Statistical analysis of DDoS attack

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Problem Statement

The main problem statement is summarised as follows:

- Proposing statistical methods for IoT (Internet of Things) attack detection with **arbitrary traffic**.
- In particular, recognising DDoS (Distributed Denial of Service) attacks in a **timely fashion** with simple statistical implementation, integrable into a hardware probe.

Prior Work

- [1] Proposed one-parameter statistical methods for DDoS attack recognition focusing on simulated attack data and concluded with approaches suggesting possibilities of early detection statistical parameters.
- [2] Extended [1] to detect the "start" of a DDoS attack - attack time and used some statistical parameters to prove their efficiency on a custom dataset.
- Other papers *(as cited in the report)* also analyse DDoS attack detection.

[1] Hajtmanek et Al. One-Parameter Statistical Methods to Recognize DDoS Attacks. *Symmetry*. 2022
[2] Smiesko et Al. Machine Recognition of DDoS Attacks Using Statistical Parameters. *Mathematics*. 2024

Proposed Approach: Premise

- We re-envision attack detection in IoT with price detection in the finance world - we create a_t (Total packets forwarded in window ending at t) as the analogue of price.
- We hence adapt complex statistical financial strategies to IoT systems and analyse their performance.
- We have established a temporal metric μ to quantify performance of various statistical strategies.

Proposed Approach: Novel points

- The algorithms proposed in various strategies are **incremental** and hence are very useful for the **online task** nature of the problem.
- Using statistical strategies allows for **fast computation** (as compared to ML based strategies) and require less resources so can be used easily on **small scale compact IoT devices**.
- Multiple strategies can be used in conjunction allowing for a diverse, adaptable and **robust IDS** (Intrusion Detection System).

Proposed Approach: Methodology

- Select appropriate time quantum ($a_t =$ total fowarded packets in t^{th} window) to resample upon depending on compute-time and window-size trade-off.
- Create time-series data to test statistical strategies based on selected time quantum.
- Evaluate strategies based on proposed metric (μ).

Data creation: How time-sampling is done?

- $A(0,t) = \sum_{i=1}^{t} a(i), \quad a(t) = A(0,t) - A(0,t-1)$

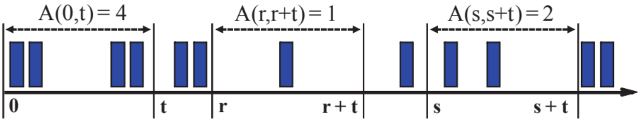


Figure: $A(s,t)$ is total packets flown between window s and t
$a(t)$ or a_t is the number of packets in window t

Data creation: Selecting the right time quantum

- 1s was chosen as the appropriate time quantum by running analysing running time of practical algorithms.

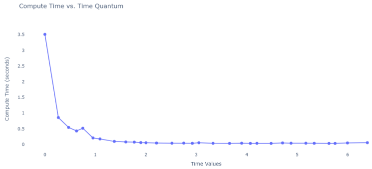


Figure: Compute time v/s Time Quantum.

- The trade-off gave 1s as the appropriate time-quantum, based on this the data is split into
  - **Regular data** Consisting of 1 value for each window.
  - **OHLC Data** Consisting of 4 values for each window.

Data Creation: Regular vs OHLC Data

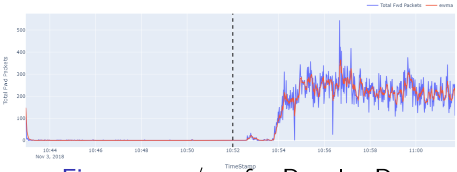


Figure: a_t v/s t for Regular Data

Figure: Zoomed-in OHLC candlestick Chart

Figure: The instant that attack begins (attack time) is shown by a vertical dashed black line.

Strategies: Studied

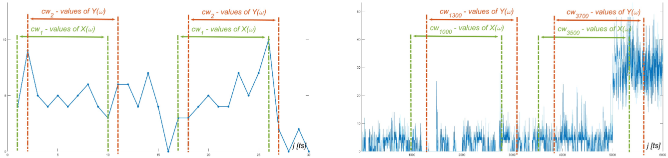
Trend & Momentum based Strategies
ATR
KCHB
AO
Stoch
AROON
UI

Multi-OHLC based Strategies
BB
RAPD
KST
MACD
RSI
TSI
TRIX
StochRSI

Non-Financial based Strategies
C/V
SKEW
KURT
R/S
D_{KL}
c

- Trend & momentum uses regular data where as Multi-OHLC uses the OHLC data. Both classes are financial strategies.

Strategies: How are they calculated?



- As we gradually analyse obtain new datapoints, we obtain a time series of the estimated values of the given statistical parameter.
- This statistical parameter "looks back" i.e. uses k previous values to compute its new current value which we term as "lag".

Strategies: Bollinger band

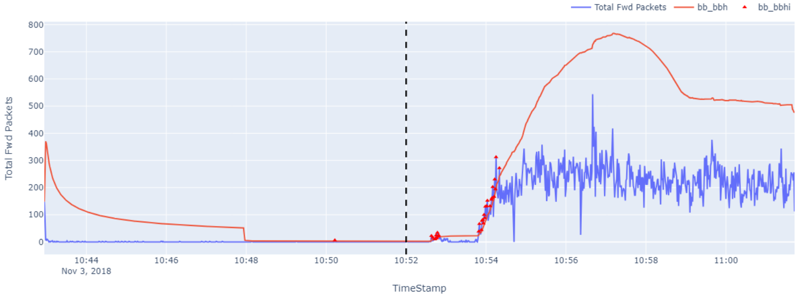


Figure: Understanding signal creation with Bollinger Bands

Results and Analysis: Metric proposed

- Previous metrics overlook temporal aspects.
- We propose a metric based on the exponential decay function which gives exponentially lower weights to signals further away from attack time (λ).

$$\boxed{\mu_\alpha(i) = e^{-\frac{x_i - \lambda}{\alpha}}} \tag{1}$$

$$\boxed{\mu_\alpha = \textstyle\sum_i \mu_\alpha(i), i \text{ ranges over all 1 in the signal array where } x > \lambda.} \tag{2}$$

- **Proximity** vs **Frequency** Trade-off is established by this metric

Results and Analysis: Analysis of strategies based on μ

- We compare Non-Financial and Financial strategies based on the μ metric.

Strategies	**FP**	**TP**	$\mu_{0.01}$	$\mu_{0.1}$	$\mu_{0.5}$	μ_1	μ_2	μ_{10}
Financial Strategies								
BB	1	29	3.24×10^{-28}	6.51×10^{-3}	2.40	6.90	13.41	24.65
RAPD	**2**	41	3.85×10^{-28}	$\mathbf{1.08 \times 10^{-2}}$	3.95	10.65	19.80	35.13
KST	0	31	4.10×10^{-91}	5.80×10^{-9}	0.30	3.04	9.68	24.55
MACD	0	57	1.10×10^{-123}	3.23×10^{-12}	0.09	2.18	11.05	40.99
RSI	0	33	3.12×10^{-28}	2.73×10^{-3}	1.16	5.05	12.41	27.00
TSI	0	**142**	1.15×10^{-89}	8.14×10^{-9}	0.50	7.06	29.99	**103.10**
TRIX	0	21	2.59×10^{-30}	6.81×10^{-3}	3.91	9.02	13.75	19.29
StochRSI	1	7	$\mathbf{5.54 \times 10^{-26}}$	7.18×10^{-3}	0.95	2.13	3.61	6.06
AO	0	3	1.11×10^{-29}	1.27×10^{-3}	0.29	0.67	1.13	2.22
Stoch	1	32	6.11×10^{-29}	3.31×10^{-3}	1.03	3.44	9.16	24.50
KCHB	0	127	7.27×10^{-29}	9.30×10^{-3}	**4.48**	**16.15**	**40.62**	99.52
Non-Financial Strategies								
SKEW	1	2	$\mathbf{3.71 \times 10^{-28}}$	$\mathbf{3.12 \times 10^{-3}}$	0.55	1.05	1.45	1.87
KURT	1	2	3.61×10^{-28}	2.80×10^{-3}	0.55	1.06	1.84	2.11
R/S	1	**46**	3.12×10^{-28}	1.80×10^{-3}	**0.88**	**5.60**	**15.74**	**37.03**

Results and Analysis: Analysis of Strategies based on compute time

- Compute-Times are analysed for Non-Financial vs Financial strategies.

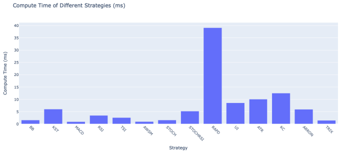


Figure: Compute time for financial strategies

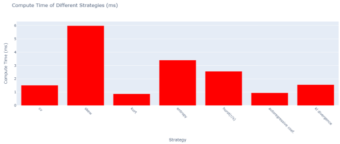


Figure: Compute time for non-financial strategies

Results and Analysis: Discussion on RAPD and StochRSI

- We choose to discuss 2 strategies showing great potential for creation of a well-balanced robust IDS and an early detection IDS i.e. RAPD and StochRSI respectively[1].
- The algorithm for RAPD was is discussed on the following slide. StochRSI has the following formula:

$$\boxed{\text{StochRSI} = \frac{\text{RSI}-\text{Min RSI}_K}{\text{Max RSI}_K-\text{Min RSI}_K}}$$

$$\boxed{\begin{aligned} \text{RSI} &= 100 - \frac{100}{1+\frac{\text{AG}}{\text{AL}}} \\ \text{AG} &= \frac{\sum_{i=1}^{n} \max(\text{C}_i - \text{C}_{i-1}, 0)}{n} \\ \text{AL} &= \frac{\sum_{i=1}^{n} \max(\text{C}_{i-1} - \text{C}_i, 0)}{n} \end{aligned}}$$

[1]Other strategies and their performance is discussed in detail in the report.

Results and Analysis: RAPD

for $i = lag + 1$ to t **do**
  if $|y(i) - \text{avgFilter}(i-1)| > \text{threshold} \times \text{stdFilter}(i-1)$ **then**
    if $y(i) > \text{avgFilter}(i-1)$ **then**
      set signals(i) to $+1$; ▷ Positive signal
    else
      set signals(i) to -1; ▷ Negative signal
    end if
    set filteredY(i) to influence $\times\ y(i) + (1 - \text{influence}) \times \text{filteredY}(i-1)$;
  else
    set signals(i) to 0; ▷ No signal
    set filteredY(i) to $y(i)$;
  end if
  set avgFilter(i) to mean(filteredY(i-lag+1),...,filteredY(i));
  set stdFilter(i) to std(filteredY(i-lag+1),...,filteredY(i));
end for

for i = lag + 1 to t **do**
  Compute *avgFilter*(i) : μ_n and *stdFilter*(i) : s_n incrementally by computing mean and standard deviation incrementally.
  $s_n^2 = \frac{n-2}{n-1} s_{n-1}^2 + \frac{1}{n}\left(x_n - \mu_{n-1}\right)^2$
  $\mu_n = \mu_{n-1} + \frac{x_n - \mu_{n-1}}{k}$
  if $|y(i) - \text{avgFilter}(i-1)| > \text{threshold} \times \text{stdFilter}(i-1)$ **then**
    $\mathit{signals}(i) = \text{sign}(y(i) - \text{avgFilter}(i-1))$;
    $\mathit{filteredY}(i) = \text{influence} \times y(i) + (1 - \text{influence}) \times \text{filteredY}(i-1)$;
  else
    $\mathit{signals}(i) = 0$;
    $\mathit{filteredY}(i) = y(i)$;
  end if
end for

Figure: Non-Incremental vs Incremental RAPD

Contd.

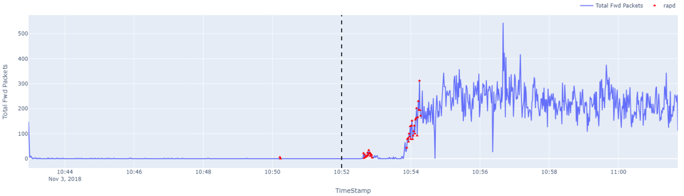


Figure: RAPD on a_t

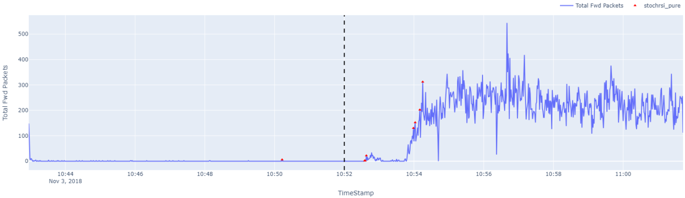


Figure: StochRSI on a_t

Non-Financial V/S Financial Strategies

- Financial strategies are **out-performing on time**
- Financial strategies **are more diverse** than non-financial strategies.
- Financial strategies **outperform on proximity** and can serve early detection systems better than Non-Financial strategies.
- Non-financial strategies like C/V which give a generalised broad peak **can work well in conjunction** with financial strategies.

Conclusion

- **Enhanced Performance with Financial Strategies** proving that adaption of IoT systems into finance world is an appreciable approach.
- **Evaluation Metric** The μ metric proves effective in assessing strategy performance.
- **Optimal Strategy Selection** We provide computational and frequency/proximity insights guiding creation of IDS systems using these strategies.
- **Robustness through Strategy Combination** Considering an attack only when the ensemble of multiple strategies are in agreement, thereby reducing false alarms and improving overall IDS reliability and resilience.

Questions and open discussion

- Any Questions?
- Our report can be found on this t.ly/BQAdC link.
- It can be downloaded directly from this t.ly/CKT39 link.

Thank you

Thank you