

Quantifiable Walking Detection Using Wi-Fi CSI for Home-Based Gait Monitoring

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Abstract—Home-based gait monitoring is important for assessing motor symptoms, but reliable gait quantification requires the exclusion of transitional and non-gait movements. This requirement is challenging in daily-living environments, where walking episodes are often short, fragmented, and mixed with activities such as sitting, standing, turning, bending, and object pickup. In this paper, we present a Wi-Fi Channel State Information (CSI)-based framework for detecting quantifiable walking segments suitable for gait speed estimation. The proposed method adopts CSI ratio phase and amplitude features with a lightweight few-shot CNN, and performs binary segmentation between quantifiable walking movement (QM) and non-quantifiable movement (NQM) using a sliding-window strategy and duration-based filtering. Experiments were conducted with synchronized Wi-Fi CSI and video data from one healthy subject under four walking orientations relative to the transmitter-receiver line-of-sight: 90°, 75°, 60°, and 45°. For each orientation, six trials were recorded and video annotations were used as ground truth. The proposed framework achieved QM F1-scores above 87% at 90°, 75°, and 60°, with gait-speed estimation errors close to video-annotated baselines. Performance degraded at 45°, indicating an angular limitation of CSI-based sensing. These results demonstrate the feasibility of the proposed approach for preliminary feasibility personalized home-based gait monitoring within a suitable angular range.

Index Terms—Wi-Fi sensing, channel state information, few-shot learning, human activity recognition, convolutional neural networks, gait analysis, digital health.

I. INTRODUCTION

Gait is an important indicator of an individual's health, as it reflects the integrated function of the neuromuscular, musculoskeletal, and sensory systems that govern mobility and postural control. At-home gait monitoring provides a means to capture walking characteristics continuously and objectively in real-world environments, thereby overcoming the temporal and contextual limitations of conventional clinic-based assessments. Longitudinal monitoring of gait parameters, such as walking speed, stride variability, symmetry, and stability, may facilitate early detection of functional decline, elevated fall risk, and disease progression, while providing clinically meaningful evidence to guide personalized rehabilitation strategies and timely intervention.

Conventional gait assessment mainly relies on periodic clinical visits and physician observation, which provide only sparse snapshots of disease status and cannot capture daily

motor fluctuations. This limitation has motivated unobtrusive sensing approaches for continuous residential monitoring. Among them, Wi-Fi Channel State Information (CSI) has attracted increasing attention because it can capture fine-grained motion-induced amplitude and phase variations using commodity wireless devices, without requiring wearable sensors or cameras.

Recent CSI-based gait studies have shown that Wi-Fi signals can be used to recognize human activities [5] and estimate gait-related parameters [6] without requiring wearable sensors or cameras. Existing works have achieved promising performance in controlled walking scenarios, where subjects usually walk along predefined trajectories and the walking direction is often arranged perpendicular to the transmitter-receiver line-of-sight (LoS). However, current CSI-based methods remain sensitive to walking orientation, since different movement directions introduce different channel variations and may lead to degraded sensing accuracy. More importantly, recognizing a segment as gait does not guarantee that the segment is suitable for quantitative gait analysis. For example, short walking fragments, turning motions, bending, or walking toward non-straight directions may still contain gait-like signal patterns, but their gait parameters cannot be reliably estimated. In realistic home environments, residents walk along different orientations and frequently perform transitional or non-gait activities, such as sitting, standing, turning, bending, or opening a refrigerator. If these unstable NQM segments are incorrectly treated as valid walking periods, they may distort gait speed estimation and reduce the reliability of long-term home-based gait monitoring.

Therefore, this study focuses on identifying QM segments, defined as stable straight-line walking periods suitable for reliable gait speed estimation, while excluding NQM such as unsuitable walking portions, transitional movements, and daily activities. To this end, we propose a CSI-based binary segmentation framework for home-based PD gait monitoring. The system adopts the preprocessing pipeline and lightweight few-shot CNN architecture from our prior work. A short-duration filtering rule is further introduced to suppress spurious detections and enforce the requirement of sustained walking.

II. METHOD

A. CSI Signal Processing Pipeline

The CSI signal processing pipeline follows our prior work. After selecting the antenna pair with the strongest cumulative RSSI, the two corresponding CSI streams are combined using CSI ratio computation [1]. Since antennas on the same network interface card share a common RF oscillator, taking the ratio between two CSI streams suppresses common phase distortions caused by carrier frequency offset (CFO) and sampling frequency offset (SFO), while preserving motion-induced variations. The CSI ratio is expressed as

$$\mathbf{H}_r(f, t) = \frac{\mathbf{H}_{s1}(f, t) + \mathbf{H}_{d1}(f, t)}{\mathbf{H}_{s2}(f, t) + \mathbf{H}_{d2}(f, t)} = \frac{AZ + B}{CZ + D}, \quad (1)$$

where $\mathbf{H}_s$ and $\mathbf{H}_d$ denote static and dynamic reflection components, respectively. Since A , B , C , and D can be regarded as constants over short intervals, variations in $\mathbf{H}_r(f, t)$ mainly reflect human-motion-induced changes in the dynamic path. Ratio phase (RP) and ratio amplitude (RA) are then extracted as complementary feature signals.

The RP and RA signals are processed using a Hampel filter [2] with a window size of 25 and threshold of 3, followed by a third-order low-pass Butterworth filter [3] with a 50 Hz cutoff frequency. Min-max normalization is applied to each subcarrier within every one-second window, and Contrast-Limited Adaptive Histogram Equalization (CLAHE) [4] is used to enhance local motion-related patterns. The processed RP and RA maps are assigned to the R and G channels of a 30×30 RGB image, with the B channel zero-padded, forming the input of the downstream classifier.

B. Few-Shot CNN-Based Recognition

The recognition model employs a lightweight few-shot CNN, as illustrated from bottom to top in Fig. 1. The model receives a 30×30 dual-feature CSI image as input. Two parallel convolutional branches independently process the RP and RA channels, and each branch contains two convolutional blocks consisting of Conv2D, batch normalization, ReLU, spatial dropout, and max-pooling layers. The extracted feature maps are concatenated, further processed by an additional convolutional block, flattened, and projected into a 64-dimensional L2-normalized embedding space.

Classification is performed using a Prototypical Network. During user-specific calibration, a small labeled support set is used to compute class prototypes for QM and NQM by averaging the embeddings of each class. During inference, each query sample is assigned to the class with the nearest prototype based on Euclidean distance, enabling rapid adaptation with only a few labeled samples.

For continuous recognition, a 30×30 window corresponding to one second of CSI data slides along the temporal axis with a stride of 0.5 s. Each window is independently classified by the few-shot CNN. To suppress transient false detections, contiguous segments predicted as QM but shorter than 2.5 s are reassigned to the NQM class, ensuring that only sustained straight-line walking is retained for gait speed estimation.

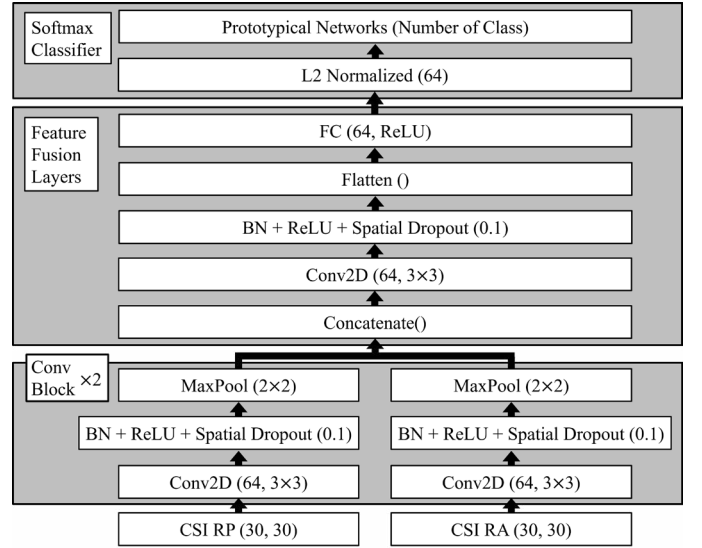


Fig. 1: Lightweight few-shot CNN architecture.

C. Ground-Truth Definition for Quantifiable Walking

To establish ground-truth labels for the binary segmentation task, a walking segment is regarded as QM, that is, suitable for reliable CSI-based gait speed estimation, only when it simultaneously satisfies a geometric condition and a gait-cycle condition. Segments that violate either condition are labeled as NQM, even when they appear visually as continuous forward walking. These two conditions are used solely as criteria for video-based ground-truth annotation, the few-shot CNN classifier does not explicitly use AR or step-cycle timing at inference.

1) *Geometric Condition — Fresnel-zone Applicable Region:* The Fresnel-zone Applicable Region (AR), adapted from the Doppler-based gait quantification model in our prior work, specifies the spatial region in which the Doppler frequency shift induced by walking can be reliably converted into gait speed under a given Tx–Rx geometry. Path-length contours with the Tx and Rx as foci form a family of confocal ellipses (Fresnel zones). The Doppler shift is maximal when the walking direction is aligned with the normal of these ellipses and approaches zero when it is tangential, which causes the inverse calibration mapping from Doppler shift to velocity to become singular and noise-sensitive.

Let the Tx–Rx midpoint be

$$(x_0, y_0) = \left(\frac{x_{Tx} + x_{Rx}}{2}, \frac{y_{Tx} + y_{Rx}}{2} \right). \quad (2)$$

For any point $P(x, y)$ inside the sensing area, the slope of the ellipse normal at P is

$$m_{\perp} = \frac{a^2(y - y_0)}{b^2(x - x_0)}, \quad (3)$$

where a and b are the semi-major and semi-minor axes of the corresponding Fresnel ellipse. Let θ denote the walking direction and, with slight abuse of notation, also denote the

angular direction associated with $m_{\perp}$. The AR is then defined as

$$\text{AR} = \{(x, y, \theta) : |\theta - m_{\perp}| \leq 45^{\circ} \text{ or } |\theta - m_{\perp}| \geq 135^{\circ}\}, \quad (4)$$

that is, the angular offset between the walking direction and the local ellipse normal lies within $\pm 45^{\circ}$ (modulo 180°). A trajectory portion is geometrically quantifiable only when its points satisfy (4); portions outside the AR are labeled NQM regardless of their gait regularity.

2) *Gait-Cycle Condition — Steady-State Walking*: The gait-cycle condition restricts the QM segment to the steady-state cruising portion of straight-line walking, during which stride length and cadence are approximately constant and the gait cycle exhibits a stable periodic rhythm. The first step initiated from a stationary posture corresponds to an acceleration phase in which stride and cadence have not yet stabilized, while the final step before stopping corresponds to a deceleration phase with shortened stride and prolonged double-support time. Both steps are therefore excluded from the QM segment.

Following this rule, the QM segment begins at the end of mid-stance of the second step and ends at the mid-swing (feet-adjacent) instant of the second-to-last step before stopping. All preceding and subsequent steps, together with transitional and non-gait activities, are labeled NQM.

Both conditions are enforced by frame-by-frame inspection of the synchronized video, and a segment is labeled as QM only when conditions 1) and 2) are jointly satisfied.

III. EXPERIMENTAL SETUP AND DATA COLLECTION

Wi-Fi CSI data were collected using commodity devices operating at 2.437 GHz with a 40 MHz bandwidth. The transmitter (Tx) sent packets at 400 Hz, while the receiver (Rx) sampled CSI at 450 Hz. Both Tx and Rx were equipped with three antennas and placed on the same side of the activity area with a 2.8 m separation. The antennas were mounted with their tips at a height of 90 cm above the floor. All subject motions were performed within a 5 m sensing region in front of the Tx–Rx pair.

Synchronized videos were recorded as ground truth for frame-level annotation, with QM and NQM labels assigned according to the criteria in Section II-C. Data were collected from one healthy adult subject under four walking-angle configurations.

To emulate daily-living motions in a home setting, a five-step activity protocol was designed and used throughout all trials. The activity list and binary labels are summarized in Table I. Three anchor positions were defined within the sensing region: S for sit-down/stand-up, F for refrigerator use, and P for object pickup.

Each trial consisted of the following sequence:

- 1) The subject sat down and stood up at the starting position S .
- 2) The subject walked forward with lateral steps toward the refrigerator location F .
- 3) The subject opened and closed the refrigerator at F .

TABLE I: Activity protocol and binary labels.

Activity	Label
Sit down & stand up	NQM
Forward walk with lateral steps	NQM
Refrigerator use	NQM
Stable straight-line walking	QM
Pick up an object	NQM

- 4) The subject walked 5 m back along the designated straight-line trajectory from F to P .
- 5) The subject bent down to pick up an object at P .

Among these steps, only Step (4) was considered the target QM segment, because it corresponds to stable straight-line walking suitable for gait speed estimation. Steps (1)–(3) and Step (5), together with the acceleration, deceleration, and turning phases around Step (4), were labeled as NQM.

To evaluate angular robustness, the same five-step protocol was repeated under four return-walking orientations relative to the Tx–Rx LoS: 90° , 75° , 60° , and 45° . The 90° configuration represents walking approximately perpendicular to the Tx–Rx LoS, whereas the 75° , 60° , and 45° configurations represent increasingly oblique return-walking trajectories. Each trajectory was labeled as QM or NQM according to its suitability for gait speed estimation, as illustrated in Fig. 2. These configurations were generated by adjusting the relative positions of F and P .

IV. RESULTS

Recognition performance is reported using frame-level confusion matrices and class-wise metrics. Downstream gait speed estimation is evaluated by feeding the recognized QM segments into the CSI-based gait speed estimation pipeline developed in our prior work [6]. The estimated gait speed is compared with the video-annotated baseline, while the reference gait speed is measured from synchronized video using Kinovea-based marker tracking.

A. Recognition Performance

The frame-level confusion matrices and class-wise precision, recall, and F1-score are summarized in Tables II and III. At 90° , 75° , and 60° , the proposed framework effectively distinguishes QM from NQM. The QM class achieves F1-scores of 94.51%, 87.67%, and 92.68%, respectively, while the NQM class remains above 99% in all three cases. These results indicate that the proposed framework can reliably isolate valid walking segments when the walking direction is perpendicular or moderately oblique to the Tx–Rx LoS.

In contrast, performance degrades at 45° , where the QM precision, recall, and F1-score decrease to 44.74%, 65.38%, and 53.12%, respectively. The NQM class still achieves an F1-score of 97.30%, suggesting that the main limitation lies in detecting QM under this highly oblique trajectory.

B. Gait-Speed Estimation Accuracy

Table IV reports the MAPE of gait speed computed from recognition-based and video-annotated QM segments. At 90° ,

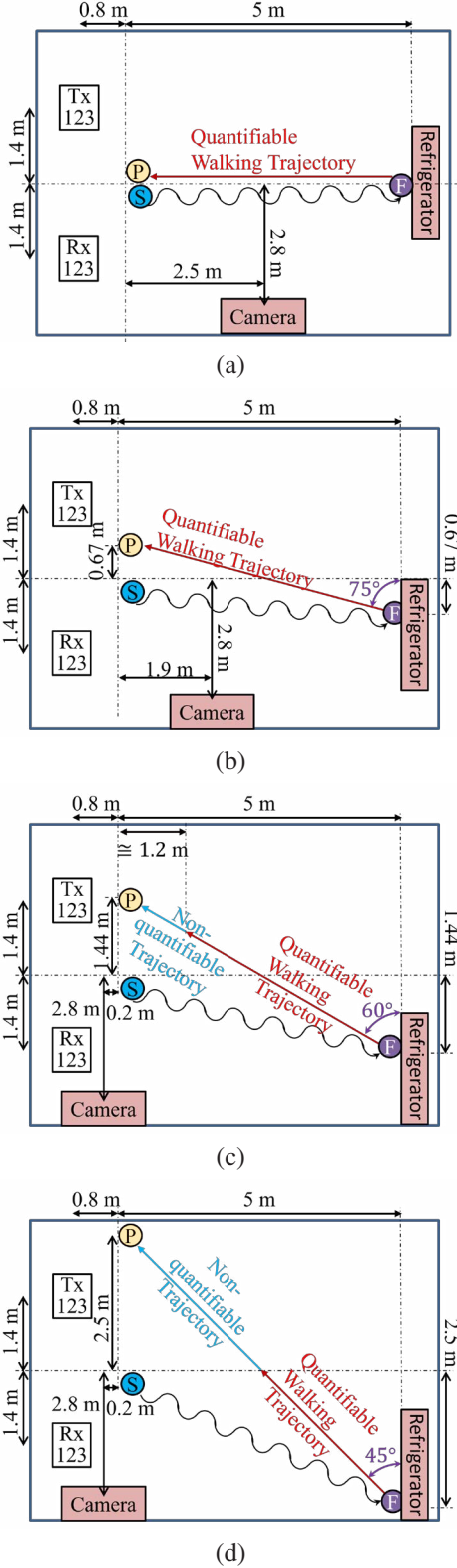


Fig. 2: Multi-angle experimental configurations under four walking orientations relative to the Tx–Rx LoS: (a) 90°, (b) 75°, (c) 60°, and (d) 45°. Red trajectories indicate QM, while blue trajectories indicate NQM.

TABLE II: Confusion matrices (in seconds) of the proposed framework under the four LoS angle configurations: (a) 90°, (b) 75°, (c) 60°, and (d) 45°. Rows correspond to the ground-truth (actual) class, and columns correspond to the predicted class.

	QM	NQM		QM	NQM
QM	21.5	0.5	QM	16.0	2.5
NQM	2.0	251.5	NQM	2.0	267.5
(a) 90°			(b) 75°		
	QM	NQM		QM	NQM
QM	19.0	1.0	QM	8.5	4.5
NQM	2.0	256.0	NQM	10.5	270.5
(c) 60°			(d) 45°		

TABLE III: Class-wise recognition performance (Precision, Recall, F1-Score, in %) of the proposed framework under the four LoS angle configurations: (a) 90°, (b) 75°, (c) 60°, and (d) 45°.

Class	Prec.	Rec.	F1	Class	Prec.	Rec.	F1
QM	91.49	97.73	94.51	QM	88.89	86.49	87.67
NQM	99.80	99.21	99.50	NQM	99.07	99.26	99.16
(a) 90°				(b) 75°			
Class	Prec.	Rec.	F1	Class	Prec.	Rec.	F1
QM	90.48	95.00	92.68	QM	44.74	65.38	53.12
NQM	99.61	99.22	99.41	NQM	98.36	96.26	97.30
(c) 60°				(d) 45°			

75°, and 60°, the mean MAPE values from recognition-based segments are 5.80%, 2.33%, and 4.37%, respectively, which are close to the video-annotated baselines of 5.46%, 3.19%, and 4.19%. The differences remain within approximately one percentage point, indicating that the detected walking segments are accurate enough to support downstream gait speed estimation.

The 45° configuration shows the largest error, with a mean MAPE of 14.27% for recognition-based segments and 14.10% for video-annotated segments. Since the video-annotated baseline also exhibits elevated error, the degradation is not solely caused by segmentation errors, but also reflects the intrinsic difficulty of CSI-based gait estimation under unfavorable walking geometry.

V. DISCUSSION

The multi-angle evaluation reveals a clear angular limitation at 45°. While the framework performs well at 90°, 75°, and 60°, the QM class F1-score drops to 53.12% at 45°. This degradation can be interpreted through the AR introduced in Section II-C: under the same Tx–Rx geometry, as the return trajectory becomes more oblique relative to the perpendicular

TABLE IV: Gait speed estimation error across the four LoS angle configurations, reported as mean $\pm$ standard deviation of the MAPE (%). “Rec.-based” denotes the segments produced by the proposed recognition framework; “Video-ann.” denotes the ground-truth segments obtained from synchronized video annotation.

Angle	Rec.-based (%)	Video-ann. (%)
90°	5.80 $\pm$ 3.21	5.46 $\pm$ 3.59
75°	2.33 $\pm$ 1.67	3.19 $\pm$ 1.80
60°	4.37 $\pm$ 2.53	4.19 $\pm$ 1.51
45°	14.27 $\pm$ 5.10	14.10 $\pm$ 8.96

direction, a larger portion of the path falls outside the AR and is therefore unsuitable for gait speed estimation.

This interpretation explains the different behaviors observed at 60° and 45°. In Fig. 2(c), only a short portion near the end of the 60° return path is labeled as NQM. This portion overlaps with the deceleration phase before stopping, whose transient motion pattern differs from steady-state walking and can therefore be classified as NQM by the few-shot CNN. In contrast, in Fig. 2(d), nearly half of the 45° return path is labeled as NQM while still exhibiting continuous forward walking. Since the current few-shot CNN does not explicitly use AR information, this walking-like but non-quantifiable portion is easily confused with QM.

The gait speed estimation results in Table IV further evaluate whether the QM segments detected by the proposed recognition framework are suitable for downstream gait quantification. Specifically, the recognition-based MAPE was computed by feeding the detected QM segments into the CSI-based gait speed estimation pipeline and comparing the estimated speed with the video-annotated baselines. At 90°, 75°, and 60°, the recognition-based MAPE values are 5.80%, 2.33%, and 4.37%, respectively, all remaining below 6% and close to the video-annotated baselines of 5.46%, 3.19%, and 4.19%. This indicates that, once the proposed framework identifies a segment as QM under appropriate walking geometries, the detected segment can be used for gait speed estimation with low relative error. In contrast, the recognition-based MAPE increases to 14.27% at 45°. Under this oblique configuration, the 45° trajectory inherently spans both AR-valid and AR-invalid regions, so that even video-annotated segments yield elevated error. Therefore, the degradation at 45° reflects both recognition difficulty and the intrinsic geometric limitation of CSI-based gait speed estimation.

From an application perspective, the proposed framework can serve as a lightweight front-end module for home-based gait monitoring. The system first performs real-time screening to extract QM segments from continuous daily-living CSI data, and only these detected segments are forwarded to the more computationally intensive gait speed estimation pipeline. This two-stage design avoids applying gait quantification to transitional or non-gait movements, thereby reducing unnecessary computation and improving the reliability of long-term gait

monitoring. Future work should incorporate geometric awareness, such as AR-based post-processing, to further exclude invalid trajectory portions before gait speed estimation. In addition, experiments should be extended to multiple subjects, real PD patients, and more diverse home environments to evaluate cross-subject and cross-environment robustness.

VI. CONCLUSION

This paper presented a CSI-based home activity recognition framework for identifying QM segments within daily-living motions for home-based PD gait monitoring. Specifically, QM detection was formulated as a binary segmentation task that distinguishes valid straight-line walking from NQM using synchronized video annotation. By adopting our prior CSI preprocessing pipeline and lightweight few-shot CNN, and extending it from discrete activity recognition to continuous walking-segment detection with an additional short-duration filtering rule, the proposed framework reduced false walking detections in daily-living scenarios. The framework was evaluated under realistic home activities, including sitting, standing, refrigerator access, object pickup, and return walking, at multiple orientations relative to the LoS (90°, 75°, 60°, and 45°). At 90°, 75°, and 60°, the framework achieved QM F1-scores above 87% and NQM F1-scores above 99%, with gait speed estimation errors close to video-annotated baselines. However, performance degraded at 45°, revealing an angular limitation caused by the geometric sensitivity of CSI sensing. These results support the preliminary feasibility of the proposed framework for personalized home-based PD gait monitoring within an appropriate angular range, while motivating future geometry-aware extensions and broader clinical validation.

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