1. Introduction

Active expansion of computer technologies, in particular in critically important information systems (CIIS), is accompanied by the emergence of new threats to cyber security (CS). It is possible to enhance CS of CIIS by using, in particular, intelligent systems (and technologies) for the detection of cyber attacks (ISDA). Given a constant complication in the scenarios of cyber attacks, ISDA must have characteristics of adaptive systems. In other words, the ability to deliberately modify the algorithm for detecting the anomalies and cyber attacks by using the methods of clustering of attributes of the recognition objects (RO), as well as machine intelligent technologies of learning (MITL).

This makes it relevant to examine improvement of those existing and development of the new algorithms for the clustering of RO attributes, as well as the applied adaptive subsystems as a part of ISDA.

2. Literature review and problem statement

Information that is accepted as the basis for building the clusters in adaptive systems of recognition (ASR) of cyber attacks was explored in many studies, for example, in the form of complex attributes of RO in CIIS [1, 2]. These studies were mainly of theoretical character. As indicators or metrics [3] for building the classifiers, the authors investigated: threshold values of parameters of the input and output
traffic [4], unpredicted addresses of packets [5], attributes of requests to databases (DB) [6, 7], etc. These articles do not take into account the possibility of parallel formation of reference deviations for the features of anomalies and cyber attacks, which increases the time of RO analysis in ASR (or ISDA) [8]. For complex targeted attacks, information attributes may be quite fuzzy [9, 10], which does not contribute to building the effective algorithms of recognition.

In papers [11, 12], it was assumed that to enhance effectiveness of recognition, it is expedient to split the set of values of each indicator into disjoint groups by certain rules. This task can be solved by using the methods and models for cluster analysis [13, 14]. However, these studies have not been brought to hardware or software implementation.

By using an information condition of functional effectiveness (ICFE) of ASR learning [15, 16], it is possible to implement adaptive algorithms for the clustering of RO attributes into ISDA.

As was shown in articles [17, 18], in case the RO attributes glossary is unchanged, it is possible to enhance effectiveness of ASR learning. These studies do not take into account the possibility of increasing the degree of intersection of the RO classes.

Thus, given the potential of the ISDA application, it appears to be an important task to improve the algorithms for clustering and formation of reference deviations of the OR attributes for the timely detection of anomalies and cyber attacks in CIS.

3. The aim and tasks of research

The aim of present research is to develop an algorithm for the partition of the feature space (FS) into clusters in the process of recognition of cyber attacks in the systems of cyber protection.

To achieve the aim of the study, the following tasks are to be solved:
- to improve algorithms for the clustering of attributes of anomalies and cyber attacks and for the simultaneous formation of verifying admissible deviations in the intelligent systems of cyber attack detection;
- to conduct simulation in order to test and verify the adequacy of the proposed algorithms.

4. Algorithms for the clustering of attributes and the formation of verifying admissible deviations in the intelligent systems of cyber attack detection

Splitting FS and further clustering, for any RO class \( CT^a \), in accordance with [19, 20], was carried out by transforming FS to a hyper-spherical form. Since the main stage of clustering when splitting FS into groups is an increase in the radius (\( cr_a \)) of container (RC) at every step of ASR (or ISDA) learning, it is possible to use the following recurrent expression:

\[
cr_a(\text{ls}) = \left[ cr_a(\text{ls} - 1) + \xi \right] \text{ls} \in IS_{CE}^a,
\]

where \( \text{ls} \) is the number of steps of increasing RC \( C^a \); \( \xi \) are accepted for the chosen attributes of steps of increasing RC; \( IS_{CE}^a \) is the permissible value of RC.

In the process of ASR learning, we make an assumption about fuzzy compactness of the implementation of binary learning matrices (BLM) [16, 21, 22], obtained at the stage of splitting SF into relevant RO classes. Fuzzy partition \( RC^M \) includes the elements that can be attributed to fuzzy RO classes, for example, when it is difficult to distinguish a DoS attack from a DDoS attack [4, 16].

The rules of ASR learning, according to [1, 2, 14, 23, 24], are built based on the iteration procedure of searching for the maximum boundary magnitude of an information condition of functional effectiveness (ICFE):

\[
is^*_k = \text{Argmax} \{ \text{max} \{ \text{max} \{ \max_{\text{ls} \in IS_{CE}} \{ \text{max}_{M=1}^M CE_{\text{ls} M} \} \} \} \},
\]

where \( CE_{\text{ls} M} \) is the ICFE of ASR learning to recognize RO that belong to class \( C^a \); \( IS_{CE} \) is the permissible range of values of the k-th informative attribute of RO; \( IS_{CE} \) is the permissible range of ICFE in the course of ASR learning.

The following constraints are imposed on expression (2):

\[
\begin{align*}
\left[ CT^a \neq \emptyset \right] & \left\{ \forall CT^o \in RC^M \right\}, \\
\left[ CT^a \neq CT^o \right] & \left\{ \begin{array}{l} CT^o \cap CT^a \neq \emptyset, \\
\exists CT^o \in RC^M, \exists CT^a \in RC^M \end{array} \right\}, \\
\left[ CT^a \neq CT^b \right] & \left\{ \begin{array}{l} BCT^a \cap BCT^b = \emptyset, \\
\forall CT^a \in RC^M, \forall CT^b \in RC^M \end{array} \right\}.
\end{align*}
\]

where \( BCT^a \), \( BCT^b \) are the nuclei of RO classes \( CT^a \) and \( CT^b \), respectively;

\[
\bigcup_{CT \in RO} CT^o \subseteq RS_{\text{ls} a} \setminus a = b, a, b, m = 1, M.
\]

Accepted assumptions: classes \( CT^o \) are \( CT^a \) adjacent; the classes have a minimum distance between the centers of clusters \( cr(\text{ct}_a @ \text{ct}_b) \) among all classes for RO: RO are described by binary learning matrices (BLM) [21–23]. We accepted that \( \text{ct}_a \) and \( \text{ct}_b \) are the reference vectors of RO classes, in particular, by the KDD Cup 1999 Data [2, 5, 7].

The ASR learning procedure is given in the form of predicate expression:

\[
\begin{align*}
\left[ CT^a \neq CT^b \right] & \rightarrow [cr^a < cr(\text{ct}_a @ \text{ct}_b)], \\
& \rightarrow [cr^a < cr(\text{ct}_a @ \text{ct}_b) \in \forall CT^o \in RC^M \forall CT^b \in RC^M],
\end{align*}
\]

where \( cr^a \), \( cr^b \) are the optimal radii of containers \( C^a \) and \( C^b \), respectively.

To reduce the number of cycles during a learning procedure, the sets of input signals (factors) that influence ASR were determined. These sets correlate with the dimensionality of the vector of ASR testing parameters \( is_{\text{ls} M} \) in the course of recognition of the templates of attacks. ASR (or ISDA) learning is an iteration procedure of searching for global ICFE [2, 5, 8, 20, 24]:

\[
a^a = \text{Argmax} (\text{max} \{ CE \}),
\]

where \( IS_{\text{ls} M} \) is the admissible range of magnitudes of reference deviation (ca) for RO class \( CT^o \); \( IS_{CE} \) is the operation
range of determining ICFE indicator $CE$; $IS_{cr}$ is the permissible range of $RC$ magnitude $cr$. The algorithm of OR classification is functional at the following restrictions:

\[
\begin{align*}
\text{Stage} & \quad \text{Action} & \quad \text{Description} \\
1 & \quad \text{Step counter (SC) of changing VAD ca by features of RO is set as "0":} & \quad 1 := 0 \\
2 & \quad \text{Calculation of the lower } A_{lo}[1] \text{ and the upper } A_{up}[1] \text{ of VAD of RO features for entire FS} & \quad A_{lo}[1] = \text{lm}_i - \frac{ca_{lo} \times 100}{100} ; \quad A_{up}[1] = \text{lm}_i + \frac{ca_{lo} \times 100}{100} \\
3 & \quad \text{Formation of BLM } \{ct_{\xi}\} & \quad \text{Rule: } ct_{\xi} = 1, \text{ if } A_{lo}[1] < \text{lm}_i \times 100 < A_{up}[1] ; \quad 0, \text{ else} \\
4 & \quad \text{Value of SC for increasing RC} & \quad \xi := 0 \\
5 & \quad \text{Initialization of SC for increasing RC} & \quad \xi := 1 \\
6 & \quad \text{Splitting NMLM } \{ct_{\xi}\} \text{ into two clusters} & \quad \text{Verification of conditions:} \\
6.1 & \quad \text{Initial original standard vectors for RO attributes } \{ct_{\xi}\} \text{ for } C_\xi^0 \text{ are calculated} & \quad 1) \text{ cr}(ct_{\xi} \otimes ct) \rightarrow \text{min} ; \quad 2) \text{ cr}(ct_{\xi} \otimes ct) \rightarrow \text{max} ; \quad \text{where } ct^0, ct^1 \text{ are zero and unity vectors.} \\
6.2 & \quad \text{Value of } C_\xi^0 \text{ is set as "0"} & \quad \text{Rules:} \\
6.3 & \quad \text{RO implementations, belonging to clusters } CT_{\xi}^0 \text{, are defined} & \quad \text{Verification of conditions:} \\
\end{align*}
\]

For better visualization, the stages of splitting FS of RO into clusters in ASR are represented in tabular form in Table 1.

As a criterion of the optimization of parameters, during ASR learning, we used statistical parameters (information measures) for the variants of solutions with two alternatives [18, 25, 26] for a modified entropic indicator, as well as the Kullback-Leibler divergence (for three hypotheses) [27].
|   |   |   |
|---|---|---|
| 1 | 2 | 3 |
| **6.4** | Calculation of current ICFE [2, 5, 8, 24, 25] | \( \text{ICFE} = \left( \frac{1}{M} \right) \sum_{m=1}^{M} \max \limits_{l\in \{1,...,L\}} \text{CE}_m \), where CE\_m is the value of ICFE of ASR learning for the realization of class of anomalies or cyber attacks – CT\_m; \( \{ls\} \) is the set of steps for ASR learning as a part of ISDA |
| **6.5** | Formation of set \( \{ct_m\} \) of standard realizations for clusters \( \{\text{CT}_m \{\xi\}\} \) | Rule for defining coordinates: 
\[
ct_m = \begin{cases} 
1, & \text{if } \sum_{j=1}^{M} ct_{m,j} > \sqrt{2}; \\
0, & \text{else}
\end{cases}
\]
| **6.6** | Conditions verification | 
\[
\text{if } N' = \sum_{n=1}^{N} n_n < N \text{ then } \rightarrow 6.7 \& 6.3 \\
\text{else } 6.9
\]
| **6.7** | Conditions verification | 
\[
\text{if } cr_m[\xi] < cr(ct_i \oplus ct_j) \text{ then } \rightarrow 6.8 \& 6.3 \\
\text{else } 6.9
\]
| **6.8** | Increasing RC | 
\[
cr_m[\xi] = cr_m[\xi] + 1
\]
| **6.9** | Calculation of ICFE and optimal radii of clusters \( \{\text{CT}_m \{\xi\}\} \) | Under conditions: \( N' = \sum_{n=1}^{N} n_n < N \), where \( N' \) is the number of RO implementations that belong to \( \text{RC}_{\xi} \) and \( cr_m[\xi] < \text{cr}(ct_i \oplus ct_j) \)
| **7** | Increasing SC | 
\[
\xi = \xi + 1
\]
| **8** | Splitting a binary space of features (BSF) into 3 clusters | \( \{\text{CT}_m \{\xi\} \mid m = \{1,3\} \} \)
| **8.1** | Calculation of BLM for cluster \( \text{CT}_m \{\xi\} \), the standard vector-realization \( ct_3 \) of which satisfies the conditions | Verification of conditions: 
\[
\text{cr}(ct_i \oplus ct_j) \rightarrow \text{min} \& \text{cr}(ct_2 \oplus ct_i) \rightarrow \text{min}, \text{ where } ct_1, ct_2 \text{ are the standard realizations of clusters } \{\text{CT}_m \mid m = \{1,3\} \}, \text{ restored at performing stage 6}
\]
| **8.2** | Value of radius of cluster \( \text{CT}_m \{\xi\} \) is set as "0" | 
\[
\text{cr}_m[\xi] = 0.
\]
| **8.3** | Determining the cases of obtaining RO features implementations in cluster \( \text{CT}_m \{\xi\} \) | Rules for determining the cases of obtaining RO features implementations in cluster \( \text{CT}_m \{\xi\} \): 
\[
\begin{align*}
&\text{ct}_i \in \text{CT}_m \{\xi\}, \text{ if } \text{cr}(ct_i \oplus ct_j) <= \\&\text{cr} \& \text{cr}(ct_i \oplus ct_j) <= \\&\text{cr}(ct_i \oplus ct_j) \& \text{cr}(ct_i \oplus ct_j) <= \\&\text{cr}(ct_i \oplus ct_j),
\end{align*}
\]
 where \( ct_i \mid i = \{1,3\} \) are the implementations of BLM \( \text{ct}_m[\xi] \)
| **8.4** | Correction of containers for clusters \( \{\text{CT}_m \mid m = \{1,3\} \} \) is performed | Implementations \( \{\text{ct}_m[\xi] \mid j = \{1,3\} \} \), which arrived to container of category \( \text{CT}_m \), are removed from container \( \{\text{CT}_m \} \). \text{Radius of container } \{\text{CT}_m \}: 
\[
\text{cr}_m[\xi] = \text{cr}_m[\xi] - 1
\]
| **8.5** | Calculation of current ICFE | Expression – stage 6.4 |
| **8.6** | Formation of set \( \{ct_m\} \) of standard implementations \( \{\text{CT}_m \{\xi\}\} \) | Rule for defining coordinates: 
\[
ct_m = \begin{cases} 
1, & \text{if } \sum_{j=1}^{M} ct_{m,j} > \sqrt{2}; \\
0, & \text{else}
\end{cases}
\]
| **8.7** | Condition verification | 
\[
\text{if } cr_m[\xi] < cr(ct_i \oplus ct_j) \& cr_m[\xi] < \\
\text{cr}(ct_2 \oplus ct_j) \text{ then } \rightarrow 8.8; \\
\text{else } 8.9
We developed the algorithm that allows us to perform parallel formation of reference tolerances during an analysis of attributes of anomalies and cyber attacks, which are difficult to explain [1, 7, 16, 18]. This approach, when a parallel formation of VAD – \{ca_{K,i}\} is performed, makes it possible to change VAD for all attributes at every step of learning simultaneously. The algorithm enables in the course of learning to update optimal parameters of containers for the recognition classes \(0_{mCT}\).

The stages of splitting FS of RO into clusters are presented in tabular form in Table 2.

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| 1 | 2 | 3 |
|---|---|---|
| 8.8 | Increasing radius | \(c_{r_i}[\xi] := c_{r_i}[\xi] + 1\) |
| 8.9 | Optimal radius of cluster container \(CT_i^4\) is calculated | At conditions: \(c_{r_i}[\xi] < c_r(ct_i \otimes ct_j) \& c_{r_i}[\xi] < c_r(ct_i \otimes ct_j)\) |
| 9 | Condition verification | \[\text{if } ca_l[1] \leq 0.5 \cdot ca_{\text{low}} \text{ then } \rightarrow 2\] else 10 \(ca_{\text{low}}\) is the VAD for RO attributes, which are determined based on [5, 8, 25] |
| 10 | Condition verification | \[\text{if } CE_l[1] \notin IS_{\text{low}} \text{ then } \rightarrow 11\] else 2 |
| 11 | Search for global maximal (GMAX) value \(CE\) in the operating range of RO attributes | \(ca^i = \arg \max\{\max_{\xi_{1,\text{low}}} CE_l[1]\} \& CE_l[1] = \text{extrem}_{IS_{\text{low}}}[l]\) |
| 12 | Based on methods [5, 8, 25] and others, optimal parameter of fields \(ca\) of RO attributes for the container is defined | \(A_{\text{low}} = \text{ln}_i - ca^i \cdot ca_{\text{low}} / 100\) \(A_{\text{up}} = \text{ln}_i + ca^i \cdot ca_{\text{low}} / 100\) |
| 13 | Procedure of splitting BSF of RO into 4 clusters: | \(\{CT_i^4[\xi] | i = 1, 4\}\) |
| 13.1 | Binary matrix of cluster is defined \(CT_i^4\) | Under conditions: \(c_r(ct_{i} \otimes ct_{j}) \rightarrow \min\) \& \(c_r(ct_{i} \otimes ct_{j}) \rightarrow \min\) \& \(c_r(ct_{i} \otimes ct_{j}) \rightarrow \min\), where \(ct_{i}, ct_{j}, ct_{k}\) are the standard implementations of clusters \(CT_i^4[m = 1, 4]\), restored when performing stage 8 |
| 13.2 | Value of radii of cluster \(CT_i^4\) is set as ’0’ | \(c_{r_i}[\xi] := 0\) |
| 13.3 | Determining RO realizations, which arrived to cluster \(CT_i^4\) | Rule: \(ct_i \in CT_i^4\), if \(c_r(ct_i \otimes ct_i) = c_r[\xi]\), where \(ct_i = i \cdot \text{ln}_i \text{ are the implementations of BLM \(|\xi|\)}\) |
| 13.4 | Calculation of current ICFE | Expression – stage 6.4. |
| 13.5 | Formation \(\{ct_{m}\}\) of standard implementations for clusters \(\{CT_i^4[\xi]\}\) | Rule for defining coordinates: \(ct_{m} = \left\{\begin{array}{ll}1, & \text{if} \sum_{i=1}^{n} c_{r_i}[\xi] > \frac{\sqrt{n}}{2}; \\
o, & \text{else} \end{array}\right.\) |
| 13.6 | Conditions verification | \(\text{if } c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j}), c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j}), c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j})\) then \(\rightarrow 8.3 \& 8.8\); else 8.9 |
| 13.7 | The next RO attribute in cluster \(CT_i^4\) is added | \(ct_i := ct_i + 1\). |
| 13.8 | Optimal radius of container \(CT_i^4\) is determined | At conditions: \(c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j}), c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j}), c_{r_i}[\xi] < c_r(ct_{i} \otimes ct_{j})\) |
| 14 | Adding results to a knowledge base (KB). End of algorithm operation. | |
Input data for ASR are an array of learning samples, obtained based on data from Tables 1, 2, as well as results of \[10, 16\]:

\[
LM[kl][\text{implementation}][j],
\]

where \(kl\) is the number of learning matrix for RO class; implementation is the number of implementation in BLM \[10, 16\]; \(j\) is the number of recognition attribute for RO.

To assess ASR effectiveness and optimality of defined VAD for RO classes of ISDA, the Pareto method was used.

### Table 2

**Stages of algorithm of VAD formation for the attributes of recognition of cyber attacks, anomalies or threats**

| Stage | Action | Clustering algorithm for a mathematical description of RO attributes |
|-------|--------|---------------------------------------------------------------|
| 1     | Value of meter of steps of VAD change \(ca\), for RO attribute “0” | \(l := 0\) |
| 2     | Calculation of \(A_{im}[1]\) and \(A_{i0}[1]\) of VAD of RO attribute for entire FS | \(A_{im}[1] = \text{lm}_{im} - \frac{ca_{im}}{100}\) \(A_{i0}[1] = \text{lm}_{i0} + \frac{ca_{i0}}{100}\) where \(\text{lm}_{im}\) is the \(i\)-th attribute of vector-standard of implementation \(lm_{im}\) for basic class \(CT_{im}\). (It was accepted that \(CT_{im}\) characterizes the most acceptable states of IB). |
| 3     | Formation of BLM \(I_{l1}^{[cl]}\) | Rule: \(ct_{m,i}^{[cl]} = \begin{cases} 1, & \text{if } A_{im}[1] < \text{lm}_{im} < A_{i0}[1]; \\ 0, & \text{else} \end{cases}\) |
| 4     | Formation of set \(\{ct_{m}\}\) for vectors-standards of implementation of RO \(CT_{m}\) | Rule: \(ct_{m,i} = \begin{cases} 1, & \text{if } \sum_{i=1}^{n} \frac{ct_{m,i}}{ct_{m,i}} > \frac{1}{2}; \\ 0, & \text{else}, \end{cases}\) where \(n\) is the number of implementation of RO (attributes), which belong to the cluster of correspondent class \(CT_{m}\) |
| 5     | Splitting \(\{ct_{m}\}\) into pairs of the nearest adjacent vectors-standards | Methods and models \[8, 10, 12, 14, 23, 25\] are used |
| 6     | Restoration of container for \(CT_{m}\) | Expression – stage 6.4 Table 1 |
| 6.1   | Values of meter of recognition classes “0” | \(m:=0\) |
| 6.2   | Increasing the value of meter | \(m:=m+1\) |
| 6.3   | Value of meter of steps of RC change “0” | \(cr:=0\) |
| 6.4   | Increasing the value of meter | \(cr:= cr +1\) |
| 6.5   | Calculation of current ICFE | Expression – stage 6.4 Table 1 |
| 6.6   | Condition verification | \(\text{if } CE_{m} \notin IS_{cr} \text{ then } \rightarrow 6.4 \) \(\text{else } 6.7.\) |
| 6.7   | Calculation of current ICFE | Expression – stage 6.4 Table 1 |
| 6.8   | Calculation of GMAX of ICFE | \(CE_{m}[1] := \text{extrem} CE_{m}[1, cr]\) |
| 6.9   | Calculation of optimal RC of RO class \(CT_{m}\) | \(cr_{m}[1] := \text{arg extrem} CE_{m}[1, cr]\) |
| 7     | Condition verification | \(\text{if } m \notin M \text{ then } \rightarrow 6.2 \) \(\text{else } 8\) |
| 8     | Calculation of averaged ICFE value | \(\overline{CE_{cr}} = (1/M) \sum_{m=1}^{M} CE_{m}\) |
| 9     | Condition verification | \(\text{if } ca[1] \leq ca_{cav} / 2 \text{ then } \rightarrow 2 \) \(\text{else } 10\) |
| 10    | Condition verification | \(\text{if } CE \notin IS_{cav} \text{ then } \rightarrow 11 \) \(\text{else } 6.8 \& 6.9\) |
| 11    | Calculation of GMAX ICFE in admissible function determination range | \(ca^{*} = \text{arg max}(\max_{m} \{ \max_{l} \overline{CE}\})\) |
| 12    | Adding results to a knowledge base (KB). End of algorithm operation. | |

Input data for ASR are an array of learning samples, obtained based on data from Tables 1, 2, as well as results of \[10, 16\]:

\[
LM[kl][\text{implementation}][j],
\]

where \(kl\) is the number of learning matrix for RO class; implementation is the number of implementation in BLM \[10, 16\]; \(j\) is the number of recognition attribute for RO.
The membership degree of the best, from the standpoint of ARS or an expert, variant of Pareto-optimal solution in terms of strategies for providing cyber protection was determined by formula:

$$\max \left[ \sum_{j=1}^{k} \sum_{l=1}^{J} z_{ij} \otimes p_{ij} \otimes p_{j} \right] = \max_{w,w'} \text{CE} \{ W \{ x \} \}$$  \hspace{1cm} (14)$$

where $\otimes$ is the triangular norm (T-norm) [5, 28]; $W(x)$ is the final choice of the solution option of ARS (or an expert); $z_{ij}$ is the fuzzy assessment of usefulness of the $i$-th option of solving the problem of recognition of anomaly or cyber attack, which is determined by value of ICFE; $p_{ij}$ is the assessment of CHS states in the process of RO recognition; $p_{j}$ are the assessments of ARS states in the process of anomalies or cyber attack recognition.

Membership degree of the best variant of Pareto-optimal fuzzy solution for the formation of KB for ARS was defined using the modified Wald criterion and the Savage criterion [5].

5. Simulation of the clustering algorithm and the formation of VAD for the attributes of anomalies and cyber attacks

The algorithms were implemented in the MATLAB 7/2009 and Simulink programming environments in order to subsequently study the operation modes of ARS of anomalies and cyber attacks in CHS (under conditions of countering the targeted cyber attacks [1, 7, 10, 16, 18]).

In accordance with recommendations of [8, 20, 21, 25], multidimensional binary learning matrices (MBLM) of RO classes had from 50 to 65 implementations. For the classes of network attacks [7, 8] (DoS/DDoS, Probe, R2L, U2R), the number of recognition attributes made up 12–41 [13, 23, 15], for virus attacks, 7–15 [5, 7] attributes. Fig. 1, a-e, shows dependences of ICFE learning of simulation model (SM) of ARS [23] on RO and cr. In Fig. 1, a-e, the middle section (marked in blue) corresponds to the operation area of the selected recognition attributes, that have the highest informativeness indicator (ICFE) [23].

After formation of MBLM for the normal behavior of a system, according to the proposed algorithm, binary trees of traffic are constructed for network attacks, as well as error-free descriptive rules, by the appropriate learning matrix of attributes [16, 18, 23]. Next, MBLM are determined and registered for the system, which allows us to form controlling commands for responding to the deviations of parameters from the estimated values, please refer to Fig. 2, a, b.

Fig. 3 shows results, obtained in the course of simulation modeling and testing of algorithms of parallel clustering and formation of reference deviations for the recognition attributes, on the example of a DoS class of attacks. Results of the clustering of attack attributes in the process of testing the improved algorithm and the formation of VAD are shown in blue color. Similar results were also obtained for other classes of anomalies and cyber attacks.

An analysis of results of the simulation experiment (Fig. 3) on determining the dependence of ICFE of ARS learning allows us to draw the following conclusions:

- the averaged maximum value of ICFE of ARS learning is equal to, for attacks of the DoS/DDoS class, $CE = 3.19$; for attacks of the Probe class $CE = 3.15$; for attacks of the R2L class $CE = 2.84$; for attacks of the U2R class $CE = 3.27$; for virus attacks (VA) $CE = 2.56$;

- the averaged value of optimal radius cr equals in code units for RO classes, given in Table 3, respectively: for $h_{cr}$ class: DoS/DDoS – $c_{cr} = 4$; Probe – $c_{cr} = 3$; R2L – $c_{cr} = 4$; U2R – $c_{cr} = 4$; BA – $c_{cr} = 5$; for $h_{cr}^{+}$ class: DoS/DDoS –
The values of optimal RC cr, taking into consideration additional hypotheses for the examined simulation models of ASR learning, are given in Table 3.

Table 3

| No. | Accepted hypotheses for RO | Values of optimal RC cr | | | |
|---|---|---|---|---|---|---|
| 1 | Basic working hypothesis – hy: attribute (attributes) rc of RO and indicator IE (characterizes stability of CIIS functioning [18, 23]) is within the normal state of CIIS | cropt = 4–5 | cropt = 3–4 | cropt = 4–5 | cropt = 4–5 | cropt = 5–6 |
| 2 | Hypothesis hy: attribute (attributes) allows drawing a conclusion that indicator IE is lower than the norm | cropt = 2–3 | cropt = 1–2 | cropt = 1–2 | cropt = 1–2 | cropt = 2–3 |
| 3 | Hypothesis hy: attribute (attributes) allows drawing a conclusion that indicator IE is higher than the norm | cropt = 3–4 | cropt = 3–4 | cropt = 2–3 | cropt = 2–3 | cropt = 3–4 |

Additional hypotheses for simulation model

| 4 | Hypothesis hy: node of CIIS demonstrates increased network activity | cropt = 4 | cropt = 4 | cropt = 3 | cropt = 3 | – |
| 5 | Hypothesis hy: node of CIIS demonstrates increased activity during external traffic | cropt = 3 | cropt = 3 | cropt = 3 | cropt = 2 | – |
As was shown by data analysis, for IM, Fig. 1–3, quasi-optimal value of parameter $c_{a,n}$ of VAD equals VAD$=8–16\%$ at maximum value of $CE_{max}=6.16$.

Thus, it was proved in the course of the simulation experiment that the proposed algorithms for the clustering of RO attributes enable us to obtain efficient learning matrices for ASR as a part of ISDA.

6. Discussion of results of testing the algorithms and prospects of further research

Scientific and practical results of research in the form of software applications were implemented in ASR and adaptive expert systems (AES) of cyber protection, implemented at the state enterprise “Design and engineering technological bureau of automation of control systems on railway transport of Ukraine” of the Ministry of Infrastructure of Ukraine, as well as in the information security services of computing centers at the industrial and transportation enterprises in the cities of Kyiv, Dnipro and Chernihiv.

The proposed algorithms differ from the existing ones by the possibility of simultaneous formation of reference tolerances in the course of analysis of complex attributes of anomalies and cyber attacks. This allows changing VAD for all attributes simultaneously during the procedure of training the existing and promising ISDA. The improved algorithms are also focused on the possibility of processing a large amount of specialized data during procedures of the recognition and analysis of various types of attributes of anomalies and targeted cyber attacks in CIIS.

The effectiveness of using the proposed algorithms depends on the number of informative attributes, which are used for the formation of BLM. In addition, efficiency of algorithms is determined by the input data for ASR or AES, formed at each step of clustering. When the number of attributes is insignificant, the effect of using the modified algorithm is negligible.

The results presented are a continuation of the research, results of which were described earlier in articles [10, 18, 23]. The prospects of further research include the enlargement of attributes knowledge base and the formation of BLM of ASR.

7. Conclusions

1. We proposed to refine the algorithm of splitting the feature space into clusters in the course of implementation of procedure for the recognition of anomalies and cyber attacks, which differs from the existing algorithms by the simultaneous formation of reference tolerances during analysis of complex RO attributes, and allows simultaneous changing of VAD for all attributes at every step of learning. The proposed refinements make it possible to prevent possible cases of the absorption of one RO class of basic attributes of anomalies and cyber attacks by another class. In this case, predicate expressions were obtained for ASR that is capable of self-learning.

2. We examined the devised algorithms on the simulation models in MatLab. It was proved that the proposed algorithms for the clustering of RO attributes enable to obtain effective learning matrices for ASR as a part of ISDA.

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