustering method. In the case of original data, 33 is the minimum number of clusters without error choosing the appropriate distance method. In both cases, the sEuclidean distance minimizes the number of clusters.

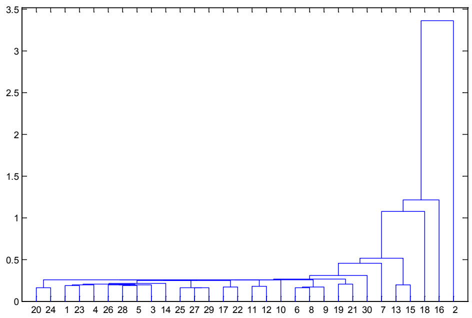
The results depicted on Fig. 10 (traffic visualization and the associated dendrogram to agglomerative clustering) are associated to the following details: sEuclidean distance, linkage single, cutoff: 0.15, 31 groups with FPR = 0.1363 %.

Fig. 10**.** Best results of agglomerative clustering under the frame of MOVICAB-IDS for Dataset 3.

10.a Agglomerative clustering on projected data: sEuclidean, linkage: single, cutoff: 0.15.



10.b Corresponding dendrogram.



4 Conclusions

This paper has proposed the use of clustering techniques to perform ID on numerical traffic data sets in unison with neural projection techniques. Simple clustering methods have been applied to SNMP anomalous situations to get an idea about the performance of the proposal.

Detailed conclusions about experiments on the different datasets and with several different clustering techniques and criteria, can be found in section 3. The studied SNMP-related anomalous situations (network scans and MIB information transfers) have been both independently and jointly analyzed. Experimental results show that some of the applied clustering methods, mainly hierarchical ones, obtain a good clustering performance on the analysed data, according to false positive and negative rates. The obtained results vary from the different analysed datasets and the behaviour of the applied clustering techniques is not always the same.

In general terms, it can be said that the performance of the clustering techniques varies between the two different SNMP anomalous situations. Regarding the distance criteria, none of them is clearly the best one, so its selection will depend on the analysed data. Finally, by considering projected versus original data, it can be said that the latter obtained higher FNR, but one of its main advantages is the smaller execution time, what is not covered in present work.

Finally, it can be concluded that the applied methods are able to properly detect anomalous situations when projected together with normal traffic. It has been proven that clustering methods could help in intrusion detection not only by applying them to the same data that is projected but in a subsequent way.

Acknowledgments

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