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Toward Ambient Intelligence: Federated Edge Learning with Task-Oriented Sensing, Computation, and Communication Integration

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Introduction

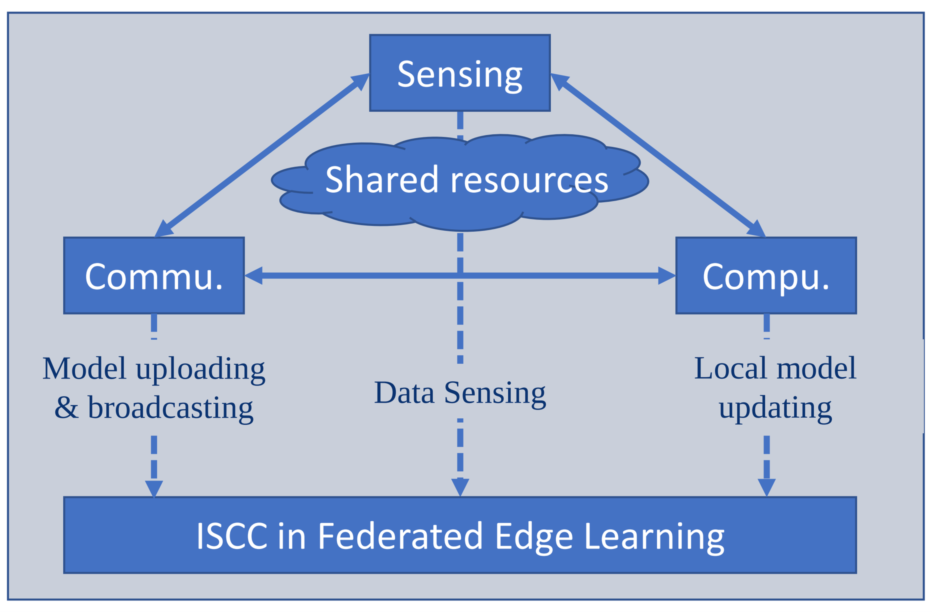
Future next-G network: The future next-G network will no longer serve only the single purpose of data transmission, but will need to *support connected intelligence services and ubiquitous intelligence applications* [1].

Ambient intelligence: The goal of ambient intelligence is to build physical spaces that are sensitive spaces that are sensitive and responsive to the inputs triggered by humans and to provide low-latency, high-accurate, scalable, and resilient services with the help of *AI technologies and contactless sensors* [2].

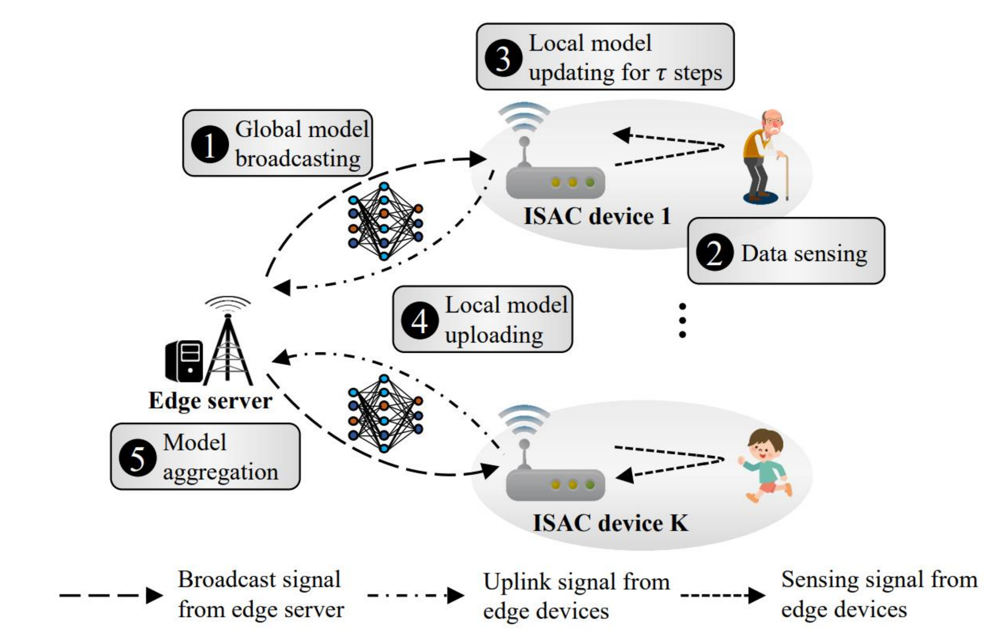
Federated edge learning (FEEL): FEEL is a popular collaborative distributed learning paradigm that trains a global machine learning (ML) model over wireless networks while helping to preserve data privacy [3]. Prior works mainly focused on the communication and/or computation perspectives and assumed that the data used for training are readily available without considering the data sensing process.

Integrated sensing, computation, and communication (SC²): SC² are highly coupled in FEEL and thus need to be seamlessly integrated in a joint design to fully unleash the potential of FEEL.

Two challenges: 1) how to generate data samples with approximately the same satisfactory quality for FEEL over time by wireless sensing; 2) how to jointly allocate the SC2 resources in an task-oriented manner so as to yield the best learning performance.



System Model



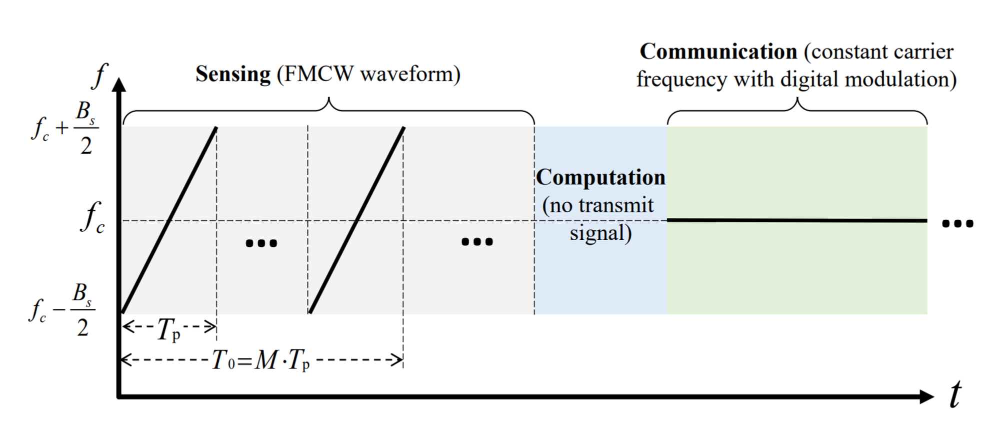
➢ **FEEL training process**

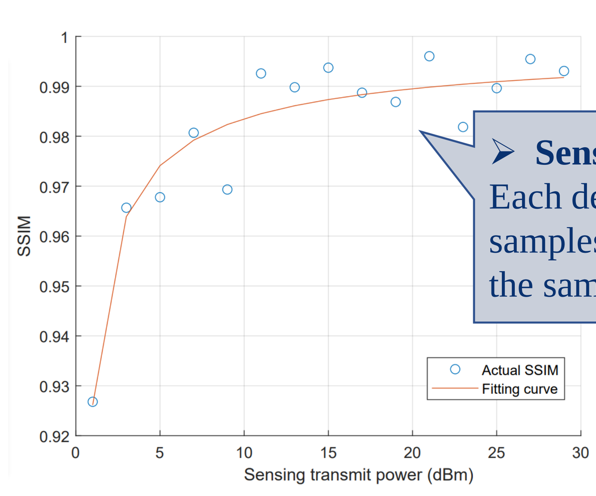
For any arbitrary r, mainly five steps are executed as follows:

1. Global model broadcasting: Each ISAC device downloads the global FL model $\boldsymbol{w}^{(r)}$ from the server via the wireless broadcast channel.
2. Data sensing: Each ISAC device switches to the sensing mode, and transmits dedicated sensing signals for sensing. Then, a batch of sensing data, $b^{(r)}$ can be attained at each ISAC device by processing its received echo signals.
3. Local model uploading for τ steps: Each device updates its model by running τ steps of stochastic gradient descent (SGD) from $w^{(r)}$.
4. Local model uploading: Each ISAV device switches to communication mode and uploads its local model after τ local updates, i.e., $w^{(r,\tau)}$, to the server via the uplink wireless channel.
5. Global aggregation: Once the server receives the models from all the devices, it aggregates them to obtain a new global ML model.

- Sense-then-compute: This batch of data with size $b^{(r)}$ sensed in Step 2 will be used for local computation in Step 3.
- The batch size $b^{(r)}$ can vary adaptively over different rounds, but keep unchanged within any particular round.

OUR FOCUS: Sensing quantity

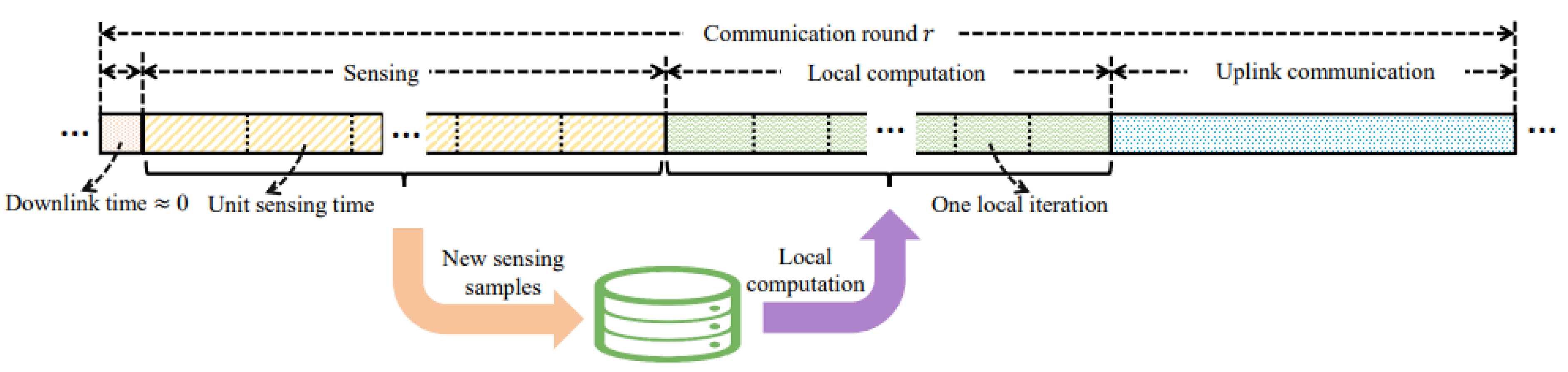


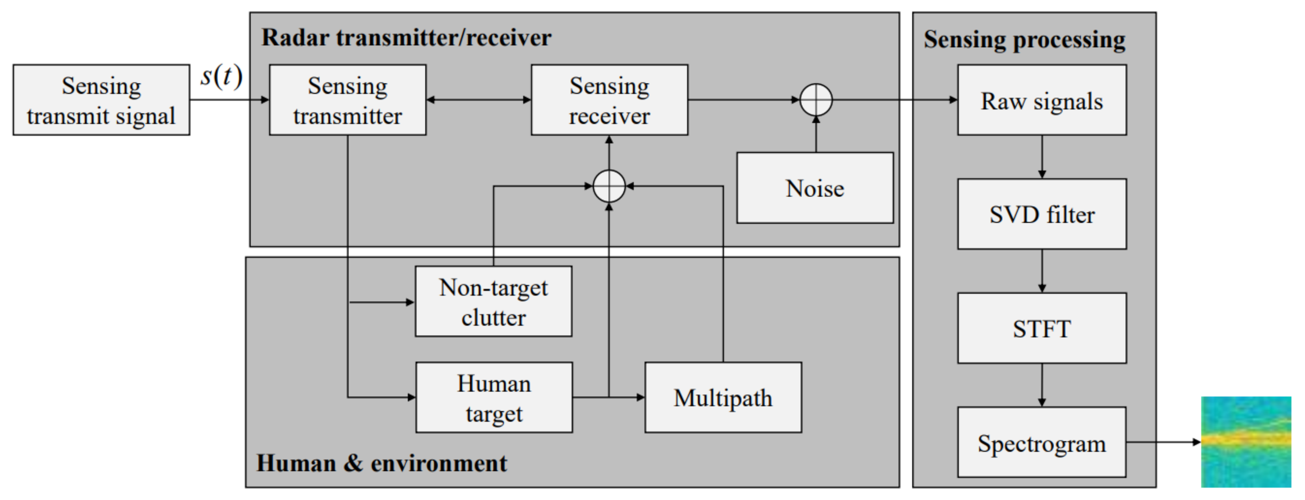


➢ **Sensing Analysis**
Each device can generate data samples with approximately the same satisfactory quality.

➢ **Sensing signal model**
- Dedicated radar waveform known as frequency-modulated continuous-wave consisting of multiple up-chirps is transmitted.
- We use a primitive based method [3] to model the scattering from the entire human body to the device sensing receiver.

➢ **Communication signal model**
- Each device occupies a non-overlapping communication frequency subcarrier, and the transmission of the devices are interference-free from each other.
- The communication channels from the devices to the server are assumed to be fast Rayleigh fading channel.





Problem Formulation & Solution

Target: Optimize the sensing and communication transmit power, the communication time, and the batch sizes for each round to maximize the training speed under time, energy, and peak power constraints.

$$\min_{\{b^{(r)}\},\{p_{c,k}\},\{p_{s,k}\},\{T_{cm,k}\}} \mathbb{E}\left[\frac{1}{\tau R}\sum_{r=1}^{R}\sum_{l=1}^{\tau}\left\|\nabla F(\bar{\boldsymbol{w}}^{(r,l)})\right\|^2\right], \text{s.t.} \quad \text{(C1)-(C5)}$$

Commun. Sensing Comput.

Time	Energy
(C1) Commun. rate constraint $T_{cm,k}C_k(p_{c,k}) \geq D_b, \forall k \in [K]$	$E_{cm,k}^{(r)} = T_{cm,k}p_{c,k}$
$T_{s,k}^{(r)} = T_0 b^{(r)}$	$E_{s,k}^{(r)} = T_{cp,k}^{(r)}p_{s,k} = T_0 b^{(r)} p_{s,k}$
$T_{cp,k}^{(r)} = \frac{\tau b^{(r)}\nu}{f_{cpu}}$	$E_{cp,k}^{(r)} = \tau\theta\nu f_{cpu}^2 b^{(r)}$

(C2) Latency $\sum_{r=1}^{R}\max_{k\in[K]}\{T_{s,k}^{(r)} + T_{cp,k}^{(r)} + T_{cm,k}\} \leq T_{\max}$

(C3) Energy $\sum_{r=1}^{R}(E_{s,k}^{(r)} + E_{cp,k}^{(r)} + E_{cm,k}^{(r)} \leq E_{\max}), \forall k \in [K]$

(C4) Peak commun. power $0 \leq p_{c,k} \leq P_{c,k}^{\max}, \forall k \in [K]$

(C5) Peak sensing power $P_{s,k}^{\min} \leq p_{s,k} \leq P_{s,k}^{\max}, \forall k \in [K]$

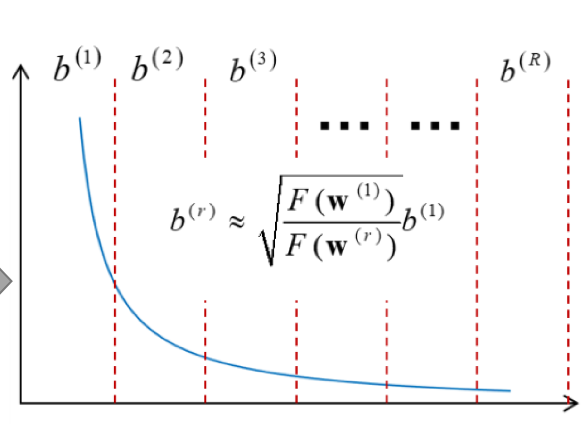
Step 1: Maximize total sensed samples

$$b_{\text{sum}}^* = \arg\max_{b_{\text{sum}},\{p_{c,k}\},\{p_{s,k}\},\{T_{cm,k}\}} b_{\text{sum}} \quad \text{s.t.} \quad \text{(C1)-(C5)}, \quad b_{\text{sum}} = \sum_{r=1}^{R} b^{(r)}.$$

$$\begin{cases} p_{s,k}^* = P_{s,k}^{\min} \\ p_{c,k}^* = \arg\max_{p_{c,k}} \Phi_k(p_{c,k}) \\ \quad \text{s.t.} \quad 0 \leq p_{c,k} \leq P_{c,k}^{\max} \end{cases}$$

Step 2: Allocate batch size over commun. rounds given total sensed samples

$$\min_{\{b^{(r)}\}} \mathbb{E}\left[\frac{1}{\tau R}\sum_{r=1}^{R}\sum_{l=1}^{\tau}\left\|\nabla F(\bar{\boldsymbol{w}}^{(r,l)})\right\|^2\right] \quad \text{s.t.} \quad \sum_{r=1}^{R} b^{(r)} = b_{\text{sum}}^*$$

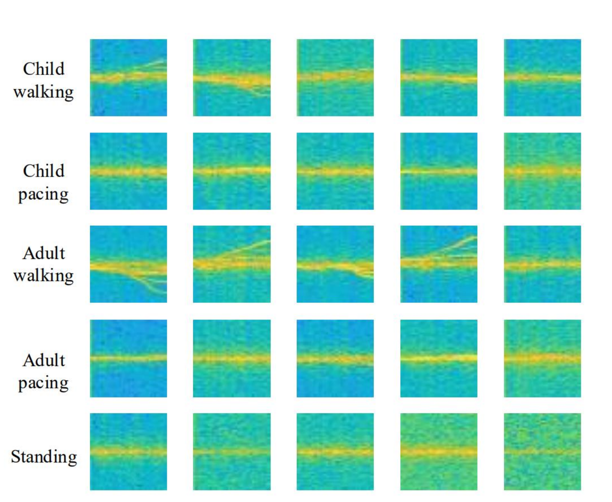


$$b^{(r)} \approx \sqrt{\frac{F(\mathbf{w}^{(1)})}{F(\mathbf{w}^{(r)})}} b^{(1)}$$

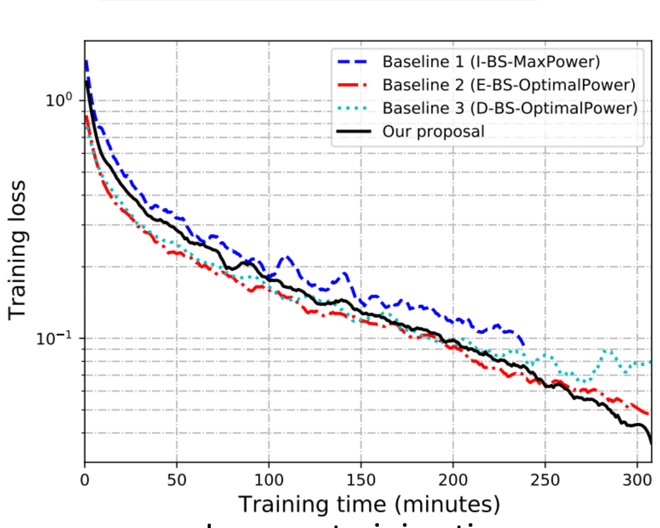
➢ **Sensing signal model**
- Each of the value of loss function decreases approximately in an order of $O(1/r)$ when training with SGD [4].
- It follows that the optimal batch size $b^{(r)}$ at communication round r should decrease in an order of $O(1/\sqrt{r})$.

$$\left.\begin{aligned} b^{(r)} &\approx \alpha\sqrt{r} + b_0 \\ \sum_{r=1}^{R} b^{(r)} &= b_{\text{sum}}^* \end{aligned}\right\} \Rightarrow b^{(r)} \approx \left\lfloor \frac{(b_{\text{sum}} - b_0 R)\sqrt{r}}{\sum_{r=1}^{R}\sqrt{r}} + b_0 \right\rfloor$$

Simulation Results



Examples of data samples



Loss v.s. training time

- **Dataset:** high-fidelity human motions by wireless sensing simulator in [5]
- **Learning model:** ResNet10 (#params=4,900,677)
- **Baselines:** increasing batch size & maximum transmit power (I-BS-MaxPower) constant batch size & optimal transmit power (E-BS-OptimalPower); decreasing batch size & optimal transmit power (D-BS-OptimalPower);

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