

Fuzzy Logic Based Anomaly Detection for Embedded Network Security Cyber Sensor

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Abstract— Resiliency and security in critical infrastructure control systems in the modern world of cyber terrorism constitute a relevant concern. Developing a network security system specifically tailored to the requirements of such critical assets is of a primary importance. This paper proposes a novel learning algorithm for anomaly based network security cyber sensor together with its hardware implementation. The presented learning algorithm constructs a fuzzy logic rule base modeling the normal network behavior. Individual fuzzy rules are extracted directly from the stream of incoming packets using an online clustering algorithm. This learning algorithm is specifically developed to comply with the constrained computational requirements of low-cost embedded network security cyber sensors. The performance of the system was evaluated on a set of network data recorded from an experimental test-bed mimicking the environment of a critical infrastructure control system.

Keywords— *Anomaly Detection; Cyber Sensor; Embedded Systems; Fuzzy Logic System; Online Clustering;*

I. INTRODUCTION

Critical infrastructure control systems, typically composed of interconnected computer-based stations, exchange crucial information via the computer network. These critical components, which can be found in systems such as SCADA or nuclear power plants, constitute a focus of an increased cyber security [1], [2]. Breaking into such systems with network intrusion attacks can have severe effects on multiple levels, such as security, public safety, industrial or economical. The danger is even higher considering that critical infrastructures are not immune to these threats and that they possibly may be more vulnerable than common information technology systems [3]. Therefore, network traffic anomaly detection for critical infrastructures is an obvious need [4].

Network intrusion detection systems originated in 1980's and in the seminal work of Denning [5], [6]. Generally speaking, two kinds of IDS can be found; anomaly detection and signature based detection systems. Signature based detection system attempt to match the observed behavior against a database of known attack signatures. On the other hand, an anomaly based detection system seeks deviations from the learned model of normal behavior [7], [8]. The system builds a representative model exclusively based on the previously collected normal behavior. The system is capable

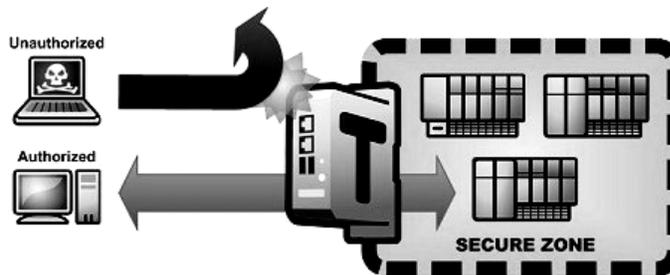


Fig. 1 Schematic diagram of the network security cyber sensor [20].

of detecting novel and dynamically changing intrusion instances, assuming that these are substantially different from the model of normal behavior. Unfortunately, any normal acceptable behavior not included in the training set will likely not match the model and generate false alarm. Hence, acquiring descriptive training dataset is of a crucial importance. The anomaly detection approach is adopted in the presented paper.

Computational intelligence techniques have been extensively applied to the problem of network intrusion detection [7], [9]. Techniques such as artificial neural networks [10]–[13], support vector machines [14], genetic algorithms [15], fuzzy logic [16], [17] or unsupervised clustering [18]–[20], proved to be powerful learning tools for modeling the network behavior. The attractiveness of computational intelligence comes from the ability to learn from multi-dimensional non-linear data [9].

The presented paper proposes a learning algorithm for a fuzzy logic based anomaly detection system specifically developed for the constrained resources of embedded network security cyber sensors [21]. A schematic view of the presented system is depicted in Fig. 1. Here the implemented cyber sensor creates a secure zone around the control system. The learning algorithm builds a fuzzy rule base, which describes the previously seen normal network communication behavioral patterns. This fuzzy rule base is constructed directly from the stream of incoming packets using the online version of the nearest neighbor clustering algorithm. Subsequently, the set of extracted clusters is transformed into individual fuzzy rules. Moreover, the algorithm can be re-trained on newly available normal behavior data, while

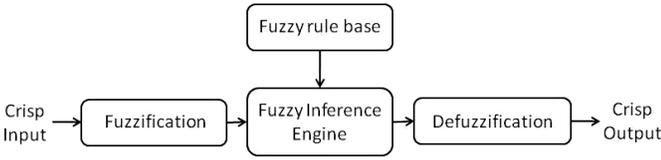


Fig. 2 Fuzzy logic system.

maintaining the previously acquired knowledge. The performance of the algorithm was tested on an experimental test-bed mimicking the critical infrastructure control system.

The rest of the paper is structured as follows. Section II provides a brief overview of fuzzy logic systems and the nearest neighbor clustering algorithm. The considered hardware platform for the embedded network security device is described in Section III. Section IV and V explain the network behavior feature extraction technique and the proposed anomaly detection algorithm, respectively. The system is experimentally evaluated in Section VI and Section VII concludes the paper.

II. BACKGROUND OVERVIEW

This section provides a brief background overview of fuzzy logic systems and the nearest neighbor clustering algorithm.

A. Fuzzy Logic Systems

Fuzzy logic has been originally proposed by Zadeh as a tool for dealing with linguistic uncertainty and vagueness ubiquitous in the imprecise meaning of words [23]. A Fuzzy Logic System (FLS) is composed of four primary parts – input fuzzification, fuzzy inference engine, fuzzy rule base and output defuzzification, as depicted in Fig. 2. The Mamdani FLS considered in this work maintains a fuzzy rule base populated with fuzzy linguistic rules in an implicative form. Consider rule R_k that is described as follows [24], [25]:

$$\text{Rule } R_k: \text{IF } x_1 \text{ is } A_1^k \text{ AND } \dots \text{ AND } x_n \text{ is } A_n^k \\ \text{THEN } y_k \text{ is } B^k \quad (1)$$

Here, symbol A_i^k and B^k denote the i^{th} input fuzzy set and the output fuzzy set of the k^{th} rule, respectively, n is the dimensionality of the input vector \vec{x} and y_k is the associated output variable. Each element of the input vector \vec{x} is first fuzzified using the respective fuzzy membership function (e.g. Gaussian, triangular, trapezoidal, etc.). The fuzzification of input value x_i into fuzzy set A_i yields a fuzzy membership grade $\mu_{A_i^k}(x_i)$. Using the minimum t-norm the degree of firing of rule R_k can be calculated as:

$$\mu_{R_k}(\vec{x}) = \min\{\mu_{A_i^k}(x_i)\}, \quad i = 1..n \quad (2)$$

After applying the rule firing strength via the t-norm operator to each rule consequent, the output fuzzy sets are aggregated using the t-conorm operator (e.g. the maximum

operator) resulting in a output fuzzy set B . For detailed description of the fuzzy inference process refer to [24], [25].

In order to obtain the crisp output value, one of the available defuzzification techniques is applied. Upon discretizing the output domain into N samples, for example the centroid defuzzifier can be applied:

$$y = \frac{\sum_{i=1}^N y_i \mu_B(y_i)}{\sum_{i=1}^N \mu_B(y_i)} \quad (3)$$

B. Nearest Neighbor Clustering

The Nearest Neighbor Clustering (NNC) algorithm is an unsupervised clustering technique [9]. The clustering process is controlled by an established maximum cluster radius parameter. The smaller the radius the more clusters will be generated and vice versa.

Assume an input dataset X composed of N input patterns denoted as:

$$X = \{\vec{x}_1, \dots, \vec{x}_N\}, \quad \vec{x}_i \in \mathfrak{R}^n \quad (4)$$

Here, n denotes the dimensionality of the input domain. Vector \vec{x}_i can be expressed as $\vec{x}_i = \{x_i^1, \dots, x_i^n\}$.

Each cluster constitutes a prototype of similar instances, subject to a specific similarity measure. The Euclidean distance similarity measure is considered in this work. Each cluster P_i is described by its Center Of Gravity (COG) \vec{c}_i and its associated weight w_i . The weight w_i stores the number of patterns previously assigned to cluster P_i . Following this notation, cluster P_i can be expressed as:

$$P_i = \{\vec{c}_i, w_i\}, \quad \vec{c}_i \in \mathfrak{R}^n, w_i \in \mathbb{N}^+ \quad (5)$$

The learning process of the NNC algorithm begins by creating an initial cluster P_1 at the location of the first input pattern \vec{x}_1 . Next, input patterns from dataset X are selected in a sequential manner. The nearest prototype from the set of available clusters is determined for each instance. For an input pattern \vec{x}_i , the nearest cluster P_a is determined using the Euclidean distance norm:

$$\text{dist}(\vec{c}_a, \vec{x}_i) = \min_j \sqrt{(c_j^1 - x_i^1)^2 + \dots + (c_j^n - x_i^n)^2}, \quad j = 1..C \quad (6)$$

Here, C denotes the number of currently acquired clusters. Using the maximum cluster radius parameter - rad , the input pattern \vec{x}_i is assigned to cluster P_a if the following condition holds: $\text{dist}(\vec{c}_a, \vec{x}_i) \leq rad$. In this case, the parameters of cluster P_a are updated as:

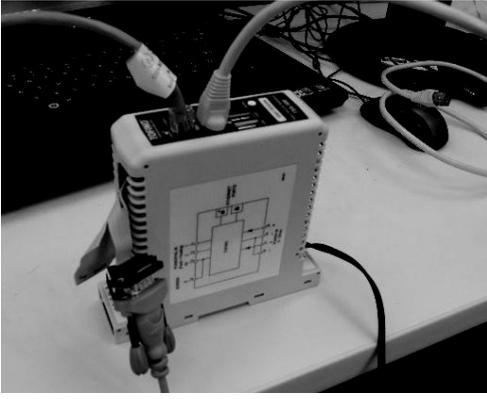


Fig. 3 Photo of the TOFINO network security cyber sensor plugged-in into the test system.

$$\bar{c}_a = \frac{w_a \bar{c}_a + \bar{x}_i}{w_a + 1}, w_a = w_a + 1 \quad (7)$$

If $dist(\bar{c}_a, \bar{x}_i) > rad$, a new cluster is created at the location of input pattern \bar{x}_i , and its weight is set to 1.

III. EMBEDDED NETWORK SECURITY CYBER SENSOR

The Tofino embedded network security device, depicted in Fig. 3, is manufactured by Byres Security Inc. [22]. Originally, the device was developed for pre-emptive threat detection, termination and reporting, specifically tailored for the needs of SCADA and industrial control systems. Its major advantages are primarily its low-cost and ease of deployment in real world systems. In the presented work, the Tofino cyber sensor was used as an embedded development platform for implementation of the proposed anomaly based detection learning algorithm.

The Tofino platform consists of an Arcom Vulcan single board computer. The main processor is an Intel IXP425 XScale processor running at 533MHz with 64MB of DRAM and 32MB of flash memory. The Intel IXP425 XScale is based on an ARM V5TE instruction set [26]. Two Ethernet ports are provided along with two USB ports. The Ethernet ports are used in processing packet data and the USB ports are used for storage of statistics. The operating system is based on the OpenWRT distribution of Linux.

One of the specifics of this embedded platform is that the Intel IXP425 XScale processor used in the Tofino platform does not have a floating point unit (FPU). Instead, the floating point arithmetic used in the presented algorithm is emulated. Future work will include modification of the current implementation to use fixed point (integer) arithmetic. Depending on the implementation, a large performance gain may be achieved by using the SIMD Multiply-Accumulate unit coprocessor unit available on the IXP425. This coprocessor allows 16x32 multiply-accumulate operations to complete in a single cycle.

While not of utmost concern in an academic setting, the implementation of the proposed algorithm on a hardware platform is relevant. Sommer and Paxson [7] argue that it in

terms of capabilities and limitations it is important to obtain insight into the performance of an anomaly detection system from an operational point of view. The focused implementation is here at a very low level with an envisioned deployment just before some critical equipment, such as a Programmable Logic Controller (PLC). With the increasingly common usage of network based control systems and the current deployment of smart grid systems hundreds, thousands and possibly millions of devices will be interconnected. This makes the cost and reliability of an implemented hardware solution a relevant concern. In addition, the proposed hardware implementation of the embedded network security cyber sensor provides a performance baseline that might prove useful for comparison in future work.

IV. DATA ACQUISITION AND FEATURE EXTRACTION

This section describes the network data acquisition process and reviews the previously published window based feature extraction technique.

A. Control System Experimental Test-Bed

The hardware experimental test-bed system that was used for network data acquisition represents several aspects of an operational control system, such as operational control structure, control system network and hardware control of actual physical processes. RSView32, a Rockwell Software HMI product, provides an integrated component based interface for monitoring of the system behavior. The interface runs on a Windows XP laptop connected via an IPv4 network. A Moxa EDS-505A operated Ethernet switch provides network connectivity for the controller. This switch is mounted on a DIN-Rail and powered by the control system source. All network traffic to and from the controller is transported via the switch. Port mirroring has been enabled on the control traffic port connected to the HMI machine. A Linux laptop with the *tcpdump* software application was

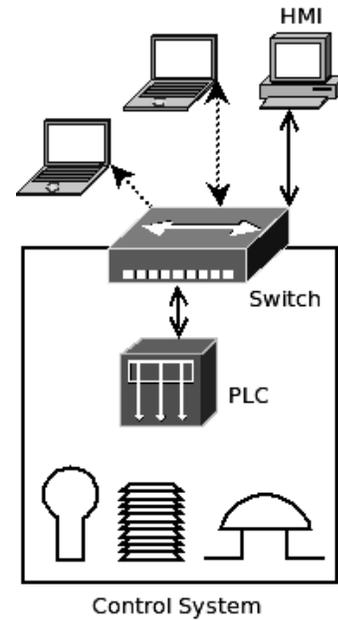


Fig. 4 Network data acquisition setup. A PLC is connected through a hub to the control PC station using an Ethernet network.

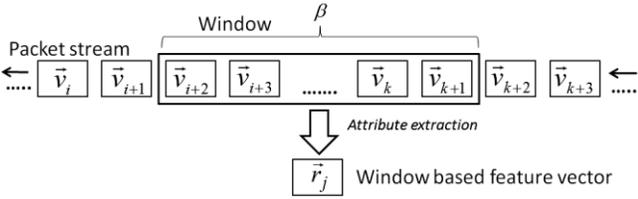


Fig. 5 Window based feature extraction process [13].

TABLE I
SELECTED WINDOW-BASED FEATURES

Num. of IP addresses	Num. packets with 0 win. size
Avg. interval between packets	Num. packets with 0 data length
Num. of protocols	Average window size
Num. of flag codes	Average data length

attached to the mirror port allowing for network traffic capturing and monitoring. Finally, a second Linux-based laptop representing the attacker-compromised machine was attached to a third port. All anomalous traffic was instantiated from this machine.

The control system itself consists of an Allen-Bradley MicroLogix 1100 PLC [27]. Attached to the PLC are 6 lighted buttons, 7 lights, 2 potentiometers, 2 temperature sensors and a small electric fan constituting both digital and analog input/output points. All of the items are capable of being controlled individually from the PLC or directly by pressing a button. The experimental is depicted in Fig. 4.

B. Feature Extraction from Packet Stream

In a previous work of the authors, an Artificial Neural Network (ANN) based intrusion detection system was developed [13]. The ANN was trained on a sub-set of available network traffic features extracted by a window-based feature extraction technique applied directly to the stream of packets. This feature extraction technique is also utilized in the presented work. Here, the inherent time series nature of the packet stream data is described by a vector capturing the statistical behavior of the network traffic. The applied window segments the packet stream and monitors only a limited set of consecutive packets.

As described in [13], a window of specified length β is being shifted over the stream of network packets. At each position of the window a feature vector \vec{r}_j is computed from all the packets \vec{v}_i currently presented in the window. The next

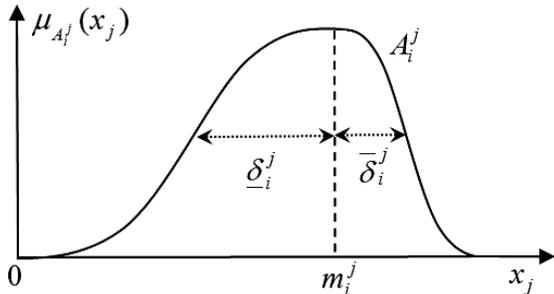


Fig. 6 Illustration of the non-symmetric input Gaussian fuzzy set A_i^j .

arriving packet is pushed into the window, while the last packet is removed from the end. The process of window based feature extraction is illustrated in Fig. 5.

Table I summarizes the list of extracted window-based statistical features. This set of features was empirically selected based on the analysis of the recorded network traffic and the motivation to most accurately capture the time series nature of the packet stream. For further details and evaluation of the window based feature extraction refer to [13].

V. ONLINE LEARNING FOR ANOMALY IDS

This section presents the learning algorithm for the fuzzy logic based anomaly detection for an embedded network security cyber sensor. First, rule extraction via adapted online NNC algorithm is presented. Next, the fuzzy rule based normal behavior modeling is explained.

A. Rule Extraction via Online Clustering

The proposed rule extraction algorithm takes into account the constrained computational resources of the available embedded network security cyber sensor. Other learning approaches, such as the previously published IDS-NNM algorithm [13], pursue offline learning approach once all training data have been acquired. However, such learning process is typically computationally unfeasible for the considered embedded devices, given the typically encountered network traffic density [21].

This paper proposes a new low-cost online rule extraction technique. The presented algorithm learns directly from the stream of incoming packets. In this manner, the need for storing all packet information into memory is eliminated. The final normal network behavior model is composed of a set of fuzzy rules. Each rule is extracted using an online version of the adapted NNC algorithm. The algorithm maintains additional information about the spread of data points associated with each cluster throughout the clustering process.

Each cluster P_i of encountered normal network behavior is described by its center of gravity \vec{c}_i , weight w_i and a matrix of boundary parameters M_i . Hence:

$$P_i = \{\vec{c}_i, w_i, M_i\}, \vec{c}_i = \{c_i^1, \dots, c_i^n\}, M_i = \begin{bmatrix} \bar{c}_i^1 & \dots & \bar{c}_i^n \\ \underline{c}_i^1 & \dots & \underline{c}_i^n \end{bmatrix} \quad (8)$$

Here, i is the index of particular cluster, c_i^j is the attribute value in the j^{th} dimension, \bar{c}_i^j and \underline{c}_i^j are the upper and lower bounds on the encountered values of the j^{th} attribute for data points assigned to cluster P_i and n denotes the dimensionality of the input. The algorithm maintains a set of clusters Ω . Initially, the algorithm starts with a single cluster P_1 positioned at the first supplied training data point \vec{x}_1 . This initial data point becomes available once the shifting window first fills with the incoming packets.

Upon acquiring a new data point \vec{x}_i from the shifting window buffer, the set of clusters Ω is updated according to the NNC algorithm. First, the Euclidean distance to all

available clusters with respect to the new input feature vector \bar{x}_i is calculated. The nearest cluster P_a is identified. If the computed nearest distance is greater than the established maximum cluster radius parameter, a new cluster is created. Otherwise the nearest cluster P_a is update similarly as in (7):

$$\bar{c}_a = \frac{w_a \bar{c}_a + \bar{x}_i}{w_a + 1}, w_a = w_a + 1 \quad (9)$$

$$\bar{c}_i^j = \max(x_i^j, \bar{c}_i^j), \underline{c}_i^j = \min(x_i^j, \bar{c}_i^j) \quad j=1..n \quad (10)$$

Hence, the modified NNC algorithm also keeps track of the lower and upper bounds of the encountered input values in each dimension for every cluster.

If the nearest cluster is further away than the established maximum cluster radius, a new cluster is created according to the standard NNC algorithm.

B. Fuzzy Rule Based Behavior Modeling

Once the rule extraction phase of the learning process is finalized (e.g. user decision, time limit, limit on the number of packets, etc.), the learning algorithm maintains a final set of clusters Ω that describe the normal network communication behavioral patterns observed in the provided training data. In the next phase of the algorithm, each cluster is converted into a fuzzy logic rule. Each fuzzy rule describes the belonging of a particular sub-region of the multi-dimensional input space to the class of normal behavior.

An n -dimensional cluster P_i is transformed into its associated fuzzy rule R_i as follows. Rule R_i is composed of n antecedent fuzzy sets A_i^j , $j=1..n$. Each fuzzy set A_i^j , located in the j^{th} dimension of the input space, is modeled using a non-symmetrical Gaussian fuzzy membership function with distinct left and right standard deviations. There are three

parameters of the membership function, namely mean m_i^j and the left and the right standard deviations $\bar{\delta}_i^j$, $\underline{\delta}_i^j$, as shown in Fig. 6. The parameter values are extracted based on the computed cluster P_i in the following manner:

$$m_i^j = c_i^j \quad (11)$$

$$\bar{\delta}_i^j = \alpha(\bar{c}_i^j - c_i^j) \quad (12)$$

$$\underline{\delta}_i^j = \alpha(c_i^j - \underline{c}_i^j) \quad (13)$$

Here, symbol α denotes the fuzziness parameter, which is used to adjust the spread of the membership functions. Using the minimum t-norm, the firing strength of fuzzy rule R_i is then computed as:

$$\mu_{R_i}(\bar{x}) = \min_{j=1..n} \{\mu_{A_i^j}(x_j)\} \quad (14)$$

In this specific application, the output of the fuzzy rule is a singleton fuzzy set assigning the input pattern to the normal behavior class. Hence, in this special case the fired output of a particular fuzzy rule is actually its own firing strength $\mu_{R_i}(\bar{x})$.

The final output decision y of the anomaly detection system is obtained by applying to maximum t-conorm to the output of all available rules:

$$y(\bar{x}) = \max_{i=1..C} \mu_{R_i}(\bar{x}) \quad (15)$$

Here, C denotes the number of extracted fuzzy rules. The value of the output y denotes the degree of belonging of input pattern \bar{x} to the class of normal behavior. By applying a crisp decision threshold the input pattern can be labeled as either anomalous or normal network behavior.

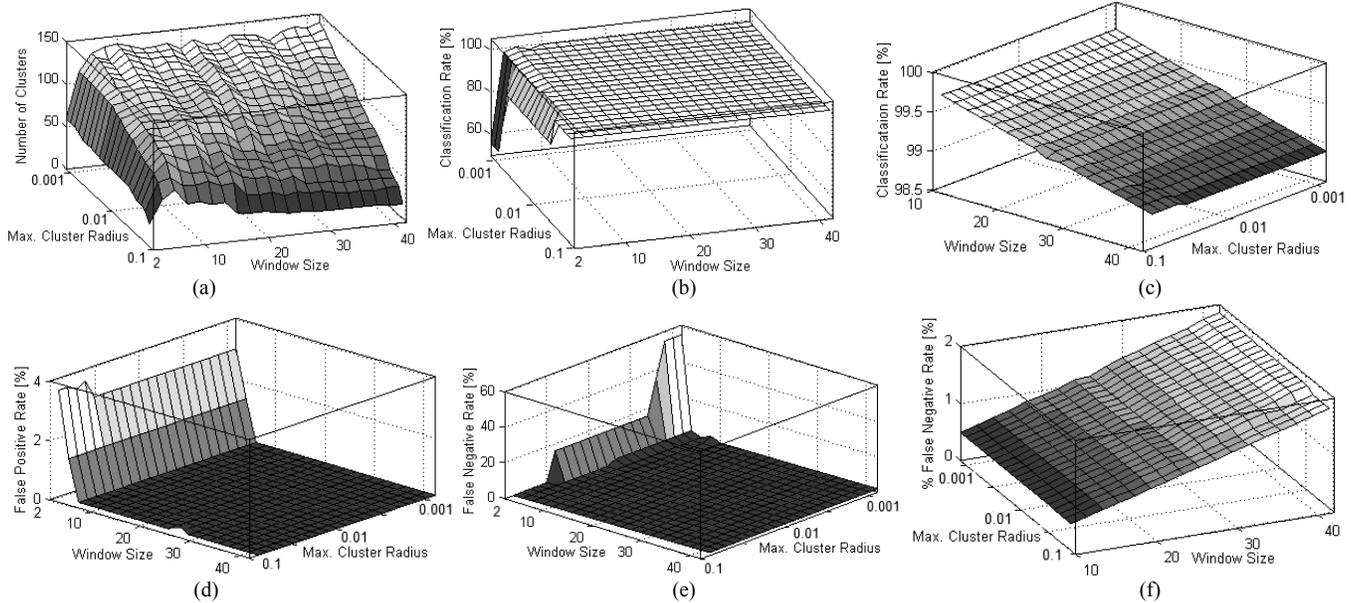


Fig. 7 Parameter control analysis of the proposed anomaly detection algorithm. Figures show the number of generated clusters (a), correct classification rate (b), zoomed-in view of the classification rate (c), false positive rate (d), false negative rate (e), and zoomed-in view of the false negative rate (f) for different values of window size and maximum cluster radius parameters.

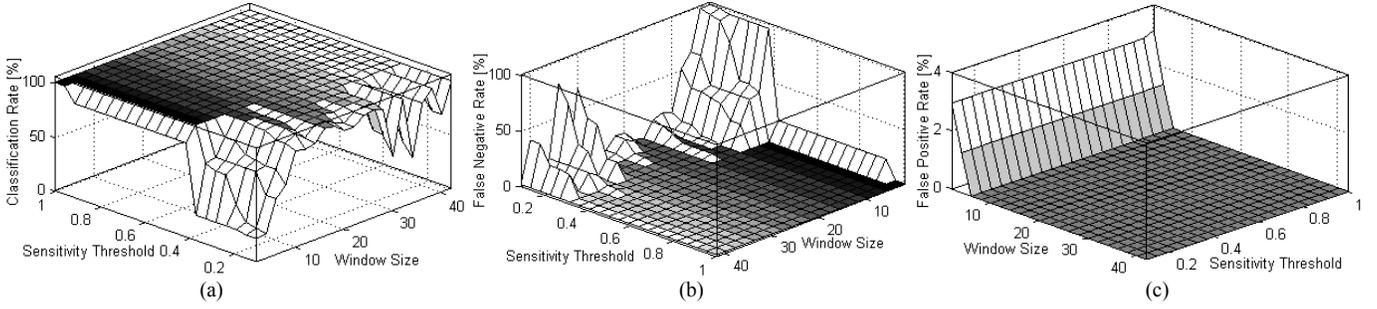


Fig. 8 Parameter control analysis of the proposed anomaly detection algorithm. Figures show the correct classification rate (a), the false negative rate (b), and the false positive rate (c) for different values of window size and the sensitivity threshold.

VI. EXPERIMENTAL RESULTS

This section first describes the acquired experimental datasets. Next, the suitable values of control parameters are found by analyzing their impact on the performance of the algorithm. Finally, the classification performance is evaluated on the acquired testing datasets.

A. Experimental Datasets

The *Nmap* [28] and *Nessus* [29] software utilities were used to create anomalous network traffic behavior in an attempt to emulate the probes of a cyber attacker. *Nmap* is a network scanning tool commonly used to identify hosts, scan ports, operating systems and to determine applications that are listening on open ports. It has many options and provides useful reconnaissance information for determining further courses of action. *Nessus* is a network scanning tool that provides auditing capabilities, vulnerability assessments and profiling information. In addition to general computer related assessments, control system specific vulnerabilities are available and were used on the previously described experimental test-bed.

The simulated intrusion attempts include: ARP pings, SYN stealth scans, port scanning, open port identification and others. Cyber attacks ranged from long attacks composed of many packets to very short intrusion sequences. Two sets of experimental data have been recorded. The recorded training set is composed of 6 dataset with only normal network behavior. Overall, 60,661 packets of normal network traffic were acquired including specialized normal behavior such as system initialization and system component reconnection. The second set is a testing set composed of 11 datasets, which include simulated abnormal behavior. Overall 213,924 packets have been recorded.

B. Parameter Tuning

The performance of the presented anomaly detection algorithm depends on the values of several control parameters: i) window size of the window feature extraction, ii) maximum cluster radius for the online NNC algorithm, iii) the fuzziness parameter α of the fuzzy membership functions, and iv) the value of the crisp threshold for normal/anomaly traffic labeling.

The correct classification, the false negative and the false positive rates were used as performance measures. The correct classification rate is the percentage of the overall correctly classified data instances. The false negative rate is the ratio of incorrectly labeled normal behavior inputs and the overall number of normal behavior instances. The false positive rate is the ratio of incorrectly label anomalous inputs and the overall number of anomalies.

Fig. 7 and Fig. 8 depict the performance for different values of window size, maximum cluster radius and the crisp decision threshold. Fig. 7(a) shows the number of generated clusters. This number monotonically increases with the decreasing maximum cluster radius and reaches its maximum for window size around 6. The more clusters generated, the more detailed the model. However, a more detailed model increases the chance of overfitting and requires additional computational time. From Fig. 7(b)-(f) it can be seen that the classification performance primarily depends on the window size. Small values of window size (e.g. 2, 4 or 6) generate increased number of false negatives with non-zero false positive rate (~4%). From the detailed view in Fig. 7(c) and Fig. 7(f) it is apparent that there is a slight gradient towards smaller values of window size. Hence, values of window size around 10 seem to yield optimal results for the given datasets.

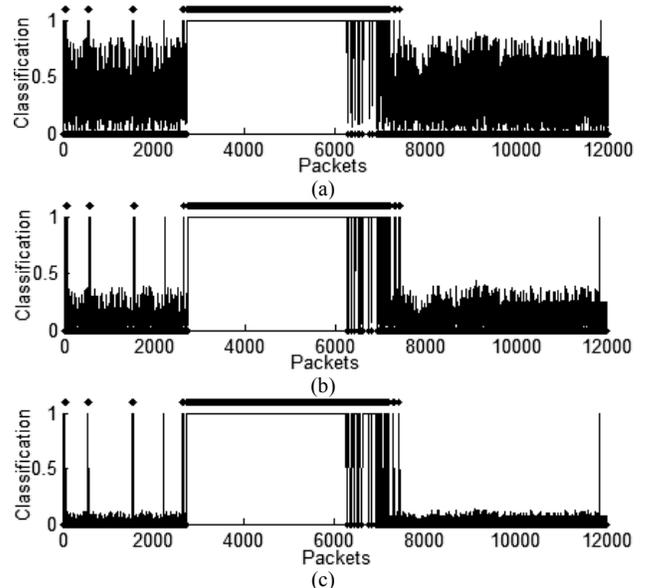


Fig. 9 Anomaly detection performance on dataset 1 for values of parameter $\alpha = 0.5$ (a), 1 (b), and 2.0 (c).

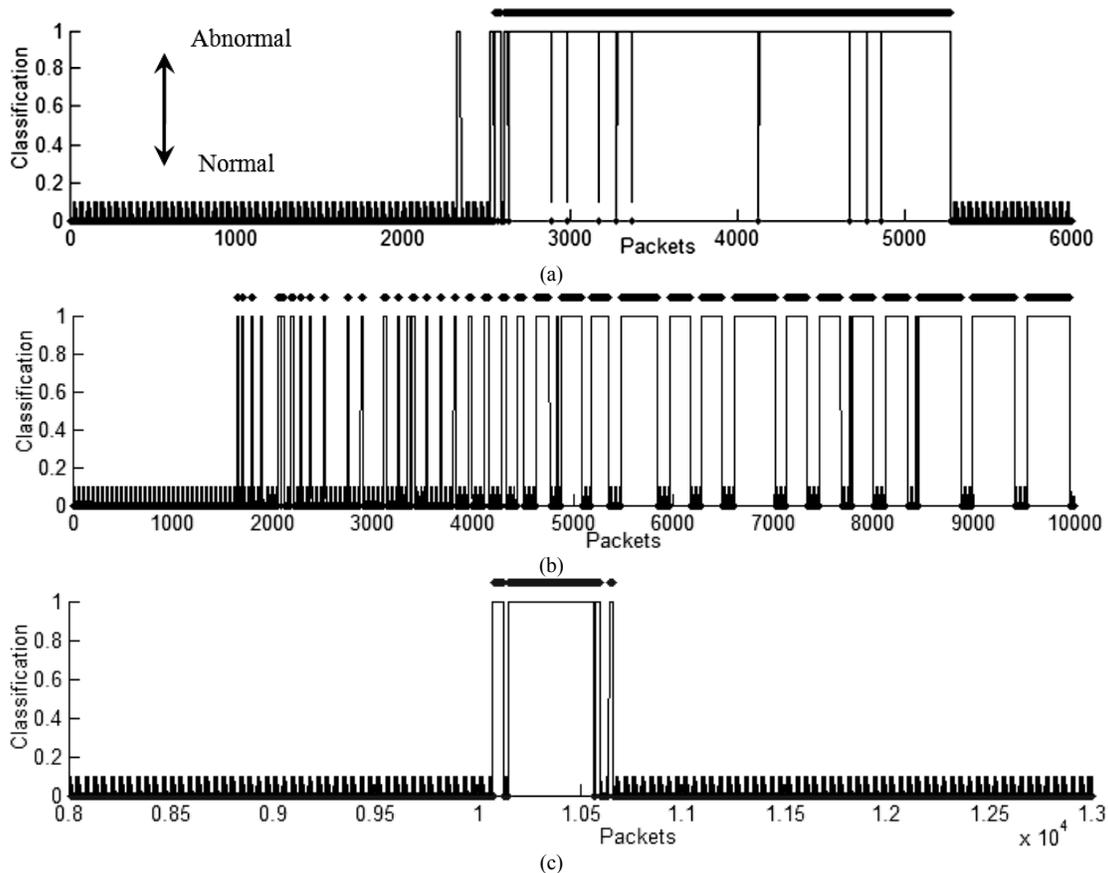


Fig. 10 Anomaly detection performance of the proposed algorithm on segments of packets from datasets 2 (a), 3 (b), and 4 (c). Thin line represents system decision, thick line denotes the known anomalous behavior.

Fig. 8 investigates the influence of the crisp decision threshold and the window size. High rates of both false positives and negatives can be again seen for smaller values of window size and for smaller values of decision threshold. The figures demonstrate that with window size of approximately 20 packets, the algorithm is least sensitive to the value of the crisp decision threshold. This is likely to be where the best separation between normal and anomaly behavior is obtained.

The influence of the fuzziness parameter of the membership function is briefly demonstrated in Fig. 9. Here, the response of the algorithm applied to dataset 1 (thin line is algorithm

output, thick line marks known intrusions) is plotted. It can be observed that smaller values of the fuzziness parameter produce narrower membership functions, which tend to reject more instances of more unusual normal behavior. However, larger values of the fuzziness parameters would eventually lead to increased false positive rate as anomaly instances would become less distinct from the normal behavior.

In summary, the following parameters have been selected as the optimal values for the acquired experimental data: window size = 20, maximum cluster radius = 0.01, the fuzziness parameter $\beta = 2.0$, and crisp threshold = 0.9.

TABLE II
CLASSIFICATION PERFORMANCE OF THE FUZZY LOGIC BASED ANOMALY DETECTION ALGORITHM ON DIFFERENT DATASETS

Datasets	Number of Packets	Classification Rate	False Negatives	False Positives	Processing Time per Packet
Data 1	35,112	99.702 %	1.485%	0.000 %	0.264 ms
Data 2	29,147	99.586 %	1.448 %	0.000 %	0.217 ms
Data 3	34,148	99.517 %	1.251 %	0.000 %	0.206 ms
Data 4	13,131	99.313 %	0.715 %	0.000 %	0.206 ms
Data 5	10,444	99.299 %	0.721 %	0.000 %	0.206 ms
Data 6	5,401	99.053 %	1.006 %	0.000 %	0.196 ms
Data 7	7,926	99.646 %	0.369 %	0.000 %	0.198 ms
Data 8	23,134	99.307 %	0.704 %	0.000 %	0.201 ms
Data 9	24,388	99.531 %	0.502 %	0.000 %	0.210 ms
Data 10	15,431	99.422 %	0.701 %	0.000 %	0.201 ms
Data 11	15,565	99.180 %	1.002 %	0.000 %	0.226 ms
Sum / Average	213,924	99.360 %	0.900 %	0.000 %	0.212 ms

C. Classification Performance Evaluation

The fuzzy logic based anomaly detection algorithms was applied to the 11 acquired testing datasets. The algorithm was trained on the 6 training datasets composed of 60,661 normal behavior packets. The training took 11.946 s resulting in a potentially maximum processing speed of over 5,000 packets per second. Altogether 71 fuzzy rules were extracted.

The classification performance is summarized in Table II. Here, the classification rate, the false negative and the false positive rates are depicted for each dataset and the average values are calculated. It can be observed that the algorithm maintained 0% false positive rate and 0.9% average false negative rate. Hence, no intrusion attempts were missed, while maintaining low false negative rate.

Fig. 10 visually demonstrates the classification of datasets 2, 3 and 4. The thin line denotes the prediction of the anomaly detection system and the thick line above the system response marks the known occurrence of the anomalous behavior. It can be seen that the proposed anomaly detection system responded well to both long and short intrusion attempts.

VII. CONCLUSION

This paper presented a novel fuzzy logic based anomaly detection algorithm for embedded network security cyber sensors. The anomaly detection algorithm was specifically designed to allow for both fast learning and fast classification on the constrained computational resources of the embedded device. The algorithm extracts fuzzy rules using an adapted version of the online nearest neighbor clustering algorithm directly to the stream of packets.

The proposed algorithm was tested on an experimental test-bed mimicking the environment of a critical infrastructure control system with emulated probes of a cyber attacker. The control parameters of the presented algorithm were tuned via performance analysis. The final performance evaluation was performed on a set of 11 test datasets with over 200,000 packets with a wide range of anomalous network behavior. The experimental analysis yielded 99.36% correct classification rate with 0.0% false positive rate and 0.9% false negative rates.

The primary direction for future work includes incorporating type-2 fuzzy logic into the algorithm design, fusing the anomaly-detection based system with intrusion signatures to improve the classification performance and deploying the algorithm in real operational settings.

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