Artificial Intelligence-based Cognitive Cross-layer Decision Engine for Next-Generation Space Mission

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Agenda

- ❑ Motivation
- ❑ Related Works
- ❑ Cognitive Cross Layer Framework
  - Physical Layer
  - Network Layer
  - Cross-Layer
- ❑ Deep Reinforcement Learning
- ❑ Conclusion

Motivation – Existing Architecture

- Bent-pipe typical of LEO satellites.
- Inter-satellite distance in LEO networks ~ prop delay milliseconds > terrestrial.
- Satellite-terrestrial segment ad hoc networking – GAMANET.
- Non-agile slow configuration – static routing, link allocation and scheduling.

[1] P. Rodrigues, A. Oliveira, R. Mendes, S. Cunha, R. Pinho, C. Salotto, and R. De Carvalho, “GAMANET: Disrupting communications and networking in space,” vol. 6, Jan 2013.

Motivation – Cross Layer Approach

- Satellite systems possess Layered Architecture.
  - Redundancies and Inefficiencies.
- QoS requirements serviced at upper layers but affected by lower level protocols.
- Lack of scalability and adaptability with varying network dynamics.
- Inefficient allocation of radio resources.
- Lack of information exchange between the layers.

Motivation – Small Satellite networks

- **ANTs** – NASA’s Autonomous NanoTechnology Swarm
- **GRACE** – joint venture by NASA and Deutsche Forschungsanstalt fr Luftund Raumfahrt in Germany
- **EDSN** – NASA’s Edison Demonstration of SmallSat Network
- **PROBA-3** – Small satellite demonstration mission by European Space Agency

Formation flying introduce swarm, cluster, constellation.

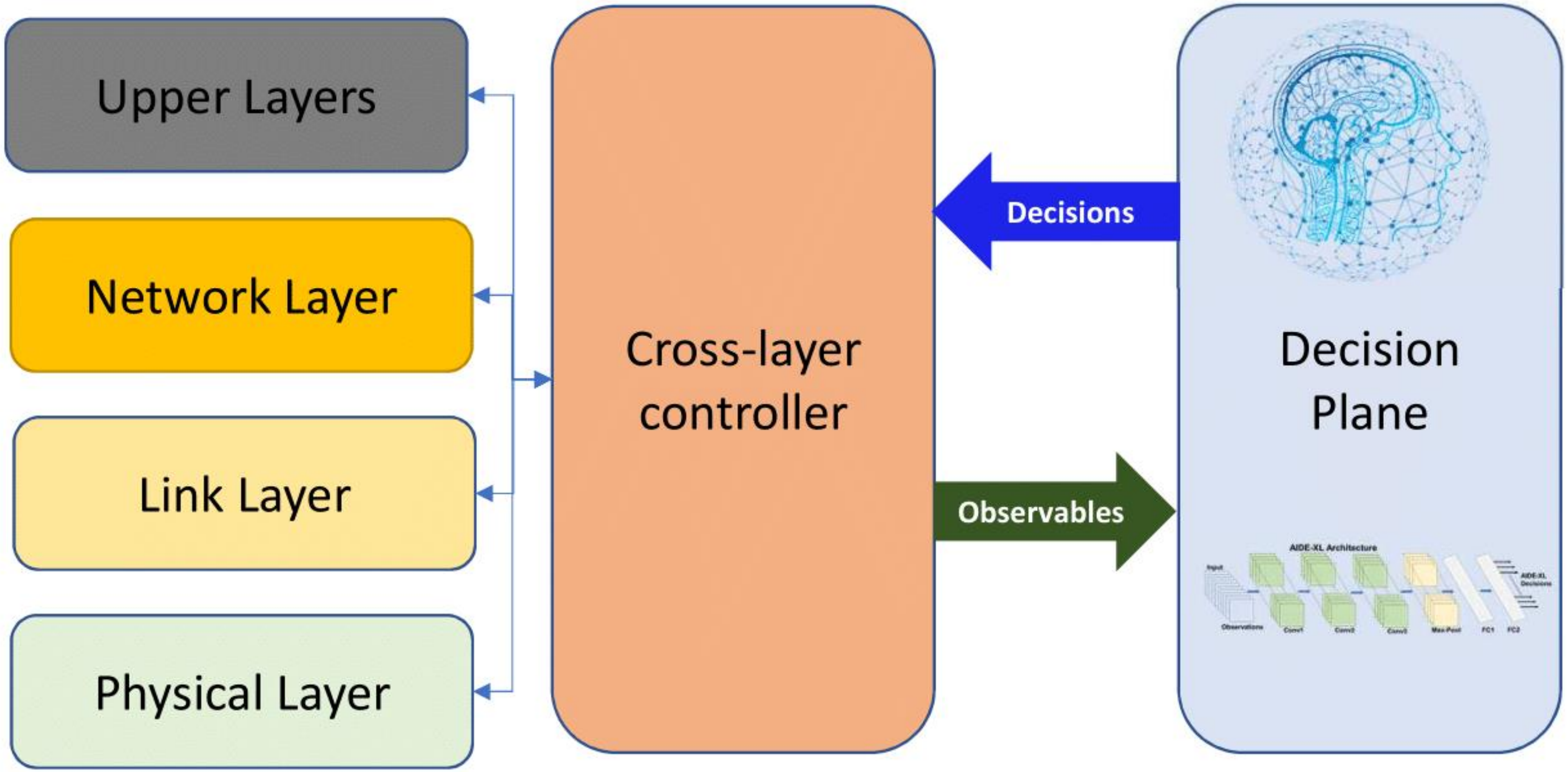
Dynamic network topology – Link Quality – Spectrum Availability – mission specific QoS

Satellite resources are limited and expensive !

Related Works – Cross Layer

- J. Jagannath, S. Furman, T. Melodia, and A. Drozd, "Design and Experimental Evaluation of a Cross-Layer Deadline-Based Joint Routing and Spectrum Allocation Algorithm," IEEE Transactions on Mobile Computing, 2018.
- J. Jagannath, H. Saarinen, T. Woods, J. O'Brien, S. Furman, A. Drozd, and T. Melodia, "COmBAT: Cross-layer Based Testbed with Analysis Tool Implemented Using Software Defined Radios," in Proc. of IEEE Conf. on Milt. Commun. (MILCOM), (Baltimore, MD, USA), Nov 2016.
- J. Jagannath, S. Furman, A. Jagannath, L. Ling, A. Burger, and A. Drozd, "HELPER: Heterogeneous Efficient Low Power Radio for Enabling Ad Hoc Emergency Public Safety Networks," Ad Hoc Networks (Elsevier), vol. 89C, pp. 218–235, 2019.
- N. Celandroni, F. Davoli, E. Ferro, and A. Gotta, "Adaptive cross-layer bandwidth allocation in a rain-faded satellite environment," International Journal of Communication Systems, vol. 19, pp. 509–530, June 2006.
- F. Vieira, M. A. V. Castro, and G. S. Granados, "A tunable-fairness cross-layer scheduler for DVB-S2," International Journal of Satellite Communications and Networking, vol. 24, pp. 437–450, Sept 2006.
- S. Kota, G. Giambene, and N. L. Candio, "Cross-layer approach for an air interface of GEO satellite communication networks," Intl. Journal of Satellite Comm. and Networking, vol. 25, pp. 481–499, Sept 2007.

Cognitive Cross-Layer Decision Framework



Physical Layer

Optimum radio resource allocation w.r.t link dynamics and spectrum availability

$$\text{Maximize:}\ score_1 = \eta_f^{nm} = \boxed{\frac{(1 - e_f^{nm})r^n}{P_f^n}}$$

$$\text{Find:}\qquad f, r^n, P_f^n$$

$$\text{Subject to:}\ r^n \geq r^{QoS}, P_f^n < \mathcal{P}, e_f^{nm} \leq e^{QoS}$$

Energy efficiency of Link $n - m$

Network Layer – Scenario Specific

Space ad hoc network – Small satellite constellation, few ground stations

Goal A: QoS aware energy efficient networking

Utility metric/score:

$$score_2^A = \frac{\max(q_n - q_m, \upsilon)}{q_n} \frac{(d^{nS} - d^{mS})}{d^{nS}} \frac{b_r^m}{b_i^m}$$

Network Layer – Scenario Specific

Spacebot swarm – Marsbees/Mars Helicopters, rover (data aggregation center)

Goal B: Resource aware reliable networking

Route reliability metric

Utility metric/score:

$$score_2^B = \boxed{\iota^{mS}} \frac{(d^{nS} - d^{mS})}{d^{nS}}$$

[2] J. Jagannath and T. Melodia, “VL-ROUTE: A Cross-Layer Routing Protocol for Visible Light Ad Hoc Network,” in Proc. of IEEE Symp. on a World of Wireless, Mobile, an
Multimedia Networks (WoWMoM), (Washington D.C., USA), June 2019.

Network Layer – Optimization

Maximize: $score_2^{\{A,B\}}$
Find: m
Subject to: Mission specific constraints

Cross Layer – Optimization

Maximize: $score_\times = w_1 score_1 + w_2 score_2^{\{A,B\}}$
Find: f, r^n, P_f^n, m
Subject to: $w_1 + w_2 \geq 1, w_1, w_2 \in (0,1)$
QoS & resource constraints

Deep Reinforcement Learning

States $s_t = (\boldsymbol{e}_t, \boldsymbol{r}_t, \boldsymbol{f}_t, \boldsymbol{P}_t \boldsymbol{i}_t, \boldsymbol{q}_t, \boldsymbol{d}_t, \boldsymbol{b}_{rt}, \boldsymbol{b}_{it}, \boldsymbol{\eta}_t, \boldsymbol{\iota}_t, \boldsymbol{N}_t)$

Actions $a_t = \left(f, r^n, P_f^n, m\right)$

Policy $a_t = \pi(s_t)$

Reward $\tau_t = \begin{cases} score_{\times}, & \text{if constraints are met} \\ 0, & \text{otherwise} \end{cases}$

Deep Reinforcement Learning

Q-function

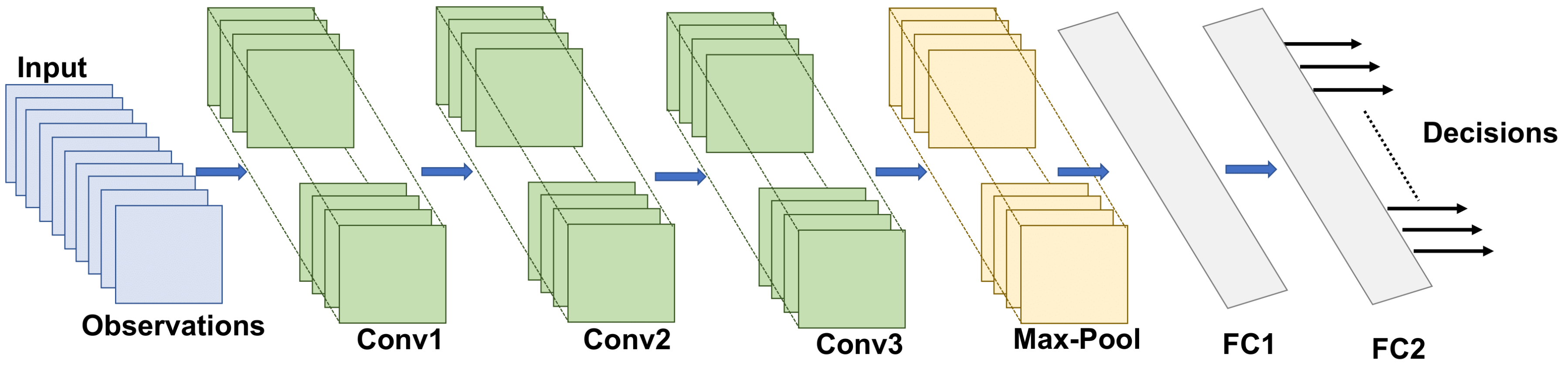
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \lambda \left[\overbrace{\boxed{\tau_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})}}^{\text{Target Q-value}} - Q(s_t, a_t)\right]$$

Learning rate $\lambda \in (0,1)$

Discount factor $\gamma \in [0,1]$

Optimal Policy $\pi^*(s_t) = \underbrace{\arg}_{a_t} \max Q(s_t, a_t)$

Deep Q-network

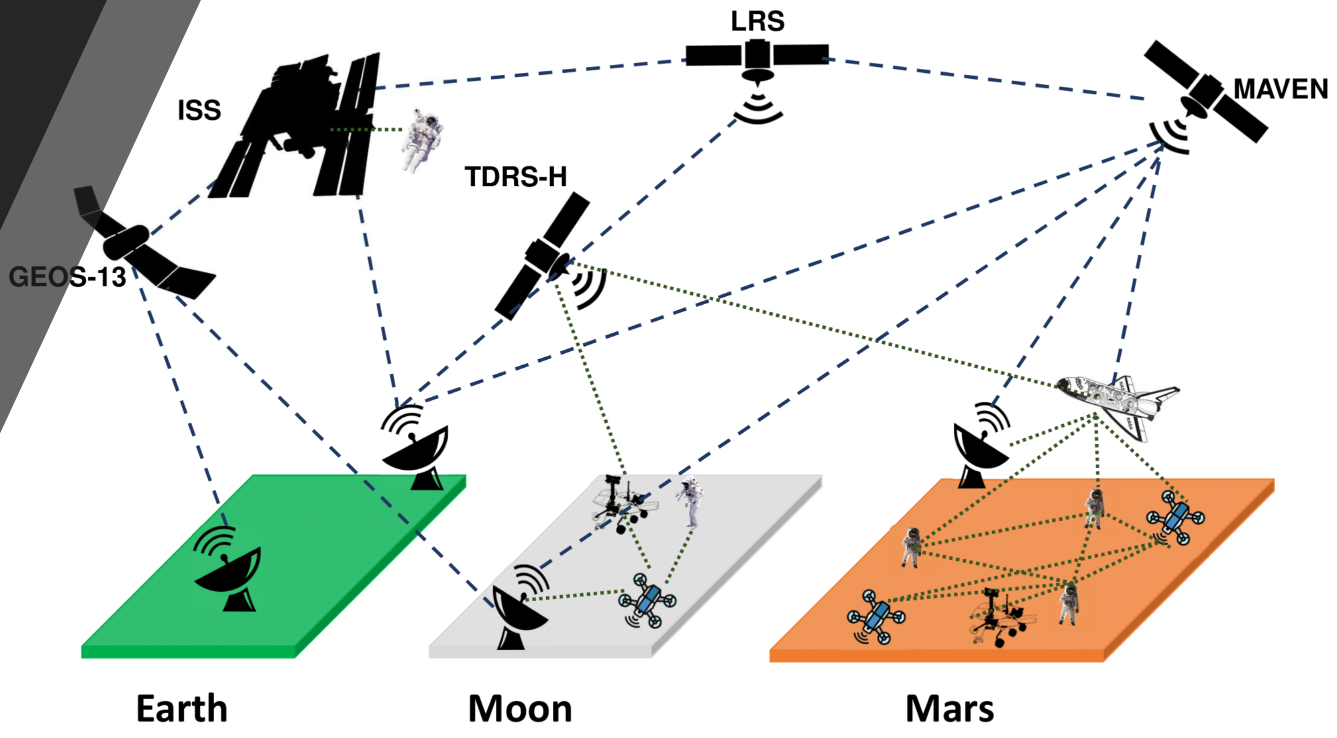


Experience-replay to train the DQN.

Batch Normalization

Conclusion & Future Works

- Motivated the need to unify cross-layer optimization with deep reinforcement learning.
- Illustrated applicable space networking scenarios.
- SDR testbeds would aid in designing and maturing these advancements.



Thank You