CAREER: Co-Design of Networking and Decentralized Control to Enable Aerial Networking in an Uncertain Airspace

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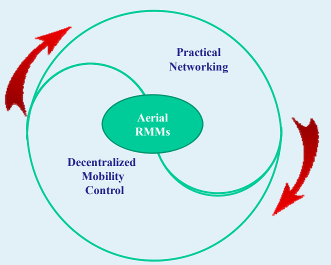
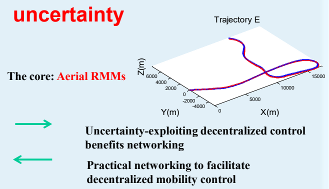
Introduction

Airborne networking utilizes direct flight-to-flight communication for flexible information sharing, safe maneuvering, and coordination of time-critical missions. It is challenging because of the high mobility, stringent safety requirements, and uncertain airspace environment.

This project uses a co-design approach that exploits the mutual benefits of networking and decentralized mobility control in an uncertain heterogeneous environment. The approach departs from the usual perspective that views physical mobility as communication constraints, communication as constraints for decentralized mobility control, and uncertain environment as constraints for both. Instead, we proactively exploit the constraints, uncertainty, and new structures with information to enable high-performance designs.



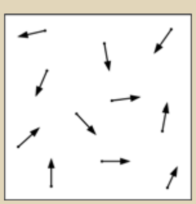
A comprehensive theoretical framework for Cyber-Physical Systems to exploit the mutual benefits of networking and decentralized control under uncertainty



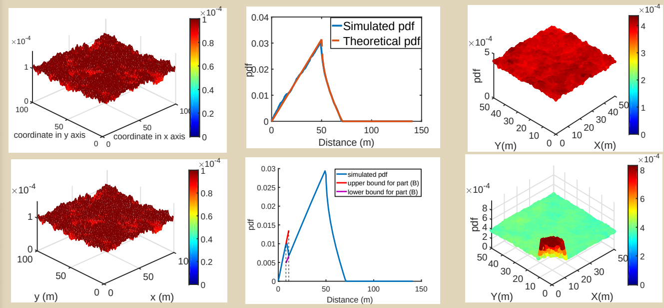
The features of the co-design such as scalability, fast response, tractability, and robustness to uncertainty advance the core CPS science on decision-making for large-scale networks under uncertainty.

UAV Random Mobility Models

In the year of 2016-2017, we enhanced the Random Direction RMM with a commonly used decentralized sense and avoid protocol—sense-and-stop (S&S) and provided analytical results on critical networking statistics such as stationary node distribution and inter-vehicular distance distributions.



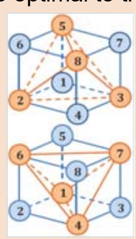
$$
\begin{cases}
\frac{1}{2}\pi d p_{1min} < f_D(d) < \frac{1}{2}\pi d p_{1max}, & 0 \leqslant d \leqslant d_o - V \\
\frac{1}{4}\pi d p_{1max} < f_D(d) < \frac{1}{2}\pi d p_{1min}, & d_o - V < d \leqslant d_o + V \\
\frac{1}{4}\pi d p_{1min} < f_D(d) < \frac{1}{4}\pi r p_{1max}, & d_o + V < d \leqslant \frac{B}{2} \\
\frac{1}{2}\left(\frac{\pi}{2} - 2arccos\left(\frac{B}{d}\right)\right) dp_{1\min} < f_D(d) & \\
< \frac{1}{2}\left(\frac{\pi}{2} - 2arccos\left(\frac{B}{d}\right)\right) dp_{1\max}, & \frac{B}{2} < d \leqslant \frac{\sqrt{2}B}{2}
\end{cases}
$$



First row: Without the sense and avoid protocol. Second row: With the sense and avoid protocol. From left to right: Not distribution, pdf of inter-vehicular distance (2D), density of inter-vehicle relative position

Uncertainty Exploited Control

In the year of 2016-2017, we used two multi-dimensional uncertainty evaluation based approaches that we developed previously to address the scalability issue of stochastic optimal control and learning-based control for systems of high-dimensional uncertainties. Three scenarios are considered: 1) uncertain parameters changing independently across time, 2) uncertain parameters evolving according to Markov chains, and 3) infinite-horizon forward-in-time optimal control. We proved that the control solution optimal to the sampled uncertainty space produced by M-PCM or M-PCM-OFFD is also optimal to the original uncertainty space.

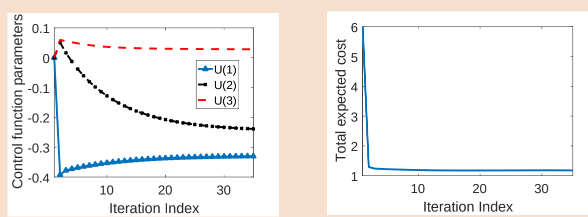


$$V_k^*(\mathbf{x}[k]) = \min_{\pi} E_{\mathbf{a}[k]}\left[g_k(\mathbf{x},\mathbf{u}) + \alpha V_{k+1}^*(\mathbf{x}[k+1])\right]$$

$$G_k(\mathbf{x},\mathbf{u},\mathbf{a}) = g_k(\mathbf{x},\mathbf{u}) + \alpha V_{k+1}^*(\mathbf{x}[k+1])$$

$$G_k(\mathbf{x},\mathbf{u},\mathbf{a}) = \sum_{j_1=0}^{2n_1[k]-1} \dots \sum_{j_m=0}^{2n_m[k]-1} \Psi_{j_1,\dots,j_m}(\mathbf{x}[k],\mathbf{u}[k]) \prod_{i=1}^{m} a_i^{j_i}[k]$$

$$E_{\mathbf{a}[k]}\left[G_k(\mathbf{x},\mathbf{u},\mathbf{a})\right] \qquad E_{\mathbf{a}[k]}\left[G'_k(\mathbf{x},\mathbf{u},\mathbf{a})\right].$$



a) b)

Illustration of the a) convergence of U and b) trajectory of total expected cost

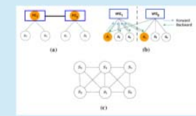
Practical Networking to Facilitate Fast Decentralized Mobility Control

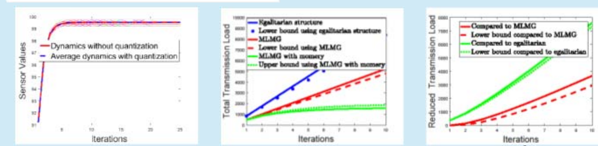
We showed that layered structures are more effective than equivalent egalitarian structures in terms of the data transmission load required to reach consensus. We provided analytical results on the asymptotic and transient performance when additional local memories are used to further reduce the data transmission load to reach consensus.

$$
\begin{cases}
\mathbf{s}_t[1] = \mathcal{Q}(\mathbf{s}_m[1]), \\
\mathbf{v}_m[1] = K_2 H \mathbf{s}_t[1], \\
\mathbf{v}_t[1] = \mathcal{Q}(\mathbf{v}_m[1]), \\
\mathbf{s}_m[2] = K_1 H^T \mathbf{v}_t[1],
\end{cases}
$$

$$
\begin{cases}
\mathbf{s}_t[k] = \mathcal{Q}(\mathbf{s}_m[k]) - \mathcal{Q}(\mathbf{s}_m[k-1])), \\
\mathbf{v}_m[k] = K_2 H \mathbf{s}_t[k] + \mathbf{v}_m[k-1], \\
\mathbf{v}_t[k] = \mathcal{Q}(\mathbf{v}_m[k]) - \mathcal{Q}(\mathbf{v}_m[k-1]), \\
\mathbf{s}_m[k+1] = K_1 H^T \mathbf{v}_t[k] + \mathbf{s}_m[k].
\end{cases}
$$

$$\mathcal{Q}_i(\mathbf{d}) = \begin{cases} \lfloor d_i \rfloor, & \text{with probability } \frac{\lceil d_i \rceil - d_i}{\Delta}, \\ \lceil d_i \rceil, & \text{with probability } 1 - \frac{\lceil d_i \rceil - d_i}{\Delta}. \end{cases}$$





d) e) f)

a)b)c): The illustration of layered structure. d) Dynamics with the equipment of memory. e)f) Reduction of transmission load.

Testbed Enhancement

We enhanced the testbed that uses ROS and Beaglebone.

a) b)

Some References

1. J. Xie, Y. Wan, K. Mills, J. J. Filliben, and F. Lewis, "A Scalable Sampling Method to High-dimensional Uncertainties for Optimal and Reinforcement Learning-based Controls," IEEE Control Systems Letters, vol. 1, no. 1, pp. 98-103, July 2017.
2. J. Yan, Y. Wan, S. Fu, J. Xie, S. Li, and K. Lu, Received Signal Strength Indicator based Decentralized Control for Robust Long-distance Aerial Networks using Directional Antennas, IET Control Theory and Applications, vol. 11, no. 11, pp. 1838-1847, July 2017.
3. J. Chen, J. Xie, Y. Gu, S. Li, S. Fu, Y. Wan, and K. Lu, "Long-Range and Broadband Aerial Networking using Directional Antenna (ANDA): Design and Implementation, accepted by IEEE Transactions on Vehicular Technology, June 2017.