

Artificial Intelligence Techniques

in Cyber-Security Applications

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Modern Connected Society

The digital ecosystem is getting increasingly **ubiquitous** and **pervasive** Growing **complexity** due to size, distribution, and heterogeneity Growing **criticality** due to safety-related functionalities (e-health, transport, etc.) and evolving **cyber-security threats**











Security Operations Centers





Issues

- Too much information for few control room operators
- Operators overwhelmed by signals: events, states, diagnostics, alarms, warnings, etc.
- Software separation between cyber-security and physical security
 - SIEM Security Information & Event Management
 - PSIM Physical Security Information Management)
- Many false alarms and nuisance alarms (> 30% => failure)



Information fusion



FLAMMINI F., Pappalardo A, Vittorini V (2013). Challenges and Emerging Paradigms for Augmented Surveillance. Effective Surveillance for Homeland Security: Balancing Technology and Social Issues. p. 169-198, BOCA RATON, FL: Chapman & Hall/CRC Taylor & Francis Group, ISBN/ISSN: 9781439883242, doi: 10.1201/b14839-11



From smart-systems to autonomous systems





AI hierarchy





Cyber-Physical Threat Detection



Flammini F, Marrone S, Rodríguez R J, Nardone R, Vittorini V (2015). On synergies of cyber and physical security modelling in vulnerability assessment of railway systems. COMPUTERS & ELECTRICAL ENGINEERING, p. 275-285, ISSN: 0045-7906, doi: doi:10.1016/j.compeleceng.2015.07.011



Example scenario (1/2)



Example scenario (2/2)



STEP	Description	System Status	SPD norm	Level
2	In WSN_1 a bad mouthing attack has occurred. The middleware is informed that an attack is occurring and it sends a command to the smart camera to activate its security mechanisms. The SPD level decreases. WSN_1: Bad mouthing attack WSN_2: Encryption 64 bits Smart Camera: Messaging - no protection MDW_IDS: Normal	State_03	0	
3	The smart camera improves its SPD functionality and SPD level increases. WSN_1: Bad mouthing attack WSN_2: Encryption 64 bits Smart Camera: Messaging - Authentication & Integrity MDW_IDS: Normal	State_19	0,3	LOW

Linnæus University

Delli Priscoli F, Di Giorgio A, Esposito M, Fiaschetti A, Flammini F, Mignanti S, Pragliola C (2017). Ensuring Cyber-Security in Smart Railway Surveillance with SHIELD. INTERNATIONAL JOURNAL OF CRITICAL COMPUTER-BASED SYSTEMS, p. 138-170, ISSN: 1757-8779



DETECT Decision Triggering Event Composer & Tracker



FLAMMINI F., Mazzocca N, Pappalardo A, Pragliola C, Vittorini V (2011). Augmenting surveillance system capabilities by exploiting event correlation and distributed attack detection. In: Availability, Reliability and Security for Business, Enterprise and Health Information Systems. Vienna, Austria, 22-26 August 2011, BERLIN HEIDELBERG: Springer-Verlag, vol. 6908, p. 191-204, ISBN/ISSN: 978-364223299-2, doi: 10.1007/978-3-642-23300-5_15



The DETECT framework architecture





Event Trees

EDL based on the *Snoop* event algebra, considering the following operators: OR, AND, ANY, SEQ

Example Event Tree: (E1 AND E2) OR E3







First solution: distance metrics



$$D = \left|TN_A - TN_B\right| + \left|TD_A - TD_B\right| + \left|TW_A - TW_B\right| + DSL_{AB} + DSO_{AB}$$

TN: total number of nodes

TD: tree depth, that is the number of levels from leaves to the top node*TW*: tree width, that is the max number of operators at the same level*SL*: set of leaf nodes*SO*: set of operator nodes

 $DSL_{AB} = card(SL_A \cup SL_B) - card(SL_A \cap SL_B)$

$$DSO_{AB} = card(SO_A \cup SO_B) - card(SO_A \cap SO_B)$$

Flammini, F., Mazzocca, N., Pappalardo, A., Pragliola, C., Vittorini, V. Improving the dependability of distributed surveillance systems using diverse redundant detectors (2015) Advances in Intelligent Systems and Computing, 307, pp. 35-53





D = |12-10| + |3-3| + |2-1| + 0 + 1 = 4



Example (2/3)

Scenario C (aggression)



TN	8	
TD	2	
TW	1	
SL	E1-S1, E2-S1, E1-S2, E2-S2, E3-S3, E5-S6	cardinality=6
SO	SEQ, ANY	cardinality=2

Off-line distance computation (all trees available)

	A-B	A-C	B-C
ΔΤΝ	2	4	2
ΔSL	0	3	3
ΔΤD	0	1	1
ΔSO	1	2	1
$\Delta T W$	1	1	0
D	4	11	7

On-line distance computation (only ANY subtree available)

TN	8		
TD	2		
SL	E1-S1, E2-S1, E1-S2, E2-S2, E3-S3	cardinality=5	
SO	ANY, OR	cardinality=2	

	ANY-A	ANY-B	ANY-C
ΔΤΝ	4	2	0
ΔSL	2	2	1
ΔΤD	1	1	0
ΔSO	2	3	1
D	9	8	2



TEMPORAL CONSTRAINT	0	EVENT ID
ANY PARAMETER	0	SENSOR ID
ALARM LEVEL	0	POD
CONFIDENCE MODELING	0.0	FAR

Suspected Event with Id: 241 Detection Time: 01/04/12 - 09:15:51 Alarm Reliability: 96,25%

Suspected Event with Id: 241 Detection Time: 01/04/12 - 09:16:00 Alarm Reliability: 80,00%

Alarm Reliability: 97,00% Alarm Level: 2

Alarm Reliability: 99,76%

Component Event Occurrences Id: 2 3

Component Event Occurrences Id: 4 Suspected Event with Id: 241 Detection Time: 01/04/12 - 09:16:00

Component Event Occurrences Id: 3 4 Suspected Event with Id: 241 Detection Time: 01/04/12 - 09:17:07 Alarm Reliability: 91,90%

Component Event Occurrences Id: 1 5 Detected Event with Id: 241 Detection Time: 01/04/12 - 09:17:07

Component Event Occurrences Id: 3 4 1 5

Alarm Level: 2

Alarm Level: 1

Alarm Level: 3

Alarm Level: 4

X

0.0

0.0

OK

CANCEL

Stop Detection

Reset

Show graph of the selected event

Back

Example (3/3)

Detector ID	Detector Description	Event ID	Event Description	FAR
S1	Intelligent Comore	E1	Fall of person	0.25
	Intelligent Camera	E2	Abnormal running	0.20
S2	Intelligent Compre	E1	Fall of person	0.25
	Intelligent Camera	E2	Abnormal running	0.20
S3	Audio Sensor	E3	Scream	0.15
S4	IMS/SAW detector	E4	CWA detection	0.30
S 5	IR detector	E4	CWA detection	0.27

Date	Time	Event ID	Detector ID	Occurrence Nr	
01/04/2012	09:11:11	E4	S4	1	
01/04/2012	09:14:18	E1	S2	2	
01/04/2012	09:15:51	E3	S3		
01/04/2012	09:16:00	E2	S2	Suspected Event with Id: 241 Detection Time: 01/04/12 - 09:14:18	Plant Dobardian
01/04/2012	09:17:07	E4	S5	Alarm Reliability: 75,00% Alarm Level: 1	Start Delection
				Component Event Occurrences Id: 2	

Bayesian Networks

- A Bayesian Network (BN) (or "influence diagram") is a formalism suitable to model uncertainty. BNs are direct acyclic graphs in which nodes represent stochastic variables and arcs statistical dependencies between variables, quantified by conditional probabilities (Conditional Probability Tables, CPT)
- Each node X_i is be associated with a probability distribution given by all its parent nodes through the CPT.
- This can be denoted as p(X | parents(x)). Following this simplified explanation, an entire BN can then be represented by a single joined probability distribution:

$$p(X_1 \dots X_n) = \prod_{1}^{n} p(Xi | parents(Xi))$$



Eugene Charniak (1991), Bayesian networks without tears: making Bayesian networks more accessible to the probabilistically unsophisticated, AI Magazine, v.12 n.4, pp.50-63



BN in DETECT





From Event/Attack Trees to BN





How to populate BN models

- Data collection on attacks, or other data collection techniques such as honey pots and data harvested from simulations.
- Probabilities are refined as more precise data is collected using ML techniques applied to empirical evidence.
- As an example of using historical data, a study published in 2017 by Symantec Corporation titled the Internet Security Threat Report (ISTR):
 - Email phishing rate is 1 in 2995 emails.
 - Email malware rate is 1 in 412 emails.
 - From more than 1 billion requests analysed every day, 1 in 13 web-requests lead to malware.
 - 76% of websites contain vulnerabilities, out of which 9% are critical vulnerabilities.
 - Out of 8718 vulnerabilities discovered in 2017, 4262 were zero-day vulnerabilities.
- This and similar data can be customized to a specific organization and updated dynamically by counting the number of emails sent, websites accessed, etc.



Example data

For instance, if you trust the above statement "Email phishing rate is 1 in 2995 emails", and in your organization you have 1200 emails sent at a certain time, then you can get your custom value for the email phishing probability as:

$$1 - \prod_{1}^{1200} \left(1 - \frac{1}{2995} \right)$$

In this formula (1-1/2995) would be the probability of not having phishing in a single email, whereas the production refers to the probability of not having phishing in any of the 1200 emails (assuming they are not correlated). One minus the production is then the probability of having phishing after 1200 emails.

In other words, it is possible to update in real-time that probability by counting the number of emails received in the organization at any time. The same holds for the other parameters like website access. The SIEM system can be configured to monitor those parameters and provide updates to DETECT and hence to the BN detection model.







Data for the example model

Leaf node	Identifyin	Estimated	Possible Detection
	g	probabilit	Sensors
	Acronym	V	
Exploitation of Zero-Day Vulnerability	ZDV	0.03	-Anomaly detection based IDS -User Level Endpoint Monitoring
User Connects to Untrusted Network	UN	0.24	-IDS -SSL Certificate missing/rejected -Netflow Analysis -Firewall
User Accesses Malicious Website	MW	0.08	-IDS -SSL Certificate missing/rejected -Unexpected flow of data
User Connects Infected Removable Media to the System	IM	0.02	-IDS -Antivirus -System Event Logs
User Accesses Website Infected with Malware	IW	0.09	-IDS -Web Browser Plugin
User Opens Spear Phishing Email	SPE	0.03	-Human -User Level Endpoint Monitoring

Middle Node	Identifying Acronym	Estimated Probability
Exploitation of unpatched vulnerability	EUV	0.60
Attacker installs backdoor on target system	BD	0.85
Attacker gets access to internal system	AIC	0.90



Perturbation tests

Node		IM		IW		SPE
Perturbance Percentage	Value	Results	Value	Results	Value	Results
-50%	1	19.6	4.5	18.6	1.5	19.5
-25%	1.5	19.8	6.75	19.2	2.25	19.7
-20%	1.6	19.8	7.2	19.4	2.4	19.7
-10%	1.8	19.8	8.1	19.6	2.7	19.8
0%	2	19.9	9	19.9	3	19.9
10%	2.2	19.9	9.9	20.2	3.3	20
20%	2.4	20	10.8	20.4	3.6	20.1
25%	2.5	20	11.25	20.6	3.75	20.1
50%	3	20.2	13.5	21.2	4.5	20.3





BN: design time vs run time



Value	Meaning	Probability
true	Alarm on	2.273*10 ⁻⁵
false	Alarm off	0.999977
unknown	Alarm inactive	2.7*10-7

Evidence	Alarm on	Alarm off	Unobserved ev.	Alarm on	Alarm off
Тино	0.005 (tp)	0.22*10-4 (fm)	E1	0.9934	0.0066
	0.995 (tp)	0.22 10 (11)	E2	0.9941	0.0059
False	0.5*10 ⁻² (fp)	0.999978 (tp)	E3	0.9938	0.0062

FLAMMINI F., Marrone S, Mazzocca N, Vittorini V (2016). Fuzzy decision fusion and multiformalism modeling in physical security monitoring. Recent Advances in Computational Intelligence in Defence and Security. vol. 621, p. 71-100, BERLIN: Springer, doi: 10.1007/978-3-319-26450-9_4



https://lnu.se/en/research/searchresearch/cyber-physical-systems-cps/

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Cyber-Physical Systems (CPS)

The CPS research group is responsible for research, teaching, and outreach activities in the field of Cyber-Physical Systems.

The research of Cyber-Physical Systems addresses the close interactions and feedback loop between the embedded cyber components and the dynamic physical components that involve mechanical components, energy systems, human activities and surrounding environment.

Designing CPS involves the consideration of multiple factors such as timing, energy, reliability, dependability and security. Experts from different disciplines are needed to tackle the challenges on large scale analytical modeling and analysis, efficient simulations, model driven synthesis and verification, real-time data analytics and system control, etc.

The current research focuses on

- 1. model-based design, synthesis and verification of CPS,
- 2. CPS dependability, security and privacy,
- 3. big data analytics for CPS,
- cross-layer modeling and optimization for CPS, and
- 5. applications of CPS in smart energy systems and automotive systems, etc.



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Thank you for your kind attention!