

Wi-Fi CSI-Based Relative AoA Trajectory Estimation for Non-Wearable Walking Observation

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Abstract—Home-based walking observation can provide useful information for assessing mobility and motor-function changes, but continuous monitoring with wearable sensors or cameras may be limited by user compliance, privacy concerns, and environmental constraints. Wi-Fi channel state information (CSI) offers a device-free alternative by capturing human-motion-induced variations in wireless multipath propagation. This paper proposes a CSI-based angle-of-arrival (AoA) trajectory estimation framework for non-wearable walking observation using a single transmitter and a three-antenna receiver. The method applies antenna-pair phase conjugate multiplication, covariance-domain static-path suppression with automatic β selection, and sliding-window MUSIC estimation to recover the relative angular trajectory of a walking subject. Experiments performed with an Intel 5300 network interface card at 5.32 GHz showed that the proposed framework captured walking-induced angular variation with an average relative angular-change error of 11.57% and an average absolute angular-change error of 5.14° across five walking trials. These results suggest that static-path-suppressed AoA estimation can provide a low-complexity and physically interpretable representation of walking motion, supporting its potential use as a building block for future non-wearable gait observation in home-based or clinical monitoring scenarios.

Index Terms—Wi-Fi sensing, channel state information, angle of arrival, MUSIC, static path suppression, walking observation, gait monitoring.

I. INTRODUCTION

Gait is widely regarded as an important clinical indicator for evaluating human mobility and neurological motor function, especially in patients with Parkinson's disease (PD). Since PD is commonly associated with motor symptoms such as bradykinesia, postural instability, abnormal gait, freezing of gait, and reduced walking stability, quantitative gait assessment can provide useful information for observing disease progression, fall risk, and rehabilitation outcomes [1]. In conventional clinical practice, gait performance is often evaluated through physician observation, standardized clinical scales, wearable inertial sensors, pressure mats, motion-capture systems, or camera-based analysis [2]. These methods can measure gait-related parameters such as walking speed, stride length, cadence, symmetry, and body trajectory. However, clinic-based assessment only provides short-term observations under controlled conditions and may not fully reflect daily motor fluctuations. Wearable sensors may interfere with natural

movement or reduce user compliance during long-term monitoring, while camera-based systems are affected by privacy concerns, lighting conditions, occlusion, and field-of-view limitations. Therefore, a non-wearable and privacy-preserving sensing method capable of observing walking motion in daily environments is needed [3].

Wi-Fi CSI-based sensing provides a promising solution for non-wearable motion monitoring because human movement changes the multipath propagation of wireless signals. In addition to conventional temporal gait parameters, spatial information is also important for interpreting walking behavior, such as whether the subject is approaching, crossing, deviating from, or moving away from a sensing region. Angle-of-arrival (AoA) estimation can provide such information by estimating the incident angle of signal paths arriving at a receiver antenna array. Existing Wi-Fi sensing studies have investigated AoA-related spatial sensing mainly for localization and tracking purposes; for example, SpotFi [4] jointly estimates AoA and time-of-flight (ToF) for device-based localization, while mD-Track fuses AoA, ToF, and Doppler information with path separation algorithms to achieve high-resolution passive localization in real time [5]. Unlike localization-oriented Wi-Fi sensing studies, this work focuses on estimating the relative angular variation of a walking subject rather than performing absolute two-dimensional localization. The motivation is that relative AoA trajectories can provide a physically interpretable spatial descriptor of walking motion, such as approaching, departing, or changing position with respect to the sensing region. Under predefined geometric conditions, this angular variation may be further related to distance- and velocity-related deviations, providing a preliminary basis for future gait-related quantitative assessment.

The main contribution of this study is a low-complexity Wi-Fi CSI-based framework for estimating walking-induced relative AoA trajectories using a single transmitter and a three-antenna receiver. The proposed method combines antenna-pair phase conjugate multiplication, covariance-domain static-path suppression, automatic β selection, and sliding-window MUSIC estimation to enhance human-reflected dynamic paths and recover the macroscopic angular trend of walking motion. Experimental validation using video-derived reference AoA trajectories demonstrates the preliminary feasibility of the

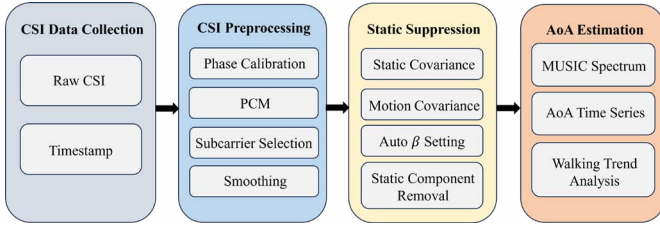


Fig. 1: Overall processing flow of the proposed Wi-Fi CSI-based AoA trajectory estimation framework.

proposed framework under a controlled 1×3 commodity Wi-Fi configuration.

II. METHODS

The proposed method estimates the walking-induced AoA trajectory from Wi-Fi CSI using a single transmitter and a three-antenna receiver. The overall processing flow consists of CSI preprocessing, covariance-domain static path suppression, MUSIC-based AoA estimation, and trajectory-level error evaluation, as shown in Fig. 1.

Before AoA estimation, the raw CSI was preprocessed to obtain stable antenna-domain observations. The preprocessing stage included linear phase slope removal, antenna-pair phase conjugate multiplication (PCM), subcarrier selection, and light phase smoothing. Linear phase slope removal was used to reduce packet-level phase distortion, whereas PCM constructed relative antenna phases that are more consistent with the three-antenna MUSIC steering vector. Unstable subcarriers were excluded to reduce noise sensitivity, and the remaining CSI vectors were used for covariance construction, static-path suppression, and sliding-window MUSIC-based AoA trajectory estimation.

A. Static Path Suppression and Automatic Beta Selection

After CSI preprocessing, the antenna-domain observation was represented using the PCM-based relative phase structure. For each selected subcarrier k , the observation vector was defined as

$$\mathbf{x}_k(t) = [1, r_{21}(k, t), r_{31}(k, t)]^T, \quad (1)$$

where

$$r_{21}(k, t) = H_2(k, t)H_1^*(k, t), \quad r_{31}(k, t) = H_3(k, t)H_1^*(k, t). \quad (2)$$

Here, the first received antenna was used as the phase reference. Therefore, the phases of r_{21} and r_{31} correspond to the relative phase differences between the second/third receive antennas and the first receive antenna. This representation is consistent with the relative phase structure assumed in the three-antenna MUSIC steering vector.

For each sliding time window T_m , the motion covariance matrix was constructed by aggregating the snapshots from all selected subcarriers:

$$\mathbf{R}_{\text{motion}} = \frac{1}{N_m} \sum_{k \in \mathcal{S}} \sum_{t \in T_m} \mathbf{x}_k(t) \mathbf{x}_k^H(t), \quad (3)$$

where $\mathcal{S}$ denotes the selected subcarrier set and N_m is the total number of snapshots used in the motion window. Similarly, the static covariance matrix was calculated from a reference interval without human motion:

$$\mathbf{R}_{\text{static}} = \frac{1}{N_s} \sum_{k \in \mathcal{S}} \sum_{t \in T_s} \mathbf{x}_k(t) \mathbf{x}_k^H(t), \quad (4)$$

where T_s is the static reference interval and N_s is the total number of static snapshots.

Since the walking-induced reflection path is usually weaker than the LoS and static multipath components, direct AoA estimation may be dominated by static paths. To enhance the dynamic reflection component, the covariance matrix used for MUSIC was obtained by

$$\mathbf{R}_{\text{dyn}}(t) = \mathbf{R}_{\text{motion}}(t) - \beta(t) \mathbf{R}_{\text{static}}, \quad (5)$$

where $\beta(t)$ is the time-varying static-path suppression coefficient. A small $\beta(t)$ may leave excessive static-path energy, whereas an overly large value may attenuate useful walking-induced reflection components.

In this study, $\beta(t)$ was automatically calculated for each sliding window according to the residual energy projected onto the dominant static subspace. Let $\mathbf{u}_s$ denote the principal eigenvector of $\mathbf{R}_{\text{static}}$. The suppression coefficient was calculated as

$$\beta(t) = \frac{\mathbf{u}_s^H \mathbf{R}_{\text{motion}}(t) \mathbf{u}_s}{\mathbf{u}_s^H \mathbf{R}_{\text{static}} \mathbf{u}_s}, \quad (6)$$

where $(\cdot)^H$ denotes the Hermitian transpose. The numerator represents the energy of the current motion window projected onto the dominant static subspace, whereas the denominator represents the corresponding energy of the static reference. Therefore, $\beta(t)$ estimates the residual static-path contribution in each motion window relative to the static reference.

To prevent excessive subtraction caused by walking-induced energy projected onto the static subspace, the calculated coefficient was constrained to

$$\beta(t) \leftarrow \min \{2, \max [0, \beta(t)]\}. \quad (7)$$

The coefficient was independently calculated for each 0.3-s sliding window and updated every 0.05 s. This procedure relied only on the CSI covariance matrices and did not use the video-derived reference trajectory for parameter selection.

B. Sliding-Window MUSIC Estimation

The MUSIC algorithm [6] was applied to $\mathbf{R}_{\text{dyn}}$ in a sliding-window manner to estimate the time-varying AoA trajectory. The window length and step size were set to 0.3 s and 0.05 s, respectively. The AoA search range was set from -90° to 90° with a 1° angular resolution, and the signal rank was set to one.

For the three-antenna uniform linear array used in this study, the steering vector was defined as

$$\mathbf{a}(\theta) = \left[1, e^{-j \frac{2\pi}{\lambda} d \sin \theta}, e^{-j \frac{2\pi}{\lambda} 2d \sin \theta} \right]^T, \quad (8)$$

where λ is the wavelength, d is the antenna spacing, and θ is the candidate AoA. The eigendecomposition of $\mathbf{R}_{\text{dyn}}$ is given by

$$\mathbf{R}_{\text{dyn}} = \mathbf{E}\mathbf{\Lambda}\mathbf{E}^H. \quad (9)$$

The eigenvectors corresponding to the noise subspace were denoted as $\mathbf{E}_n$. The MUSIC pseudo-spectrum was computed as

$$P_{\text{MUSIC}}(\theta, t) = \frac{1}{\mathbf{a}^H(\theta)\mathbf{E}_n\mathbf{E}_n^H\mathbf{a}(\theta)}. \quad (10)$$

For each sliding window, the AoA estimate was obtained directly from the global maximum of the MUSIC pseudo-spectrum:

$$\hat{\theta}(t) = \arg \max_{\theta} P_{\text{MUSIC}}(\theta, t). \quad (11)$$

The resulting sequence was interpreted as the relative angular trajectory of the walking subject with respect to the receiver, rather than as an absolute two-dimensional localization result. Owing to the limited three-antenna configuration and residual multipath components, occasional peak jumps may occur when the dominant spectral peak switches between propagation paths.

III. EXPERIMENTAL SETUP

The experimental setup is shown in Fig. 2. The system consisted of one Wi-Fi transmitter and one receiver equipped with three antennas, forming a 1×3 Tx-Rx configuration. CSI data were collected using an Intel Wi-Fi Link 5300 network interface card at a carrier frequency of 5.32 GHz. The three reception antennas were arranged as a uniform linear array with an antenna spacing of 2.8 cm. The transmitter and receiver were placed 2 m apart under line-of-sight (LoS) conditions, and the Tx-Rx line was defined as the LoS reference axis.

The subject walked along the perpendicular bisector of the Tx-Rx LoS. Each trial consisted of walking from the starting point S to the return point R and then back to S along the same path. Point S was 2.8 m away from the LoS, and point R was 0.4 m away from the LoS, resulting in a one-way walking distance of 2.4 m. This back-and-forth walking task was used to evaluate whether the proposed method could recover the corresponding relative AoA variation.

The reference AoA was derived from the experimental geometry and video-based position annotation [7]. The receiver was treated as the reference point, and the subject position was annotated from the recorded video. The annotated position was first converted into the relative displacement with respect to the receiver, and the corresponding reference angle was then calculated based on the geometric relationship between the receiver and the subject position. Therefore, the video-derived angular trajectory was used as the reference trajectory for evaluating the estimated AoA sequence.

The evaluation focused on the accuracy of relative angular variation rather than absolute two-dimensional localization. Let $\theta_{\text{CSI}}(t)$ and $\theta_{\text{ref}}(t)$ denote the CSI-estimated AoA and the video-derived reference AoA at time window t , respectively. The pointwise absolute angular error was calculated as

$$e(t) = |\theta_{\text{CSI}}(t) - \theta_{\text{ref}}(t)|. \quad (12)$$

The mean absolute error (MAE), median absolute error (MedAE), and standard deviation (SD) of $e(t)$ were used to quantify the pointwise agreement and robustness of the estimated AoA trajectory.

In addition to the pointwise trajectory error, the angular-change error was calculated to evaluate whether the proposed method could recover the overall AoA variation during walking. The angular-change error was defined as

$$E_{\Delta\theta} = \left| \left(\max_t \theta_{\text{CSI}}(t) - \min_t \theta_{\text{CSI}}(t) \right) - \left(\max_t \theta_{\text{ref}}(t) - \min_t \theta_{\text{ref}}(t) \right) \right|. \quad (13)$$

The relative angular-change error was then obtained by normalizing $E_{\Delta\theta}$ by the reference angular range:

$$E_{\text{rel}} = \frac{E_{\Delta\theta}}{\max_t \theta_{\text{ref}}(t) - \min_t \theta_{\text{ref}}(t)} \times 100\%. \quad (14)$$

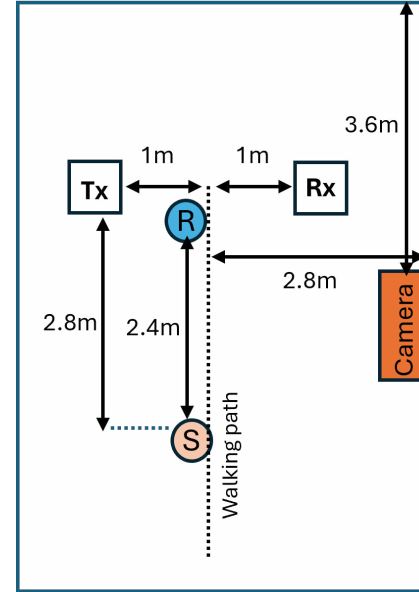


Fig. 2: Experimental setup for walking-induced AoA estimation. The subject walked along the perpendicular bisector of the Tx-Rx LoS from S to R and then returned to S . The one-way walking distance was 2.4 m.

IV. RESULTS

The proposed static-path-suppressed MUSIC framework was evaluated using five walking trials. Each trial consisted of a back-and-forth walking motion from the starting point S to the return point R and then back to S . The evaluation focused on whether the estimated AoA trajectory could recover the relative angular variation caused by walking. Therefore, the relative angular-change error, absolute angular-change error, and trajectory-level angular errors were reported as the main evaluation metrics.

Fig. 3 compares the MUSIC AoA results obtained without and with static-path suppression. As shown in Fig. 3(a), when

no suppression was applied, i.e., $\beta(t) = 0$, the dominant MUSIC peak remained close to the LoS direction throughout the walking interval. The estimated trajectory therefore failed to capture the angular variation indicated by the video-derived reference. This result shows that direct MUSIC estimation was dominated by the strong LoS and static multipath components.

After applying the automatic window-wise $\beta(t)$ selection, as shown in Fig. 3(b), the LoS-dominated component was suppressed and the walking-induced dynamic AoA trajectory became observable. The estimated trajectory generally followed the back-and-forth angular trend of the video-derived reference, although local deviations remained because of residual static multipath, weak human-reflected components, and occasional MUSIC peak switching. These results demonstrate that static-path suppression is essential for recovering the walking-induced relative AoA variation under the tested configuration.

Table I summarizes the AoA trajectory estimation performance across the five walking trials. The relative angular-change error ranged from 7.95% to 13.60%, with an average of 11.57%. The corresponding absolute angular-change error ranged from 3.84° to 6.00°, with an average of 5.14°. These results indicate that the proposed framework could recover the overall walking-induced AoA variation with reasonable consistency under the tested geometry.

TABLE I: AoA trajectory estimation performance across five walking trials. Rel. Err. denotes the angular-change error normalized by the video-derived reference angular range. MAE, MedAE, and SD denote the mean, median, and standard deviation of the pointwise absolute angular error, respectively. Angular-change error denotes the absolute difference between the CSI-estimated and reference angular ranges.

Trial	Rel. Err. (%)	MAE (deg)	MedAE (deg)	SD (deg)	Angular-change error (deg)
1	13.60	7.64	6.77	6.26	6.00
2	12.30	10.40	6.12	8.40	5.40
3	7.95	8.94	5.30	8.85	3.84
4	12.60	11.80	7.99	13.47	5.49
5	11.40	12.95	6.10	22.25	4.99
Mean	11.57	10.35	6.46	11.85	5.14

In addition to the angular-change error, trajectory-level MAE, MedAE, and SD were used to evaluate the pointwise agreement between the estimated AoA curve and the reference angular trajectory. The average MAE and MedAE were 10.35° and 6.46°, respectively. MedAE was included because occasional MUSIC peak jumps may affect the mean error, whereas the median error better reflects the typical deviation of the estimated trajectory. Overall, the results suggest that the proposed framework can recover the relative AoA variation of walking motion under the tested 1×3 Wi-Fi CSI configuration.

Therefore, the proposed method is better interpreted as an estimator of macroscopic relative angular trends rather than as a precise frame-by-frame localization method.

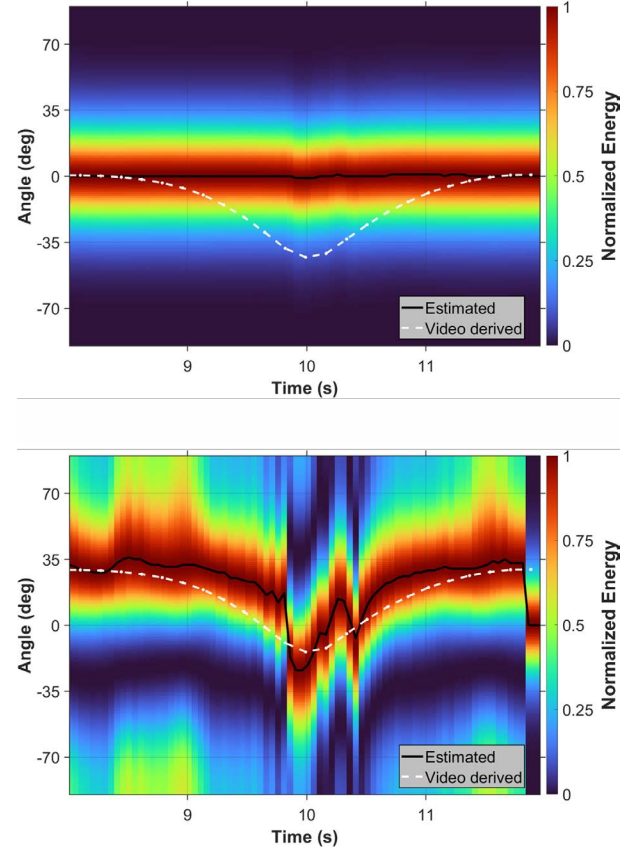


Fig. 3: Ablation comparison of the MUSIC AoA results: (a) without static-path suppression, where $\beta(t) = 0$ and the estimated AoA remains dominated by the LoS component; and (b) with the proposed automatic window-wise $\beta(t)$ selection, where the walking-induced relative AoA trajectory becomes observable. The black solid and white dashed curves represent the CSI-estimated and video-derived reference AoA trajectories, respectively.

V. DISCUSSION

The proposed framework was able to observe the overall AoA variation caused by human walking under the tested geometry. In this study, the subject walked from the far point toward the near turning region, and the estimated CSI-AoA trajectory showed a similar changing trend to the video-derived reference AoA. For absolute angular-change errors of approximately 4–6°, the corresponding distance error near the turning region was approximately 10–20 cm. If the 2.4-m walking path is completed in approximately 2 s, this distance error corresponds to an average walking-speed error of approximately 0.05–0.10 m/s. Therefore, under the tested geometry, the current framework is more appropriate for observing overall walking trends and relative changes in walking motion than for precise position tracking or direct gait-speed measurement.

One limitation of the present method is that the distance and speed interpretation depends on the walking range and the

received AoA energy distribution. From a signal-propagation viewpoint, if the starting point is placed farther away, the human-reflected component may become weaker, and the AoA estimate may be more easily affected by background multipath or noise. Therefore, future experiments should evaluate different walking ranges while jointly examining the stability of the human-reflected AoA energy. The currently tested range should not yet be interpreted as a generally recommended operating range.

The automatic window-wise selection of $\beta(t)$ improves the practicality of the proposed framework by reducing the need for manual tuning. An insufficient coefficient may leave excessive static-path energy, whereas an overly large value may attenuate useful walking-induced reflection components. By determining $\beta(t)$ from the residual energy projected onto the dominant static subspace in each sliding window, the proposed method adapts the suppression strength to the current CSI covariance structure without using the video-derived reference trajectory.

Although the proposed framework showed preliminary feasibility, the present validation was limited to five walking trials under a single controlled Tx–Rx geometry and walking direction. Therefore, the reported results should be interpreted as a proof of concept under the tested configuration rather than as general performance estimates across subjects, environments, and walking patterns. Additional experiments involving more participants, repeated sessions, different walking directions and ranges, alternative Tx–Rx geometries, and more complex indoor environments are required to evaluate the robustness and generalizability of the proposed method.

VI. CONCLUSION

This study presented a Wi-Fi CSI-based AoA trajectory estimation framework for non-wearable walking observation. By combining antenna-pair phase conjugate multiplication, covariance-domain static-path suppression with automatic window-wise $\beta(t)$ selection, and sliding-window MUSIC estimation, the proposed method extracted walking-induced relative AoA variation using a low-complexity 1×3 commodity Wi-Fi configuration. Across five back-and-forth walking trials, the framework achieved an average relative angular-change error of 11.57% and an average absolute angular-change error of 5.14° , indicating preliminary feasibility for capturing macroscopic walking trends under the tested geometry.

These findings should be interpreted as a small-scale proof of concept because the current validation was limited to five trials under a single controlled Tx–Rx geometry and walking direction, rather than as general performance estimates across subjects, environments, or walking patterns. Future work should evaluate the method across different walking ranges, orientations, participants, Tx–Rx geometries, and indoor environments. Integrating complementary features such as Doppler shift and time of flight (ToF) may further improve robustness and support future non-wearable gait observation in home-based or clinical monitoring scenarios.

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