

Widar2.0 Passive Human Tracking with a Single Wi-Fi Link

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Motivation

• Need for passive localization.

Smart Home **Health Monitoring** Intruder Detection

- RF radios VS. Cameras
	- Less privacy concern.
	- Larger surveillance area.
	- More ubiquitous deployment.

Motivation

• RF-based tracking thrives with prevail RF devices.

mmWave **FMCW Radar**

Our Early Effort

• Widar – Tracking with Doppler Frequency Shifts.

- Widar requires,
	- DFS from Multiple links to compute velocity.
	- Trial and error to resolve direction ambiguity.
	- Costly search to spot the initial location.

MobiHoc '17

State of the Arts

- Existing approaches either requires,
	- Single link but specialized hardware \rightarrow less ubiquitous
	- Commercial devices but multiple links \rightarrow less practical

Key Idea

- Can we achieve both ubiquity and practicality?
	- Yes! Using a single commercial Wi-Fi link.

• Widar2.0 – Tracking with ToF, AoA and DFS.

System Overview

CSI Model

• Due to multipath effect, CSI is modelled as:

$$
H(t, f, s) = \sum_{l=1}^{L} P_l(t, f, s) + N(t, f, s) = \sum_{l=1}^{L} \alpha_l(t, f, s) e^{-j2\pi f \tau_l(t, f, s)} + N(t, f, s)
$$

• The delay of the *l*-th path $\tau_l(i,j,k)$ is a combination of ToF τ_l , DFS f_{D_l} and AoA $\boldsymbol{\phi}_l = (\cos \phi_l, \sin \phi_l)^T$:

Parameter Estimation

• The MLE of $\boldsymbol{\theta}_l = (\alpha_l, \tau_l, \phi_l, f_{D_l})$ for all paths, $\boldsymbol{\Theta} = (\boldsymbol{\theta}_l)_{l=1}^L$ is formulated as:

$$
\Lambda(\Theta; H) = -\sum_{i,j,k} \left| H(i,j,k) - \sum_{l=1}^{L} P_l(i,j,k; \theta_l) \right|^2
$$

- L # of multi path.
	- *should be larger than* $#$ *of principle multi path.*
	- $-L = 5$, for sake of computation cost.
- Practical data input.
	- 3 antennas; 30 Subcarriers; 100 Packets (~0.1 s).

SAGE Algorithm

- SAGE algorithm is a general version of EM algorithm. – Re-estimate only a subset of parameters in each iteration.
- \bullet E Step.

$$
\hat{p}_l(i,j,k;\hat{\Theta}') = P_l(i,j,k;\hat{\theta}'_l) + \beta_l \left(H(i,j,k) - \sum_{l'=1}^L P_l(i,j,k;\hat{\theta}'_{l'}) \right)
$$

• M – Step.

$$
\hat{\tau}_l'' = \operatorname{argmax}_{\tau} \{ |z(\tau, \hat{\phi}_l', \hat{f}_{D_l}'; \hat{p}_l(i, j, k; \hat{\Theta}')| \} \n\hat{\phi}_l'' = \operatorname{argmax}_{\phi} \{ |z(\hat{\tau}_l'', \phi, \hat{f}_{D_l}'; \hat{p}_l(i, j, k; \hat{\Theta}')| \} \n\hat{f}_{D_l}'' = \operatorname{argmax}_{f_D} \{ |z(\hat{\tau}_l'', \hat{\phi}_l'', f_D; \hat{p}_l(i, j, k; \hat{\Theta}')| \} \n\hat{\alpha}_l'' = \frac{z(\hat{\tau}_l'', \hat{\phi}_l'', \hat{f}_{D_l}''; \hat{p}_l(i, j, k; \hat{\Theta}')}{TFA} \nz(\tau, \phi, f_D; P_l) = \sum_{i, j, k} e^{2\pi \Delta f_j \tau_l} e^{2\pi f_c \Delta s_k \cdot \phi_l} e^{-2\pi f_{D_l} \Delta t_i} P_l(i, j, k)
$$

CSI Cleaning

• However, CSI contains not only channel response, but also various unknown phase noises:

$$
\widetilde{H}(i,j,k) = H(i,j,k)e^{2\pi(\Delta f_j \epsilon_{t_i} + \Delta t_i \epsilon_f)}
$$

• [SpotFi'15]: The linear regression calibration fails. – Weak reflection from human body.

Conjugate Multiplication

- Our Solution: Conjugate multiplication between each antenna and chosen reference antenna. $C(i, j, k) = \widetilde{H}(i, j, k) * \widetilde{H}^*(i, j, k_0)$
- By classifying multipath into static signals P_s ($f_p = 0$) and dynamic signals P_d ($f_p \neq 0$), we have:

$$
C(i,j,k) = \sum_{n_1,n_2 \in P_S} P_{n_1}(i,j,k) P_{n_2}^*(i,j,k_0)
$$

+
$$
\sum_{l \in P_d, n \in P_S} \frac{P_l(i,j,k) P_n^*(i,j,k_0) + P_n(i,j,k) P_l^*(i,j,k_0)}{\text{Target term}}
$$

+
$$
\sum_{l_1,l_2 \in P_d} P_{l_1}(i,j,k) P_{l_2}^*(i,j,k_0)
$$

• Phase structure is preserved: $P_l(i, j, k) P_n^*(i, j, k_0) = \alpha_l \alpha_n^* e^{-2\pi \Delta f_j(\tau_l - \tau_n) - 2\pi f_c \Delta s_k \cdot \phi_l + 2\pi f_{D_l} \Delta t_i}$

Path Matching

• Multipath parameters are cluttered together.

Example of parameter estimates.

• Our approach: Graph-based Path Matching (GPM).

Range Refinement

- Range estimation with ToF or DFS
	- ToF \rightarrow coarse estimate of absolute range.
	- DFS \rightarrow fine estimate of change rate of range (WiDar).
- We adopt Kalman smoother to refine range with both ToF and DFS.

Experiment

- Implementation
	- Thinkpad laptops with Intel 5300 NIC.
- Setup
	- 3 scenarios: classroom, corridor, office.

• Tracking samples

Overall Performance

Overall Localization Accuracy Performance Comparison

- Widar2.0 achieves median tracking errors of 0.75 m and 0.63 m, with one and two links respectively.
- Widar2.0 outperforms [Dynamic-Music'16] , and has a shorter error tail than [IndoTrack'17].

Impact of Sampling Rate

- Widar2.0 works even with 250 pkts/sec.
	- The minimum rate is 200 pkts/sec, for uniqueness of DFS.
- Corresponding per second processing time is 0.7 s.
	- Real-time tracking with Widar2.0.

Conclusion

- From Widar1.0 to Widar2.0
	- From 2 links to 1 single link.
	- A unified model of ToF, AoA and DFS.
	- CSI calibration for weak reflection path.
	- Robust parameter matching and refinement for localization.

- Decimeter-level passive tracking system.
	- Median location error of 75cm with one single link.
	- In a larger 6 m x 5 m area.

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Overall Performance

- Contribution of individual modules
	- Path matching 0.09 m
	- Range refinement 0.13 m

Impact of Walking Diversity

- Tracking error reduces with more links and larger incident angles between link and walking direction.
- Widar2.0 avoids accumulation error with estimation of absolute ToF.

Impact of Context Diversity

- Tracking error slightly increases with tracking area.
	- Weaker reflection.
	- Smaller DFS.
- Consistent accuracy is achieved with multiple testers.