Essence: Pervasive & Distributed Intelligence

Time-Optimized Contextual Information Flow on Unmanned Vehicles

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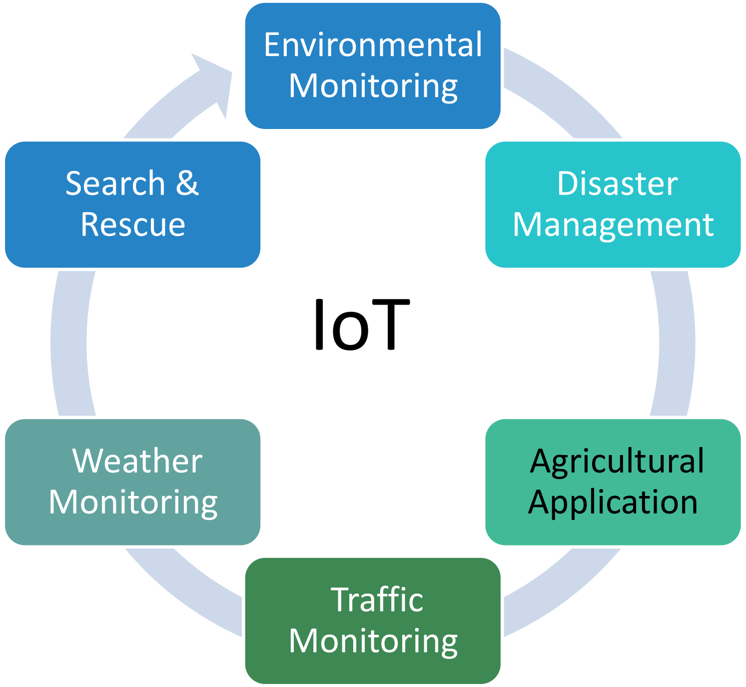
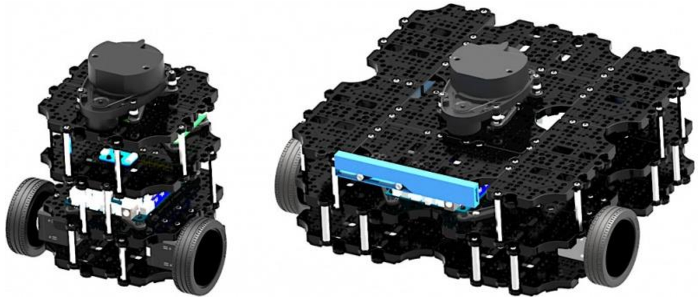
Unmanned vehicles ~future of IOT

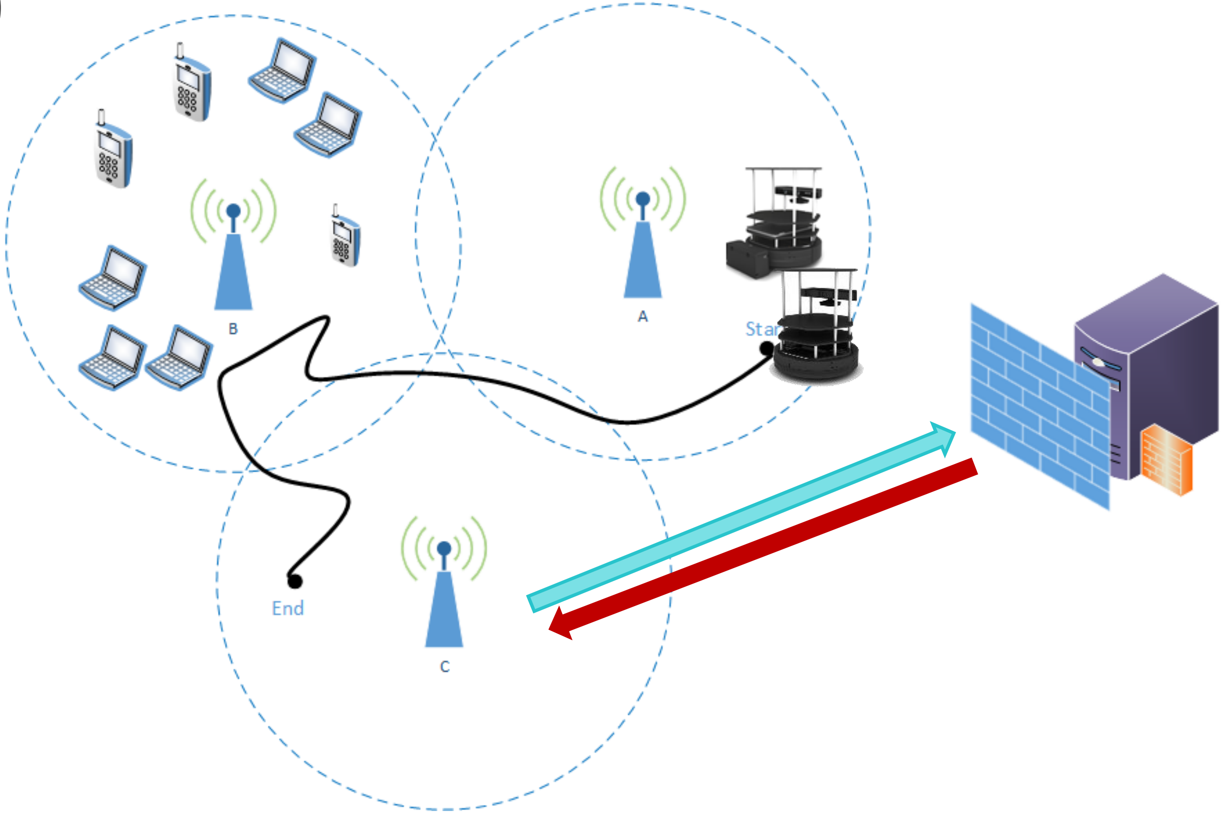


- ❑ Not static
- ❑ Deployable
- ❑ Carry flexible Payloads
- ❑ Can be re-programmable
- ❑ Can measure anything



ONE EXAMPLE (1/2)

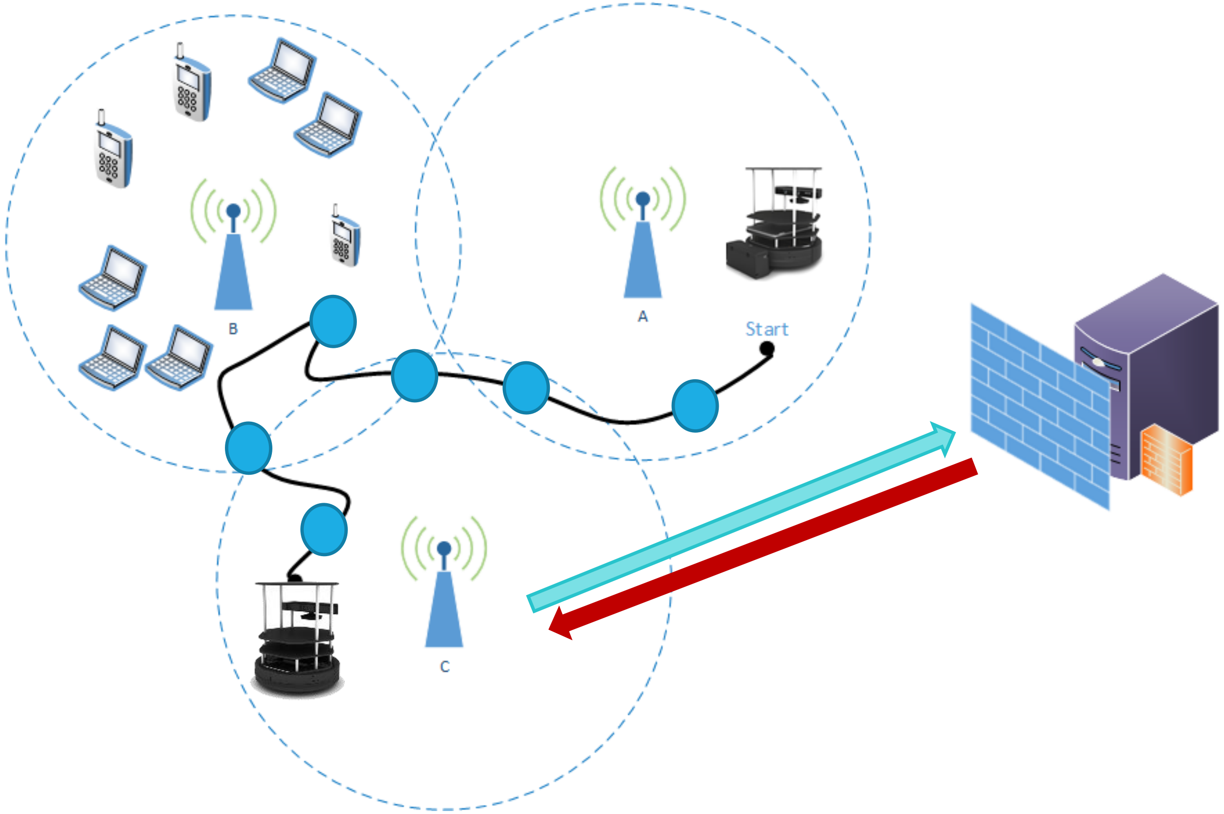
- Use of unmanned ground device (UGV)
  - equipped with video camera
  - Sensors of Temperature Humidity
  - GPS
  - Network Interface
  - Where? Unknown Area
- **Goal**: the successful execution of a mission.



ONE EXAMPLE (2/2)

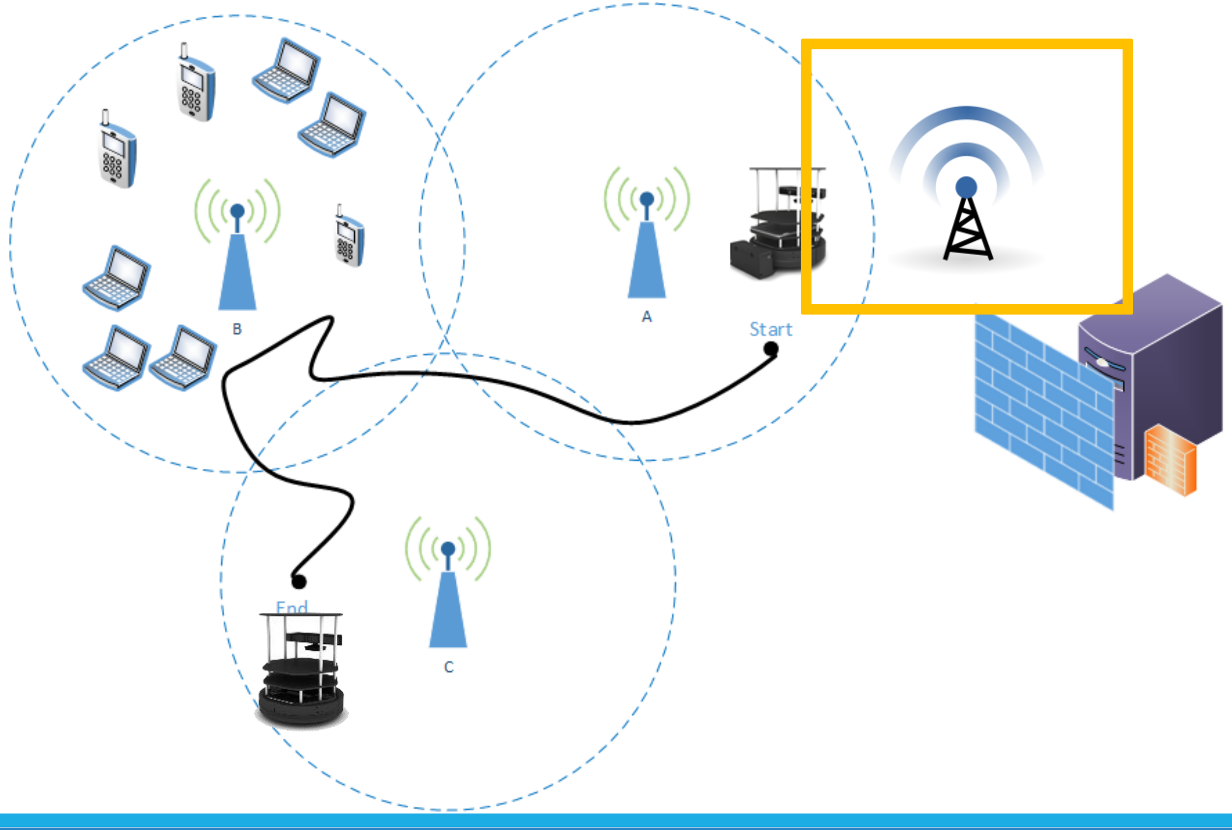
- Mission
  - is trajectory with specific way-points
  - UxV is ordered to approach and gather various
    - Sensors or images

- Ground Control Station (GCS)
  - terrestrial system,
  - coordinator/master node at distance



Problem Definition (1/2)

- Requirements of real time monitoring and control
  - Messages delivered with high accuracy and Minimal delay
  - GCS can continuously sends commands without any stop.

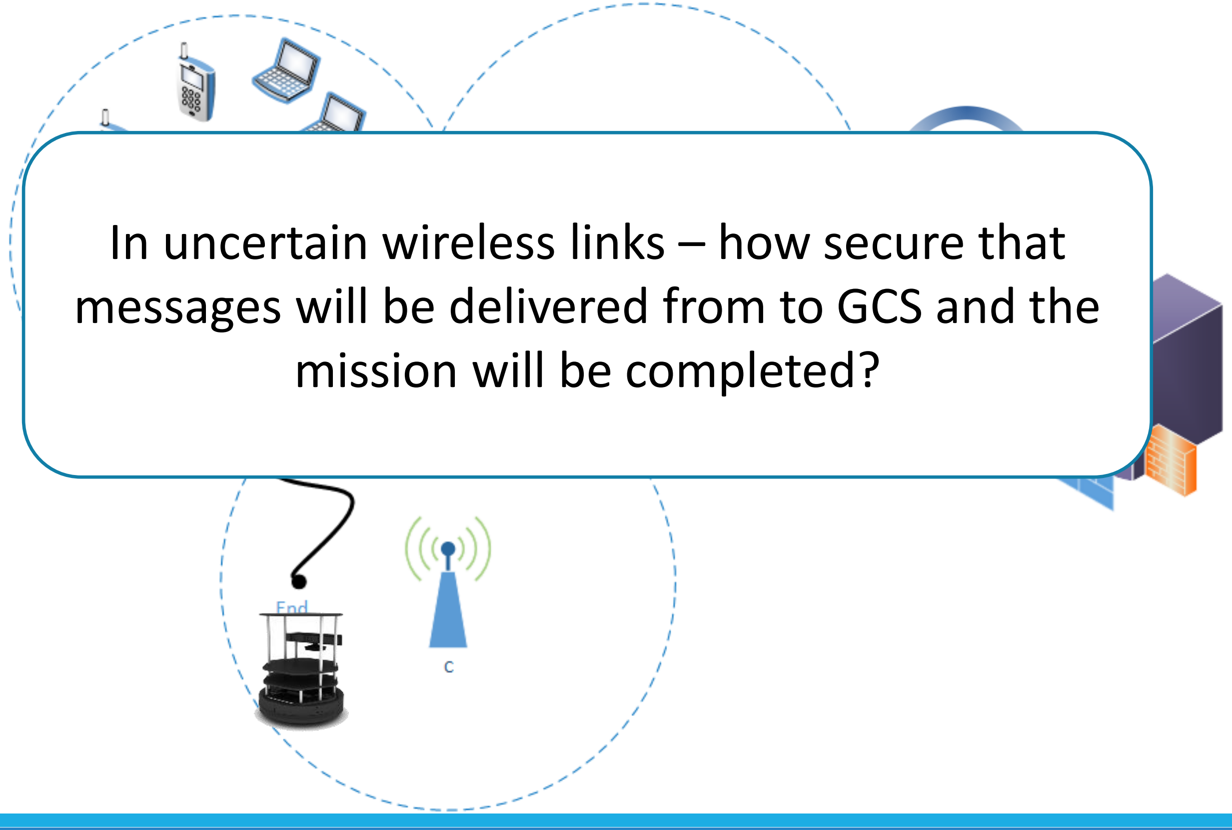


- Restrictions
  - The communication between the UxV and the GCS is established via wireless communications.
  - No assurance

Problem Definition(2/2)

- Requirements of real time monitoring and control
  - Messages delivered with high accuracy and Minimal delay
  - GCS can continuously sends commands without any stop.

- Restrictions
  - The communication between the UxV and the GCS is established via wireless communications.
  - No assurance



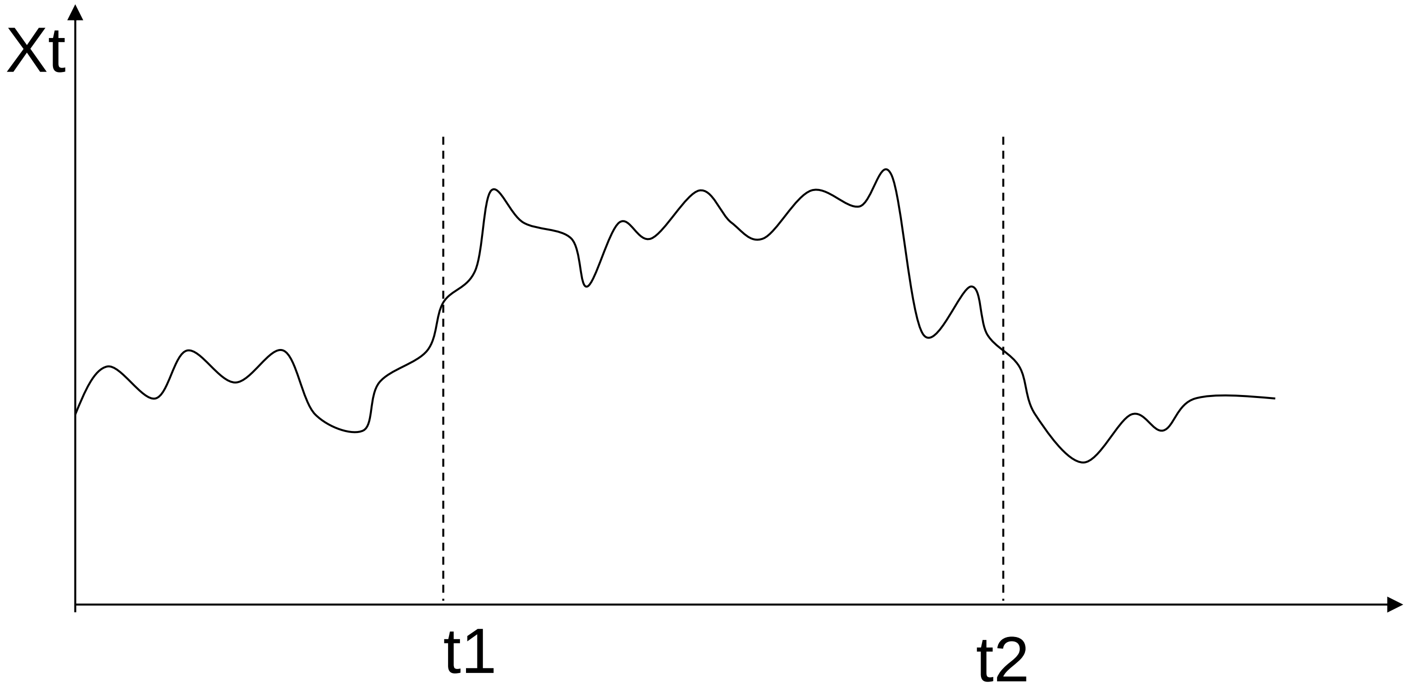
In uncertain wireless links – how secure that messages will be delivered from to GCS and the mission will be completed?

Contribution

We propose a model of o**n-line control** unit adaptive to **changes in network quality statistics** by **dynamically** pause **control** telemetry and control messages based on an Optimal Stopping rule in order to **ensure the optimal delivery** of critical information:

- an on-line network quality change detection mechanism,
- an OST rule for time-optimized change detection,
- comprehensive performance evaluation of our mechanism

Change Point Detection Theory



Data series = runtime network statistics.

Applied in Controller/UxV strategy

Identify a change in the data sequence or in distribution

- generally change in distribution

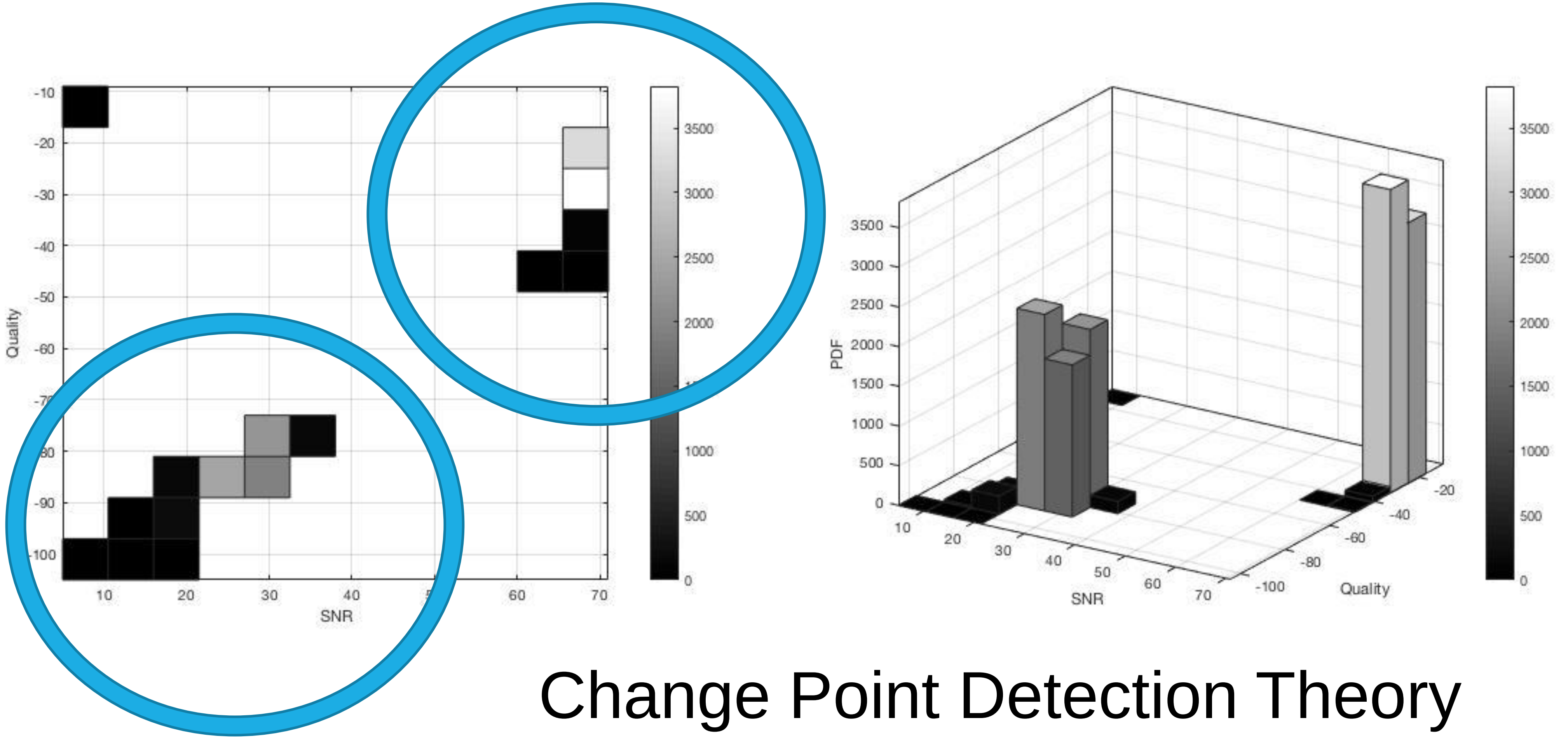
Change-point detection has its origins almost sixty years ago in the work of Page, Shiryayev, and Lorden

Quality Network Indicator -QNI (1/3)

- Quality Network Indicator - normalization
  - the SNR
  - Quality Indicator

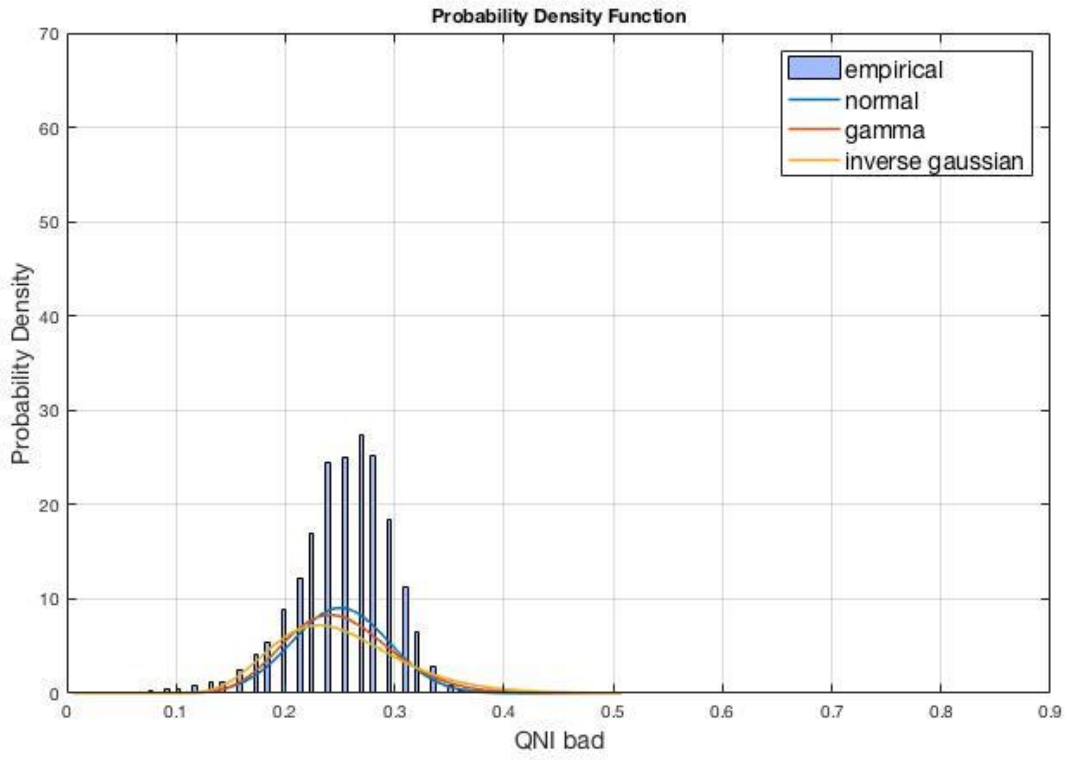
$$QNI = \alpha_1 * \frac{SNR(i) - max(SNR)}{max(SNR) - min(SNR)} + \alpha_2 * \frac{Q(i) - max(Q)}{max(Q) - min(Q)}$$

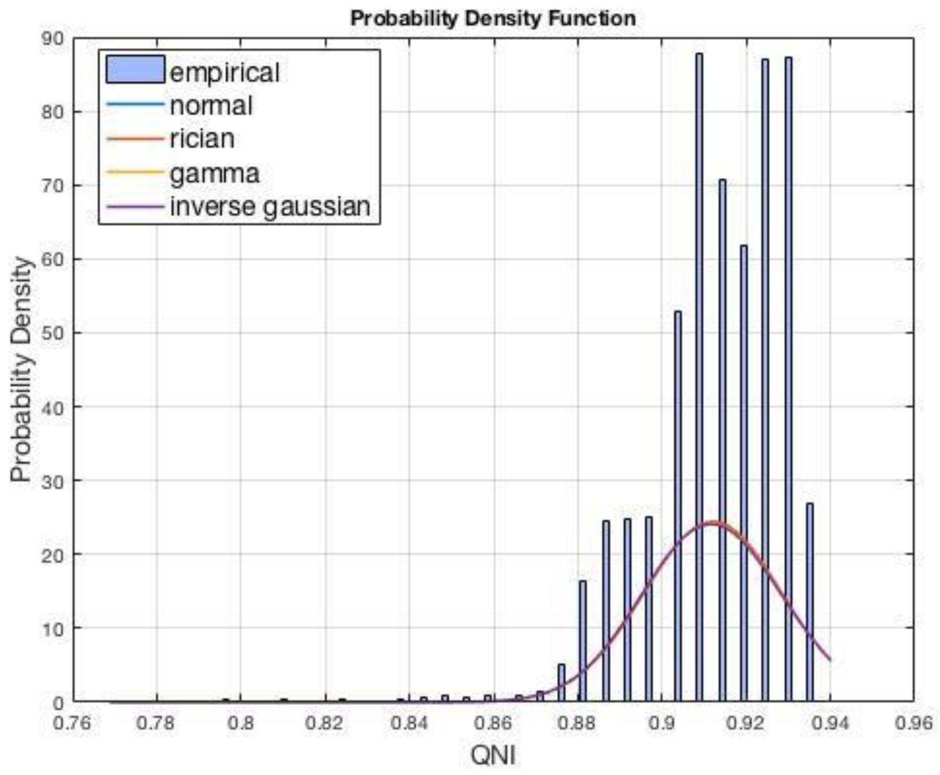
Quality Network Indicator–QNI (2/3)



Change Point Detection Theory

Quality Network Indicator–QNI (3/3)





Probability Distributions of QNI in poor and good network conditions

Change Point Detection Theory - Prerequisites

Let us assume that network readings $X_{1,}$ X_2,…, X_n are independent and identically distributed (i.i.d.) random variables and are observed sequentially in real time.

Known probability density functions f_0 and f_1, where $f_0 \neq f_1$

We are interested in finding stopping time that detects a change from one distribution to another with the minimum delay based only on the realization of the random values $x_{0,}$ $x_{1,\ldots}$ x_n

Change Point Detection Theory Solution

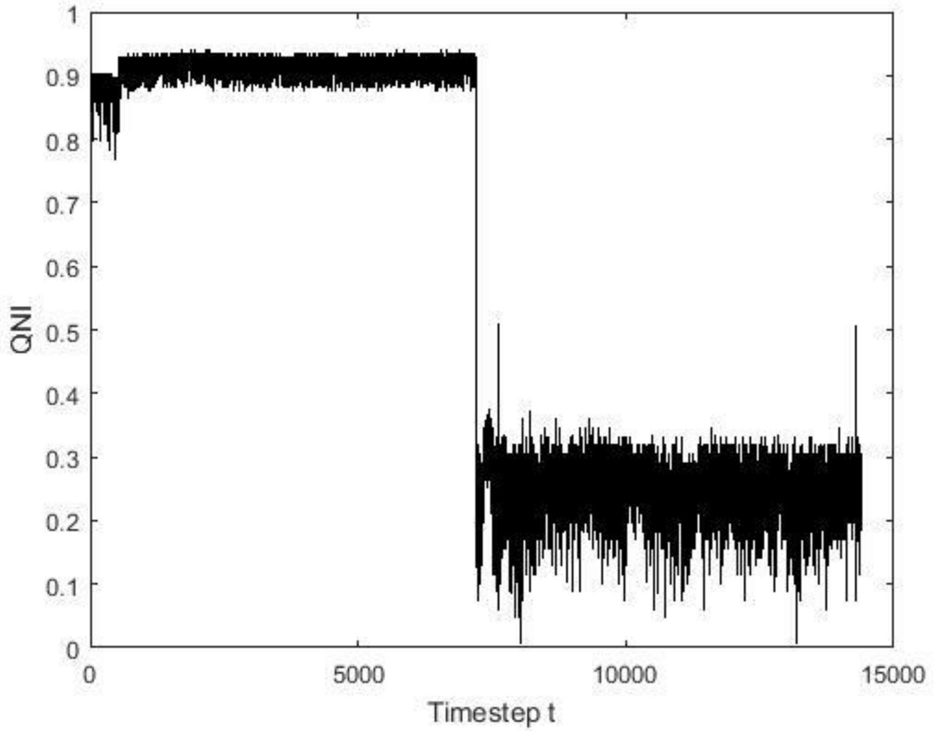
The optimal solution to was proved by that it is given by the Cumulative Sum (CUMSUM) test proposed by Page . Hence the optimal stopping time is given by:

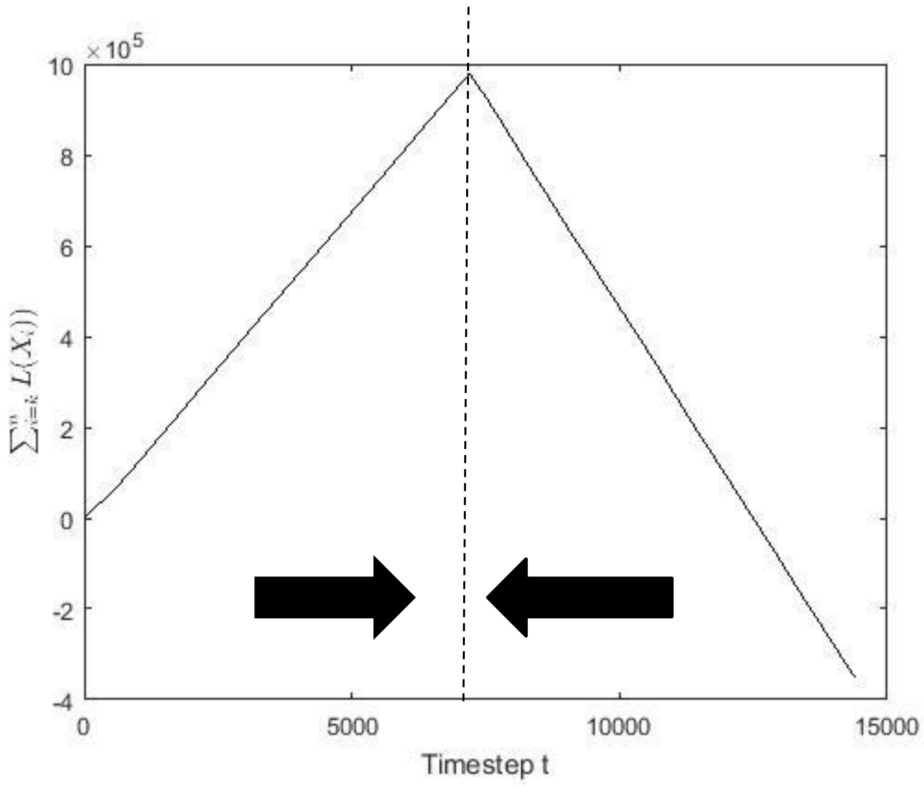
$$\tau = \inf\{n \geq 1, \max_{1 \leq k \leq n} \sum_{i=k}^{n} L(X_i) \geq \eta\}$$

Let L denote the log-likelihood ratio between $f_0(X)$ and $f_1(X)$ defined as the Radon-Nikodym derivative, i.e., $L(X) = \log \frac{f_0(X)}{f_1(X)}$. The threshold η is chosen so that $\mathbb{E}_\infty[\tau] = \frac{1}{\alpha}$.

$$L^*(X_i; \mu_0, \sigma_0, \mu_1, \sigma_1) = \ln \frac{\sigma_1^2}{\sigma_0^2} + \frac{(X_i - \mu_1)^2}{2\sigma_1^2} - \frac{(X_i - \mu_0)^2}{2\sigma_0^2},$$

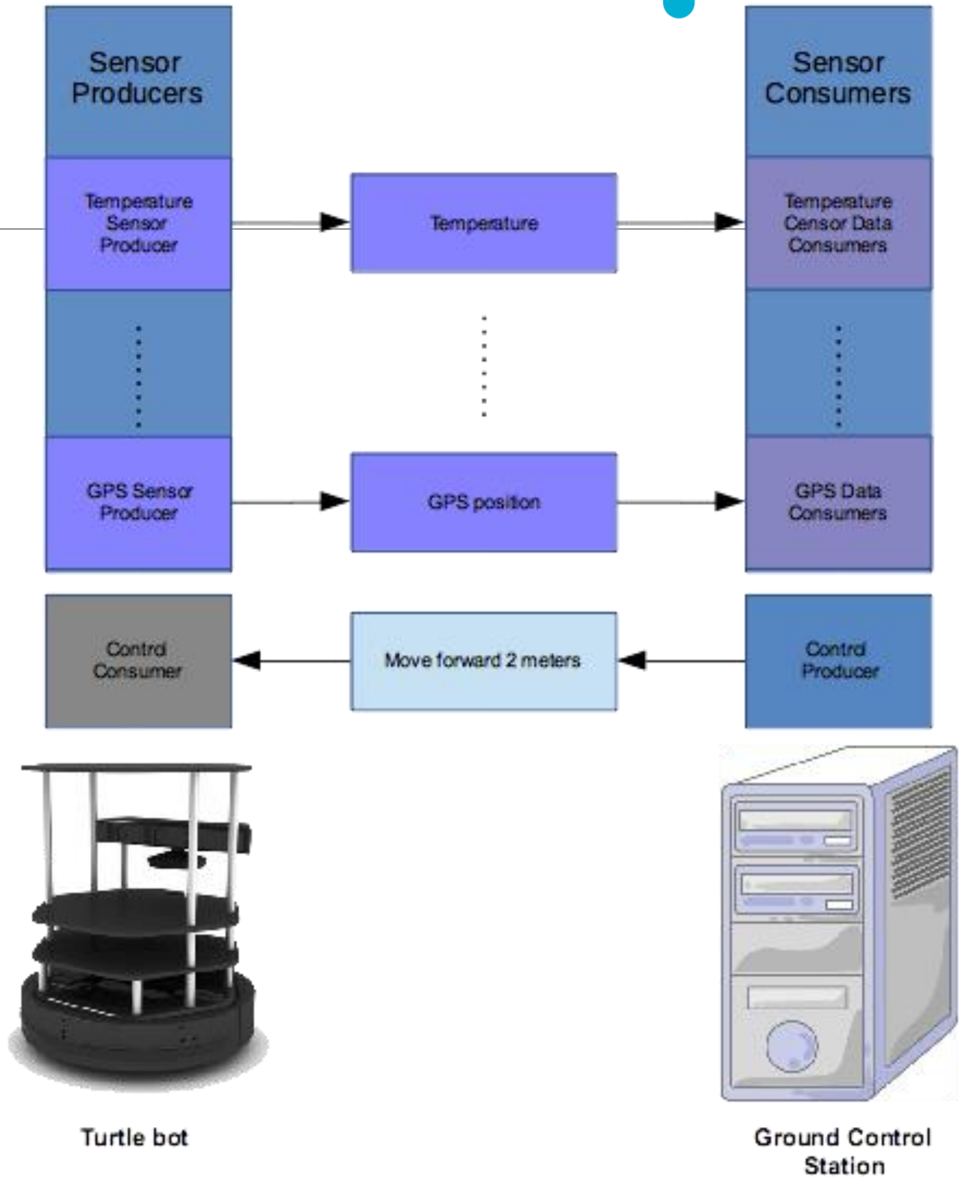
The behavior of the cumulative log-likelihood ratio corresponding to a change.





Simulation Setup

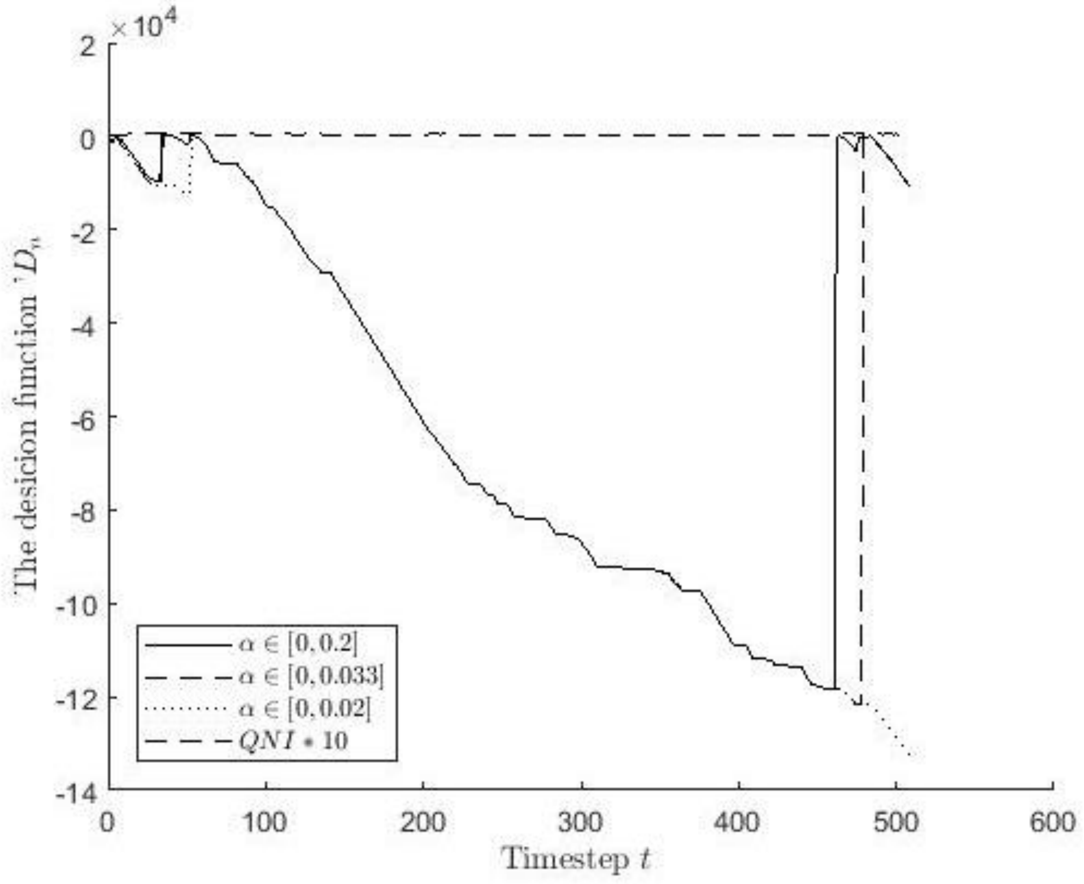
- UGV is using ROS Platform
- A GCS is a fixed server communicating with a moving UGV.
- GCS initializes a mission of an UGV following a specific trajectory.
- UGV during the mission sends back to GCS telemetry messages from its on board sensors, like health status, battery, temperature and video streaming.
- UGV is in outdoor facility faces saturated network conditions.



Analysis of simulation parameters

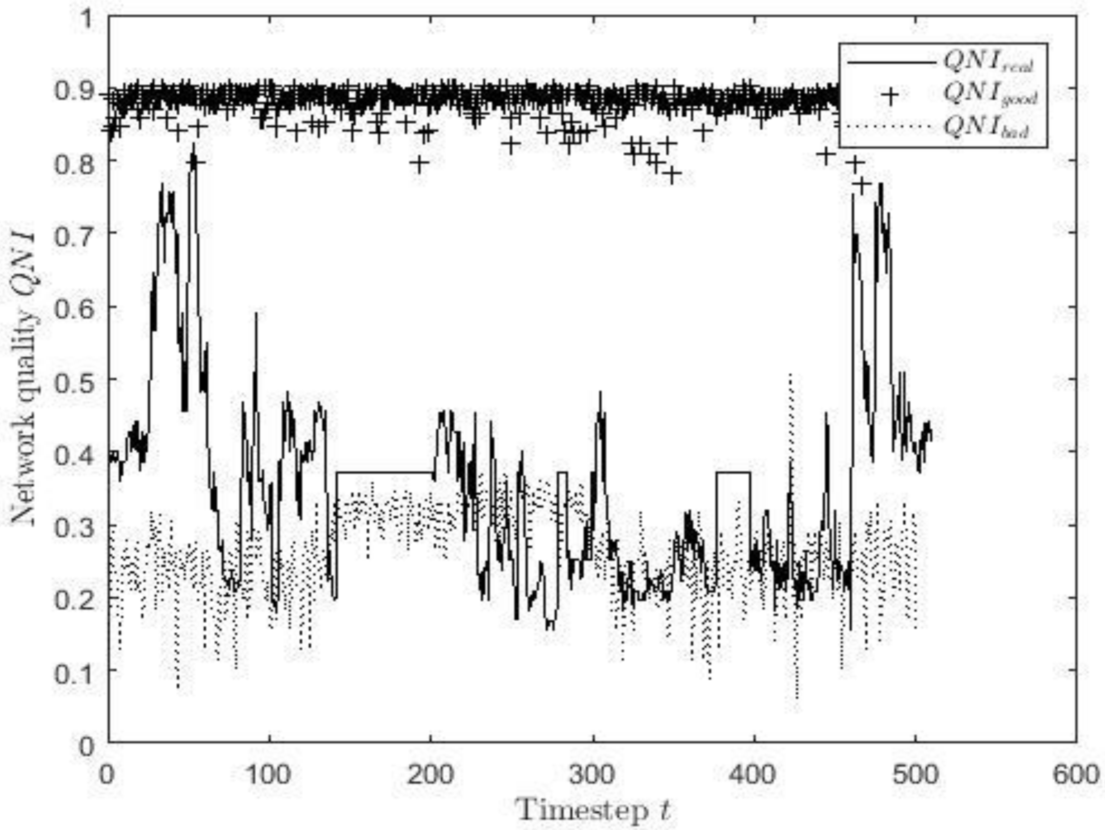
- Different values of α values were evaluated by the number of the false alarms detected in N-100 executions of the mission.
- A values were generated randomly
- lower the α values the performance of FAR reaches better scores.

α	False Alarms
$[0, 1]$	0,5
$[0, 0.2]$	0.32
$[0, 0.01]$	0.27
$[0, 0.002]$	0.18
$[0, 0.033]$	0.23



Performance evaluation

- A non policy model
  - GCS and Ux\GV continuously send and receive messages having indifference to network conditions
- A heuristic threshold-based mode
  - the transmission of messages is paused when QNI falls under the interval of [0.2,0.3] and messages are stored in a queue.
- OST model with α values in [0,0.02]
- OST model with α values in [0,0.01]

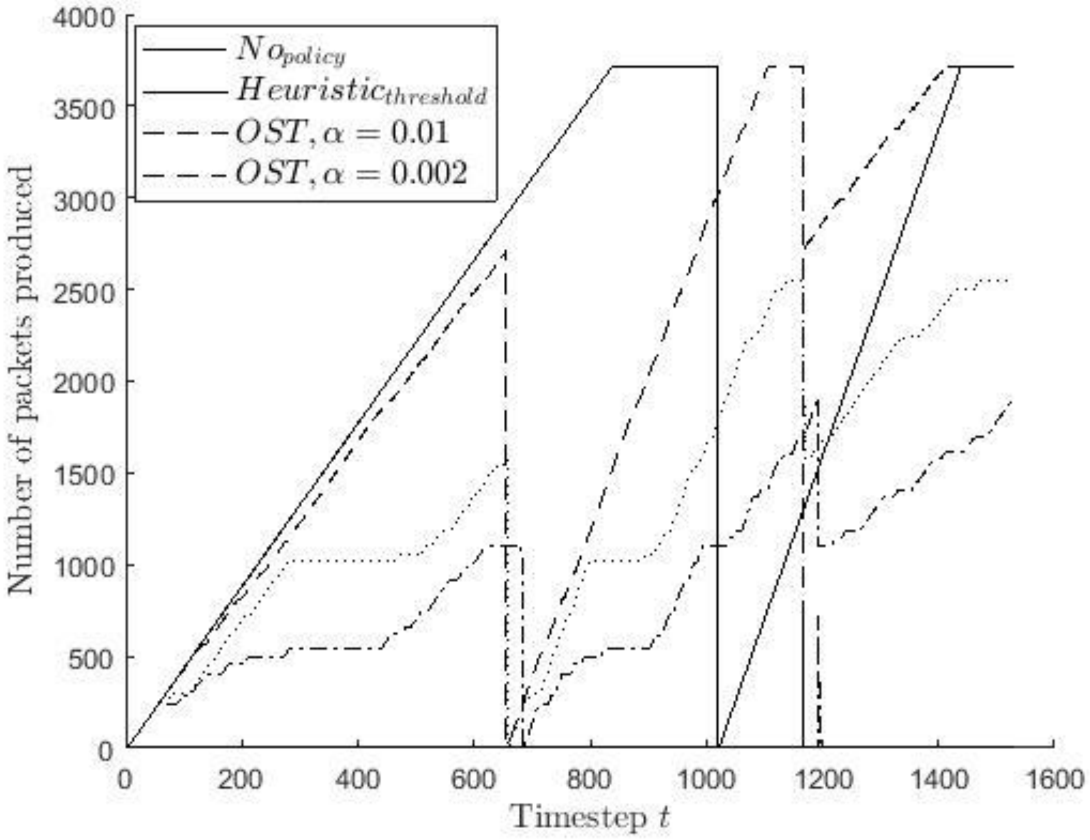


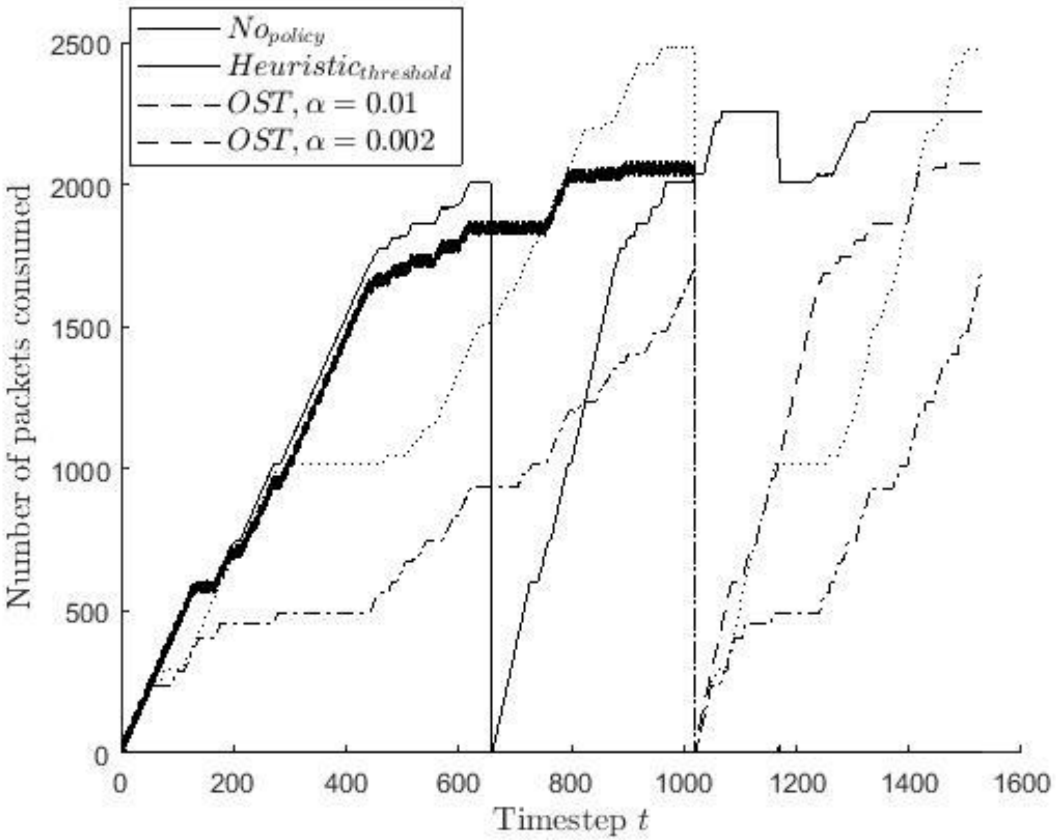
Total Produced and Consumed Packets

$ModelName$	$PacketsProduced$	Packets Consumed	Lost Packets
$Nopolicy$	3716	2253	1463
$HeuristicPolicy$	3719	2074	1645
OST $\alpha = 0.002$	2550	2478	72
OST $\alpha = 0.01$	1914	1707	207

1. No policy & Heuristic ~24% lost messages
2. OST α=0.01 ~ 4%
3. OST α=0.002~**2%**

Produced and Consumed data

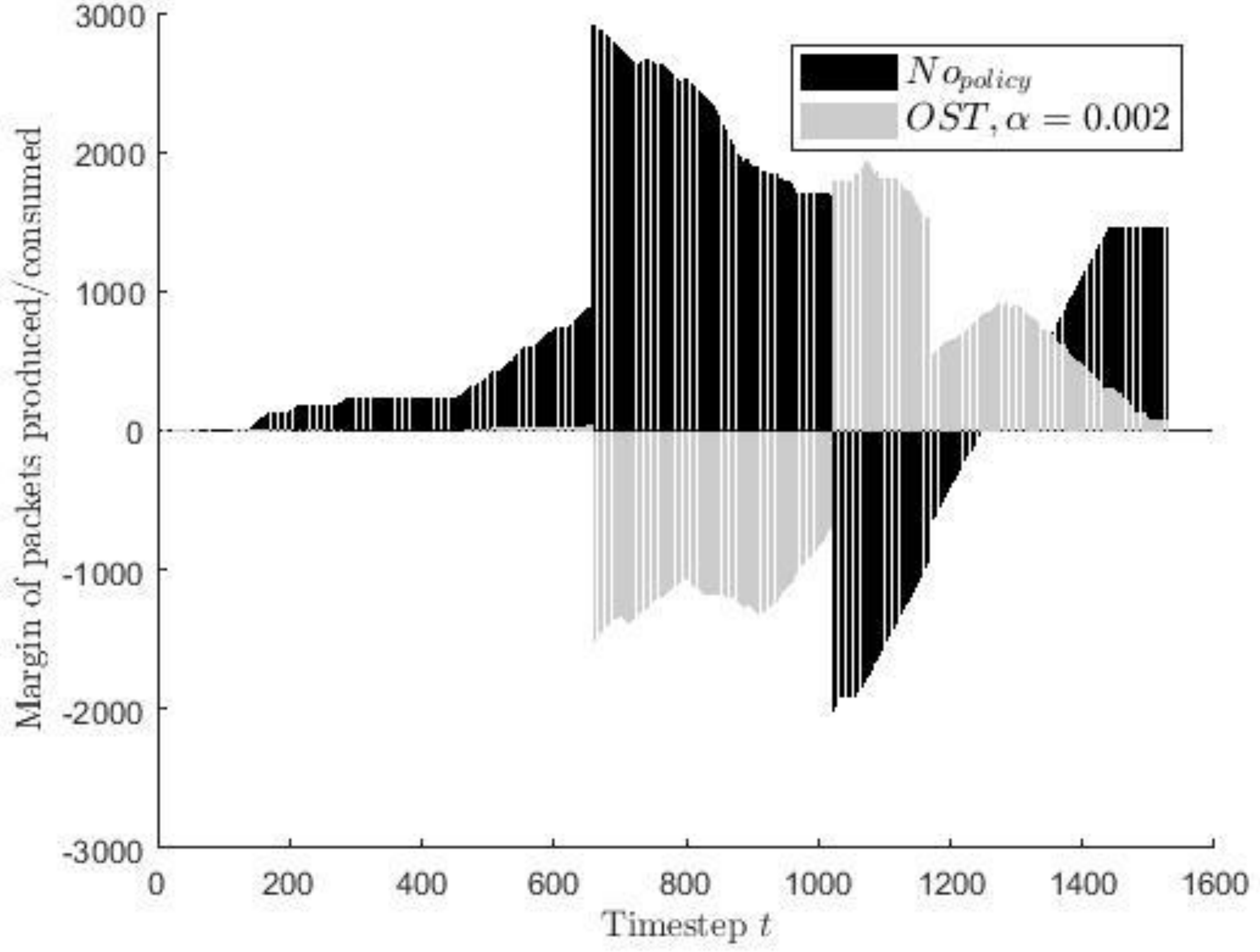




Latency Detected

This latency imported by the stopping time of the producers is balanced in the next time steps and finally close to all messages are delivered successfully.

This is not the case for the original model in which the producers continually and burdens the network and consumers with messages that re not delivered.



Conclusions and Future Work

1. Framework that monitors network conditions and changes the UxV transmission of control message and telemetry trying
   - not to overload the network in which the devices operate and move.
   - Model of dynamic decision making, adaptive to changes in network conditions, by dynamically adjusting the transmission of control messages and telemetry based on an optimal stopping rule
   - . The performance evaluation showed the successful delivery of messages in poor network conditions and the moderate production of messages so as not to burden an already saturated network.

2. Our future agenda includes a time-constraint approach with an additional OST problem of finite horizon in order to include a trade-off for the 'pausing' strategy.

Questions

References

1. M. Dunbabin and L. Marques, “Robots for environmental monitoring: Significant advancements and applications,” Robotics & Automation Magazine, IEEE, vol. 19, no. 1, pp. 24–39, 2012.
2. A. B. McDonald, “Survey of adaptive shortest-path routing in dynamic packet-switched networks,” Technical report at the Dept of Information Science and Telecommunications, April 1997.
3. S. M. Y. X. I. C. M. Chen, V. Leung, “Hybrid geographical routing for lexible energy-delay trade-offs,” IEEE Trans. Veh. Technol, vol. 58, no. 9, pp. 4976–4988, 2009.
4. Y. Cao and Z. Sun, “Position based routing algorithms for ad hoc networks: A taxonomy,” Ad Hoc Wireless Networking, Kluwer, 2003.
5. F.Fu and M. van der Schaar, “Dependant optimal stopping framework for wireless multimedia transmission,” in Accoustics speech and SignalProcessing (ICASSP). IEEE, 2010, pp. 1–6.
6. K. Kolomvatsos, C. Anagnostopoulos, “In-network decision making intelligence for task allocation in edge computing.” in ICTAI, 5-7 Nov 2018,Volos, 2018.
7. K. Anagnostopoulos, C. Kolomvatsos, “Predictive intelligence to the edge through approximate collaborative context reasoning,” Applied Intelligence, vol. 48, no. 4, p. 966991, 2018.
8. C. Harth, N. Anagnostopoulos, “Edge-centric efficient regression analytics.” in EDGE 2018, CA, 02-07 Jul 2018, 2018.
9. C. Anagnostopoulos and S. Hadjefthymiades, “Delay-tolerant delivery quality information in ad hoc networks,” Journal of Parallel and Distributed Computing, vol. 71(7), pp. 974–987, 2011.

References

10. “Optimal quality-aware scheduling of data consumption in mobile ad hoc networks,” Journal of Parallel and Distributed Computing, vol. 72(10), pp. 1269–1279, Oct. 2012.
11. T. S. Ferguson, Optimal Stopping and Applications. Mathematics Department, UCLA, Accessed May, 2018.
12. K. Panagidi, C. Anagnostopoulos, and S. Hadjiefthymiades, “Optimal grouping-of-pictures in iot video streams,” Computer Communications - In press, 2017
13. C. Anagnostopoulos and S. Hadjiefthymiades, “Advanced principal component-based compression schemes for wireless sensor networks,” ACM Trans. Sen. Netw., vol. 11, no. 1, pp. 7:1–7:34, Jul. 2014.[Online]. Available: http://doi.acm.org/10.1145/2629330
14. E. S. Page, “Continuous inspection schemes,” Biometrica, vol. 41, pp. 100–115, 1954.
15. A. N. Shirayaev, “Optimal stopping rules,” Springer-Verlag, 1978.
16. E. S. Page, “Procedures for reacting to a change in distribution,” Ann. Math. Statist., vol. 42, no. 6, pp. 1897–1908, 1971.
17. V. J. Unnikrishnan and S. Meyn, “Least favorable distributions for robust quickest change detection,” in 2009 IEEE International Symposium on Information Theory , IEEE, 2009.
18. G. V. Moustakides, “Optimal stopping time for detecting changes in

distributions,” Ann. Statist., vol. 14, no. 4, pp. 1379–1387, 1986.

Change Point Detection Theory - Prerequisites

Stopping Rule is defined by two objects

A sequence of random variables, X_1, X_2, .., whose joint distribution is assumed known

A sequence of real-valued reward functions,

- y_0, $y_1(x_1)$, $y_2(x_1,x_2)$, …, $y_\infty(x_1,x_2,…)$

$\neq$

Given these objects, the problem is as follows:

You are observing the sequence of random variables, and at each step n, you can choose to either stop observing or continue

If you stop observing, you will receive the reward y_n

You want to choose a stopping rule Φ to maximize your expected reward (or minimize the expected loss)

Change Point Detection Theory - Prerequisites

Stopping rule Φ consists of sequence

- $\Phi = (\Phi_0, \Phi_1(x_1), \Phi_2(x_1,x_2), \ldots)$

$\Phi_n(x_1,\ldots,x_n)$: probability you stop after step n

$0 <= \Phi_n(x_1,\ldots,x_n) <= 1$

If N is random variable over n (time to stop), the probability mass function ψ is defined as

$$\psi = (\psi_0, \psi_1, \psi_2, \ldots, \psi_\infty)$$

$$\psi_n(x_1,\ldots,x_n) = P(N = n | X_1 = x_1, \ldots, X_n = x_n)$$

$$=> \psi_n(x_1,\ldots,x_n) = [\prod_1^{n-1}(1-\phi_j(x_1,\ldots,x_j))]\phi_n(x_1,\ldots,x_n)$$

Change Point Detection Theory - Prerequisites

so, the problem is to choose stopping rule Φ to maximize the expected return, V(Φ), defined as

$$V(\varphi) = \mathrm{E} \sum_{j=0}^{\infty} \{\psi_j(X_1, \ldots, X_j) * y_j(X_1, \ldots, X_j)\}$$

j = ∞ if we never stop (infinite horizon)

j = T if we stop at T (finite horizon)

Change Point Detection Theory

A sequential change point detection rule is derived by stopping time τ of the observation stream.

The stopping time τ is the output of two different characteristics:

- the detection delay and Dn
- the frequency false alarm FAR

$$\mathrm{FAR}(\tau) = \frac{1}{\mathbb{E}_\infty[\tau]}.$$

Under the Lorden criterion, the objective is to find the stopping rule that minimizes the worst-case delay subject to an upper bound on the false alarm rate.

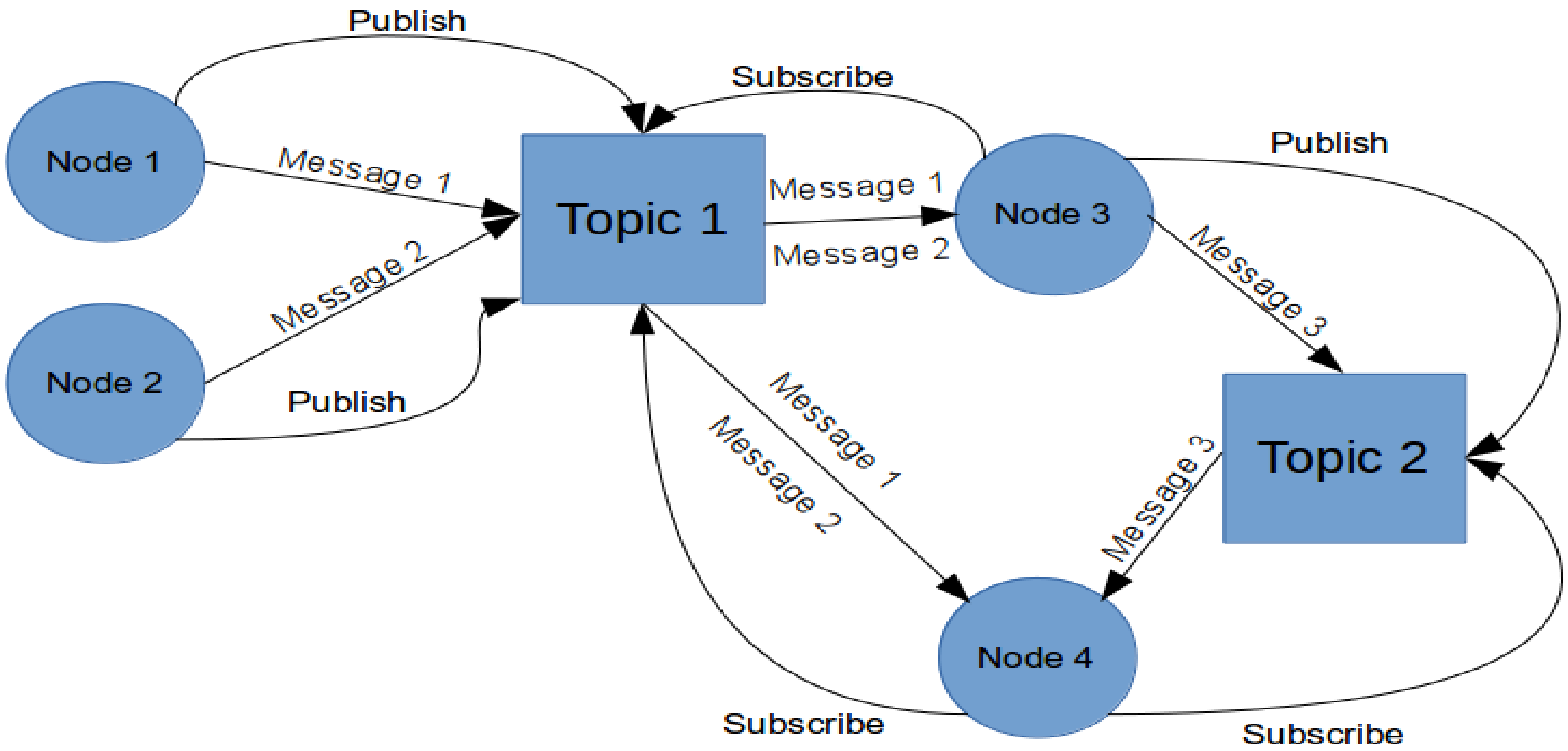
$$D_n(\tau) = \sup_{n \geq 1} ess \sup \mathbb{E}_k[(\tau - k + 1)_+ | \mathcal{F}_{k-1}]$$

Robot Operating System (ROS)

- Meta Operating System
- Open source
- Code Reuse
- Widespread use

Robot Operating System (ROS): Publish Subscribe

- Publishers
- Subscribers
- Topics



Robot Operating System (ROS): Sensors

- 1D range finders
- 2D range finders
- 3D Sensors (range finders and RGB-D cameras)
- Audio / Speech recognition
- Cameras
- Environmental (like measuring wind speed and direction)
- Force / Torque / Touch Sensors
- Motion Capture
- Pose estimation (GPS / IMU)
- Power Supply
- RFID (Radio-frequency identification