Physics-Informed Models for RFID Localization

For RFID localization using **RSSI**, **Doppler**, and **phase angle**, pure linear regression is generally unsuitable due to multipath effects, non-linear propagation, and periodic features. A better approach is to use **physics-informed models**, which combine established RF propagation equations with statistical/machine learning techniques.

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1. Path Loss + Regression Hybrid

Core Idea: Use the log-distance path loss model for RSSI to estimate range, then correct residual error with a regression model.

Path loss model:

$$RSSI(d) = P_0 - 10n\log_{10}(d) + X_\sigma$$

- **P_0**: reference power at 1 m - **n**: path loss exponent - **$X\sigma$**: Gaussian noise term

Workflow: 1. Calibrate **P_0** and **n** in the environment. 2. Convert RSSI to initial distance estimates. 3. Feed distances + Doppler + phase into non-linear regression (SVR, gradient boosting, neural net).

Pros: Simple, explainable, less data-hungry.

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2. Phase-Based Ranging with Unwrapping

Core Idea: Phase shift relates to distance modulo the wavelength.

Model:

$$\phi(d) = \frac{4\pi d}{\lambda} \mod 2\pi$$

- **λ**: carrier wavelength

Workflow: 1. Unwrap phase to estimate continuous range. 2. Fuse with RSSI-based range via Kalman or particle filter. 3. Optionally train a model to map `(unwrapped phase, RSSI, Doppler)` → position.

Pros: High precision from phase; RSSI resolves ambiguity.

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3. Doppler + Geometry Kinematics

Core Idea: Doppler shift gives radial velocity, useful for moving tags.

Model:

$$f_d = \frac{v_r}{\lambda}$$

- $\mathbf{v_r}$: radial velocity

Workflow: 1. Use Doppler in a motion prediction model (Kalman or Extended Kalman Filter). 2. Update with RSSI/phase-derived ranges.

Pros: Smooths noisy data; handles motion well.

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4. TDOA + ML

If readers are synchronized, use time differences of arrival.

Model:

$$d = c \cdot \Delta t$$

- **c**: speed of light

Workflow: 1. Compute TDOA-based positions. 2. Refine with non-linear least squares + ML corrections.

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5. Hybrid Particle Filter with Learned Measurement Model

Core Idea: Physics constrains candidate positions; ML models measurement noise.

Workflow: 1. Predict possible positions (motion model). 2. Simulate expected RSSI, phase, Doppler from physics. 3. Score particles using a trained likelihood model.

Pros: Physics narrows search space; ML learns multipath patterns.

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6. Gaussian Process Regression with Physics Kernel

Instead of a generic RBF kernel, encode spatial correlation and periodicity.

Example Kernel:

$$k(d_1, d_2) = \sigma_f^2 \exp\left(-\frac{(d_1 - d_2)^2}{2l^2}\right) \cdot \cos\left(\frac{2\pi(d_1 - d_2)}{\lambda}\right)$$

- Enforces smooth decay + wavelength-based oscillations.

Summary

A strong approach for RFID localization: 1. **Preprocess:** phase unwrapping, RSSI normalization, Doppler smoothing. 2. **Apply physics models** for initial estimates. 3. **Learn residuals** using ML (e.g., gradient boosting, SVR, neural nets). 4. **Fuse over time** with a Kalman/particle filter for stability.

This hybrid strategy outperforms both pure ML and pure physics in real-world RFID environments.