Resource Allocation for Federated Learning in UAV-aided Digital Twin Edge Networks

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Contents

Introduction

Digital Twin (DT)

- Intelligent system, digitally replicate a physical object (PO)
- To monitor, control, and optimize POs during its life cycle

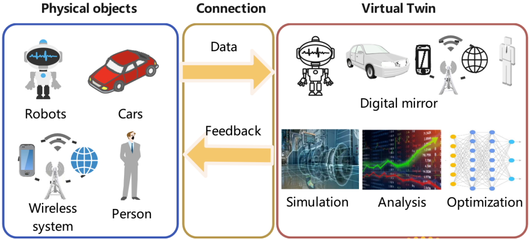

Figure 1: DT concept

TABLE 1. The three types concept of DT.

Concept	Functions	Physical-to-twin	Twin-to-physical
Monitoring DT	Virtual representation	×	×
Simulation DT	Simulation	✓	×
Operational DT	Co-evolute digital replica	✓	✓

Digital Twin Edge Networks (DITEN) - Where?

- DT are built, maintained by mobile edge computing (MEC)
- Virtual twin-to-twin comms construct a network DITEN
  - Applications: instruct POs from a centralized perspective
  - Network: optimize directly resource allocation, caching, ...

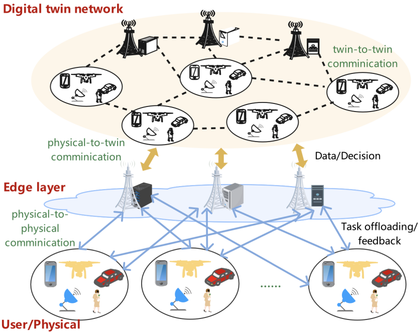

Figure 2: DITEN concept

Federated Learning (FL) - How?

- Centralized machine learning: frequent data exchange
  - High risk of data leakage
  - Synchronizing all raw data results in over-comms load
- Decentralized federated learning: model parameters exchange
  - Protect user privacy: devices locally train their ML model based on it own data
  - Reduce comms load: transmit only local model parameters

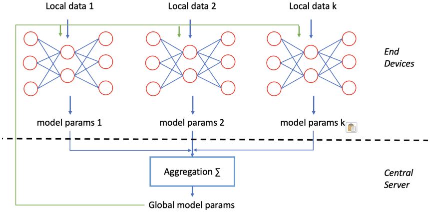

Figure 3: Federated learning

Problem: comms cost is higher than comp cost

System Model

UAV-aided DITENs for Internet of Vehicles

- K moving vehicles on the road, high density at the intersection
- A base station BS - MEC server integrated
- A UAV (fixed hovering at intersection): relay node, provides higher prob. of line-of-sight (LoS) propagation channels with additional comms time (UAV-BS)

Scenario: DT construction in UAV-aided DITENs for IoV

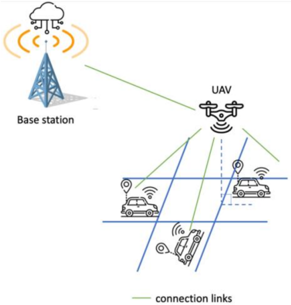

Figure 4: UAV-aided DITEN for vehicles

Federated Learning for DT construction

- DT construction time: τ
- Global accuracy: ϵ_0
- Local accuracy: η

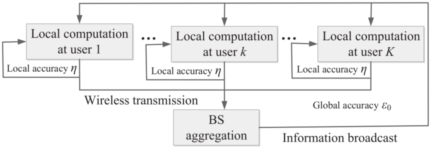

Figure 5: FL between vehs and BS

$\rightarrow$ derive the number of local rounds (i) to reach the local accuracy η and the number of global rounds (n) to reach the global accuracy ϵ_0 within the DT construction time τ

Other key-points:

- Convex loss function $\rightarrow$ global convergence
- Non-convex loss function (?)

Problem Formulation

Optimization problem

Objective: minimizing the total energy consumption

Constraint: guarantee the DT construction time

	Energy	Time	Penalty
Comp	$e_k^{cp} = i \times \kappa C_k D_k f_k^2$	$t_k^{cp} = i \times \frac{C_k D_k}{f_k}$	
Comms	$e_k^{co} = n \times p_k t_k^{co}$	$t_k^{co} = n \times \frac{s_k \ln(2)}{B \ln(1+\frac{p_k h_k}{N_0})}$	$0, \delta_t$

- $i = v * \log_2(\frac{1}{\eta})$, $n = \frac{a}{1-\eta}$
  (v, a: constants, depend on loss function, data)
- δ_t: penalty time *if* choosing UAV
- Optimization variables: η, f_k, p_k, x_k
  $x_k = 1$ *if* choosing UAV *else* 0

Problem formulation

$$
\begin{aligned}
\min_{\eta, f_k, x_k, p_k} \quad & \sum_{k=0}^{K-1} \frac{a}{1-\eta} \left(p_k \frac{s_k \ln(2)}{B \ln(1+\frac{p_k h_k}{N_0})} + v \log_2\left(\frac{1}{\eta}\right) \times \kappa C_k D_k f_k^2 \right) \\
\text{s.t.} \quad & \frac{a}{1-\eta} \left(\frac{s_k \ln(2)}{B \ln(1+\frac{p_k h_k}{N_0})} + \Delta_k + v \log_2\left(\frac{1}{\eta}\right) \times \frac{C_k D_k}{f_k} \right) \leq \tau, \\
& 0 \leq \eta \leq 1, \\
& 0 \leq f_k \leq f_k^{max}, \forall k, \\
& x_k = \{0, 1\}, \forall k, \\
& 0 \leq p_k \leq p_k^{max}, \forall k, \\
& h_k = (x_k == 1) ? h_k^{uav} : h_k^{bs}, \\
& \Delta_k = (x_k == 1) ? \delta_t : 0
\end{aligned}
$$

Network Optimization

Optimization

- Interactive bw FL and network optimization
- Iterative procedure
  - η: (fixed f_k, x_k, p_k): (convex) bound tightening by solving Lambert-W functions of constraints $\Rightarrow$ Dinkelbach method for fractional form optimization
  - f_k, p_k: (fixed η): (convex) - solving 1st derivative $\nabla f = 0$, but complex to generate closed-form solution $\rightarrow$ iterative algorithms (Newton's method, ...) to derived the solutions
  - x_k: heuristic to choose the better chooice (method depends on the above iterative algorithm cost)

Simulation

Simulation scenario

- Dataset (for train, test): represent the vehicle's data
  - Synthetic: computer generated
  - MNIST: handwritten images, 10 output classes
  - FeMNIST: Federated Extended MNIST: handwritten images + others, 62 output classes
- Loss function (convex):
  - Linear regression: Regression problem
  - Multinomial logistic regression: Classification problem
- Modeling moving vehicles

Synthetic dataset

- Input dim: 3, output dim: 5
- Loss: Linear regression
- Local rounds $i = 30$

Result:

- Loss, Acc converge after 50 global rounds
- Dissimilarity (square root of difference bw global gradient and local gradients) is small (small dataset)

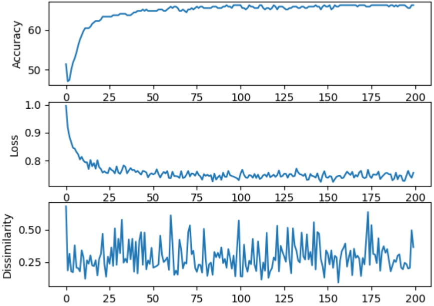

Figure 6: FL loss and accuracy - Synthetic

MNIST Dataset

- 28×28 images, input dim: 784, output dim: 10
- Loss: Multinomial logistic
- Local rounds $i = 30$

Result:

- Loss, Acc converge after 60 global rounds

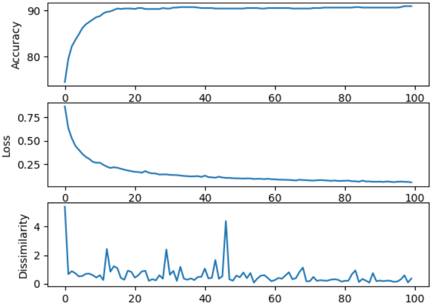

Figure 7: FL loss and accuracy - Synthetic

References

[1] F. Tang, X. Chen, T. K. Rodrigues, M. Zhao and N. Kato, "Survey on Digital Twin Edge Networks (DITEN) Toward 6G," in IEEE Open Journal of the Communications Society, vol. 3, pp. 1360-1381, 2022, doi: 10.1109/OJCOMS.2022.3197811.
[2] Z. Yang, M. Chen, W. Saad, C. S. Hong and M. Shikh-Bahaei, "Energy Efficient Federated Learning Over Wireless Communication Networks," in IEEE Transactions on Wireless Communications, vol. 20, no. 3, pp. 1935-1949, March 2021, doi: 10.1109/TWC.2020.3037554.

Thank you for your attention.