Movement Direction Estimation for Smartwatches in Diverse Exercise via Inertial–GNSS Fusion

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Abstract

Smartwatches must reliably estimate a user's movement direction during walking, running, and cycling, yet urban GNSS signal degradation and variable wrist orientations complicate existing methods. This paper presents a dual-mode framework that adapts to the user's activity for robust movement direction tracking. In walking and running, Principal Component Analysis (PCA) isolates a relative inertial direction from periodic arm-swing accelerations, which is then fused with GNSS data via Covariance Intersection (CI) to maintain statistical consistency. During cycling, an Attitude and Heading Reference System (AHRS) yaw is calibrated by a yaw-to-direction offset learned from GNSS bearing whenever signals are strong, allowing accurate direction estimates to persist through tunnels and underpasses when signals weaken. Field trials with a Samsung Galaxy Watch 5 in dense urban settings demonstrate that the proposed fusion consistently reduces direction errors compared to single-sensor baselines, automatically favoring GNSS on steady segments and leaning on the inertial estimate or offset-corrected yaw when satellite coverage degrades.

Keywords

pedestrian dead reckoning, movement direction, smartwatch, sensor fusion

1. Introduction

Accurately estimating a smartwatch user's movement direction is essential for turn-by-turn navigation, route coaching, calorie tracking, and safety services. With annual shipments of wrist-worn wearables now exceeding 100 million units, the wrist has become the dominant sensor platform for personal navigation. Unlike smartphones, however, smartwatches are constantly re-oriented by natural arm motion or by attachment to bicycle handlebars, complicating the interpretation of their inertial data.

Outdoors, most commercial systems rely on the Global Navigation Satellite System (GNSS) for an absolute reference to north. Dense city blocks and tree-lined roadways distort satellite signals through multipath and attenuation, rotating the inferred direction by tens of degrees or eliminating it altogether during complete signal blockage [1, 2, 3]. Map-matching can mitigate some errors but requires highly detailed, lane-level maps that are rarely available for sidewalks and bike paths.

Wearables' onboard three-axis accelerometers and gyroscopes provide a complementary, infrastructure-free cue. During walking or running, periodic arm swings create an ellipsoidal acceleration cloud whose dominant axis aligns with the user's movement direction. Applying Principal Component Analysis (PCA) over several steps isolates this axis and delivers a direction estimate that is immune to satellite outages [4, 5]. Yet PCA yields only a relative orientation: it does not indicate whether the user is facing east or west, and its accuracy depends on gait symmetry, step cadence, and sensor noise. GNSS directions, in contrast, remain dependable on long, straight stretches when the carrier-to-noise ratio (C/N_0) is high but degrade sharply during turns or signal fades. Although extended Kalman filters are often used to fuse multiple sensor streams, their feedback loop can amplify errors if modeling assumptions are incomplete or uncertain [6].

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The challenge is even greater during cycling, because arm swings disappear, rendering PCA unusable, and the smartwatch's yaw (from an Attitude and Heading Reference System, AHRS) is often misaligned with the bicycle's true direction due to handlebar tilt or wrist posture. GNSS bearing can reveal the correct movement direction but only when signals are strong. Consequently, a hybrid solution must combine PCA-based inertial direction with GNSS direction for walking and running—without relying on feedback-based filters that can magnify errors—while also learning and applying a yaw-to-direction offset whenever GNSS quality is high during cycling, then propagating that offset through GNSS outages. This paper introduces a dual-mode framework that meets these requirements by employing Covariance Intersection (CI) for walking/running and offset-based yaw correction for cycling. When C/N_0 exceeds a preset threshold and the bicycle follows a roughly straight path, the framework computes and updates an offset between smartwatch yaw and GNSS bearing, holding the offset fixed when signals fade so the offset-corrected yaw continues to represent the movement direction under tunnels, underpasses, and dense foliage.

Field trials in an urban apartment complex (walking/running) and on city bike lanes (cycling) with a Samsung Galaxy Watch 5 demonstrate that the proposed fusion consistently reduces root-mean-square error relative to single-sensor baselines. The framework proves resilient to multipath, brief GNSS outages, and changes in device orientation. The remainder of this paper first surveys related movement-direction estimation techniques, then details the proposed algorithm, including the CI formulation and the cycling offset-learning strategy. A comprehensive experimental evaluation follows, after which limitations and future extensions are discussed.

2. Movement Direction Estimation from Individual Sensors

Before the fusion strategy is introduced in Section 3, this section details how each sensor independently estimates movement direction and the associated confidence (error covariance) under two exercise scenarios—(i) walking or running and (ii) cycling. Throughout, movement direction (MD) denotes the user's horizontal direction in the navigation frame.

2.1. Inertial-sensor method

When a smartwatch is worn on the wrist, arm swings produce a highly periodic acceleration pattern. Over a window of M steps, these samples form an ellipsoidal cloud whose long axis aligns with the true MD. A PCA isolates that axis as follows:

$$\hat{\theta}_{PCA} = \max_{\theta}\left(\sum_{i=1}^{M}(\boldsymbol{\beta}\cdot\boldsymbol{\alpha}_i^{\boldsymbol{n}})\right), \quad \text{where } \boldsymbol{\beta} = [\cos\theta, \sin\theta]^T \tag{1}$$

where $\boldsymbol{\alpha}_i^{\boldsymbol{n}}$ is the accumulated acceleration vector projected onto the navigation frame during the i-th step. Because PCA yields no intrinsic quality metric, we derive an angular error index

$$\sigma_{PCA} = \tan^{-1}\left(\frac{\lambda_2}{\lambda_1}\right) \tag{2}$$

with $\lambda_1 \geq \lambda_2$ the largest eigenvalues of the sample covariance matrix. A sharply elongated distribution ($\lambda_1 \gg \lambda_2$) implies high confidence (small σ_{PCA}); a more circular cloud indicates ambiguity [7].

During cycling, arm-swing excitation disappears, invalidating the PCA assumption. Instead, the smartwatch's AHRS provides a yaw angle ψ_{AHRS}, computed via a Kalman-filter–based quaternion fusion of gyroscope, accelerometer, and, when available, magnetometer data. Because handlebar tilt or wrist pronation can misalign yaw with the bicycle's MD, Section 3 describes how a GNSS-derived offset compensates this bias. Wearable-based kinematic analysis has been studied in various contexts, further underscoring the importance of correct orientation handling.

Table 1
Estimated Movement Direction Quality

Exercise	AHRS	PCA	RLS	Bearing
Walking/Running	Medium (w/ offset)	High	Medium	-
Cycling	Medium (w/ offset)	-	Medium	High

2.2. GNSS method

For GNSS-based movement-direction estimation, we run two independent Recursive-Least-Squares (RLS)—one for the east axis and one for the north axis—to track velocity and position [8]. For each axis $k \in \{e, n\}$ the 2-element state is $\mathbf{x}_\mathbf{i}^{(\mathbf{k})} = [v_{k,i}, p_{k,i}]^T$, and the RLS recursion is

$$\hat{\mathbf{x}}_i = \hat{\mathbf{x}}_{i-1} + K_i(\mathbf{y}_i - \varphi_i \hat{\mathbf{x}}_{i-1}), P_i = (I - K_i \varphi_i) P_{i-1}, K_i = \frac{P_{i-1}\varphi_i^T}{1 + \varphi_i P_{i-1} \varphi_i^T} \tag{3}$$

with the regressor $\varphi_i = [(i-1)\Delta t, 1]^T$.

After convergence the horizontal velocity vector $\mathbf{v} = [v_e, v_n]^T$ produces the heading

$$\hat{\theta}_{GNSS} = \tan^{-1}\left(\frac{\hat{v}_e}{\hat{v}_n}\right) \tag{4}$$

Its one-sigma uncertainty follows from first-order error propagation of the arctangent. Using the receiver-reported horizontal position accuracy σ_{HDOP} (assumed isotropic and uncorrelated between axes), the result is

$$\sigma_{GNSS}^2 = P_{i(1,1)} \frac{\sigma_{HDOP}^2}{2\,\|\mathbf{v}\|^2}, \|\mathbf{v}\| = \sqrt{v_e^2 + v_n^2} \tag{5}$$

Thus, a higher ground speed converts the same absolute velocity noise into a smaller angular uncertainty—capturing the essential behavior without the now-omitted closed-form covariance expressions.

Android and most commercial GNSS receivers report bearing only above a minimum speed, a condition naturally satisfied during bicycling. When C/N_0 exceeds a preset threshold, the receiver outputs a bearing $\theta_{bearing}$. This bearing directly serves as a GNSS MD estimate:

$$\hat{\theta}_{GNSS} = \theta_{bearing} \tag{6}$$

During temporary signal losses, no bearing is available; Section 3 explains how a previously learned yaw-to-bearing offset maintains continuity.

3. Proposed Sensor Fusion Framework

This section describes how the individual movement-direction (MD) estimates from Section 2—namely, PCA (inertial direction), AHRS (yaw), RLS (velocity-based direction), and direct GNSS Bearing—are integrated to produce a single, high-confidence direction in real time. Table 1 provides a compact overview of how each sensor's availability and accuracy change under walking/running versus cycling, illustrating that PCA is especially accurate for pedestrian motion and that AHRS plus an offset correction is more suitable when riding a bike.

Because arm-swing is present only in walking/running, PCA becomes invalid during cycling, while GNSS Bearing typically yields high accuracy at bicycle speeds. Consequently, two distinct fusion strategies are employed to accommodate these sensor differences.

3.1. Fusion for walking and running

For walking/running, the two main contributors are PCA (inertial direction) and GNSS direction. The smartwatch's AHRS yaw is typically less reliable in this context, because arm swing and wrist pronation frequently reorient the watch. We therefore fuse:

$$\hat{\theta}_1 = \hat{\theta}_{PCA}, P_1 = \sigma^2_{PCA}, \hat{\theta}_2 = \hat{\theta}_{GNSS}, P_2 = \sigma^2_{GNSS} \tag{7}$$

Although standard Kalman filtering requires known correlations, real-world conditions—especially in urban canyons—make such correlations uncertain. We adopt CI, which provides a statistically consistent way to fuse estimates without assuming specific correlation structures [9]. CI computes the fused variance and direction as:

$$P_{CI}^{-1} = \omega P_1^{-1} + (1-\omega)P_2^{-1}, \tag{8}$$

$$\hat{\theta}_{CI} = P_{CI}(\omega P_1^{-1}\hat{\theta}_1 + (1-\omega)P_2^{-1}\hat{\theta}_2) \tag{9}$$

where the mixing parameter $\omega \in [0, 1]$ is chosen to minimize the fused covariance. In one dimension, the determinant criterion reduces to

$$\omega* = \min_{\omega} |\omega P_1 + (1-\omega)P_2| \tag{10}$$

The mixing parameter ω automatically balances the contributions based on each sensor's instantaneous reliability. When GNSS provides stable direction estimates (high C/N_0, straight paths), ω approaches values that favor GNSS; when satellite signals degrade or multipath increases, ω shifts toward the PCA estimate. This adaptive weighting occurs without requiring explicit correlation modeling, making the fusion robust to model uncertainties that are particularly challenging to characterize in urban environments. By design, CI never yields an over-optimistic variance estimate. During long, straight segments, GNSS direction can provide a solid reference, while in the presence of turns or poor signals, PCA takes precedence and stabilizes the result.

3.2. Fusion for cycling

When cycling, arm swings disappear and PCA is no longer valid. The smartwatch's AHRS yaw is more stable on a handlebar, but it can still be offset from the true direction by handlebar tilt or wrist posture. Simultaneously, a GNSS-based bearing $\theta_{bearing}$ can be quite accurate if C/N_0 is sufficiently high. Our strategy is to learn an offset between AHRS yaw and the GNSS bearing under reliable conditions, and then maintain that offset during GNSS outages or degraded signals.

To estimate this offset, we gather AHRS yaw values $\psi_{AHRS}(k)$ and GNSS bearing $\theta_{bearing}(k)$ over n consecutive samples while the bicycle follows a roughly straight path. The time-averaged yaw and bearing are:

$$\bar{\theta}_{AHRS}(k) = \frac{1}{n}\sum_{i=0}^{n-1}\hat{\theta}_{AHRS}(k-i) \tag{11}$$

$$\bar{\theta}_{bearing}(k) = \frac{1}{n}\sum_{i=0}^{n-1}\theta_{bearing}(k-i) \tag{12}$$

yielding a yaw-to-direction offset:

$$\hat{\theta}_{offset} = \bar{\theta}_{AHRS} - \bar{\theta}_{bearing} \tag{13}$$

This offset remains valid as long as handlebar tilt does not change significantly. Hence, we only update θ_{offset} when we detect good satellite conditions ($C/N_0 > C/N_{0,min}$) and near-zero turn rate. During segments of poor signal or sharp turns, the last valid offset is retained. The final cycling direction becomes:

$$\hat{\theta}_{cycle}(k) = \hat{\theta}_{AHRS}(k) - \hat{\theta}_{offset}(k) \tag{14}$$

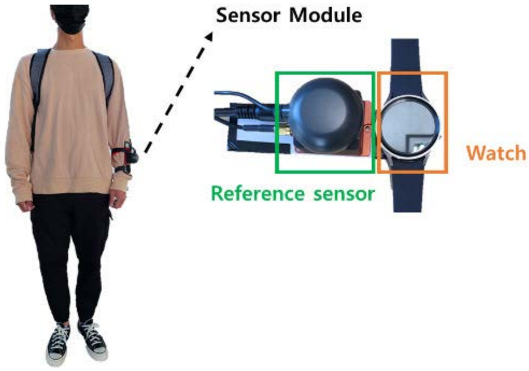

Figure 1: Experiment Equipment

Table 2
Experiment Site

Site	Exercise	Distance	GNSS conditions
Park	Walk	1.3[km]	Open sky; several sharp turns
Track	Run	1.2[km]	Open sky; steady speed
Riverside	Cycle	3[km]	Intermittent satellite outages under bridges

which continues to give an accurate direction even if GNSS drops out temporarily (e.g., under bridges or in tunnels).

With CI fusion for pedestrians and offset-compensated yaw for cyclists, this dual-mode framework provides a single, continuous MD estimate accompanied by a realistic covariance. It naturally exploits each sensor's strengths: PCA excels at capturing slow or periodic motions on wrist, GNSS enriches direction on straight segments or higher speeds, and AHRS plus offset keeps cyclists' direction accurate through signal drops. Section 4 details the experimental design and evaluates the system's performance across three distinct outdoor settings, highlighting the advantages of this hybrid approach over single-sensor baselines.

4. Experimental Evaluation

4.1. Setup

Experiments were carried out with a Samsung Galaxy Watch 5 worn on the participant's left wrist. For ground truth, an Xsens MTi-680G inertial/GNSS unit was rigidly co-mounted on an acrylic plate above the watch so that both instruments experienced identical attitude changes (see figure 1 for equipment). The MTi-680G ran in RTK mode, and its velocity vector was numerically differentiated to yield the reference MD. Table 2 lists the three outdoor venues, chosen to represent distinct satellite environments and motion dynamics. All experiments were conducted in outdoor environments to evaluate the proposed GNSS-inertial fusion under realistic satellite signal conditions, which represents the primary contribution of this work. For indoor scenarios where GNSS signals are unavailable, the framework automatically operates using only the PCA-based inertial direction estimation (Section 2.1), which remains effective regardless of satellite availability due to its reliance on consistent arm-swing patterns. The outdoor experimental design ensures comprehensive evaluation of the dual-sensor fusion capability while the PCA component alone provides robust indoor direction estimation as demonstrated in our previous work [7].

Table 3
Movement Direction Error (unit: [deg]

Site	Inertial sensor	GNSS	Fusion (proposed)
Park	9.28	19.27	10.03
Track	10.84	15.90	11.42
Riverside	8.96	10.71	6.98

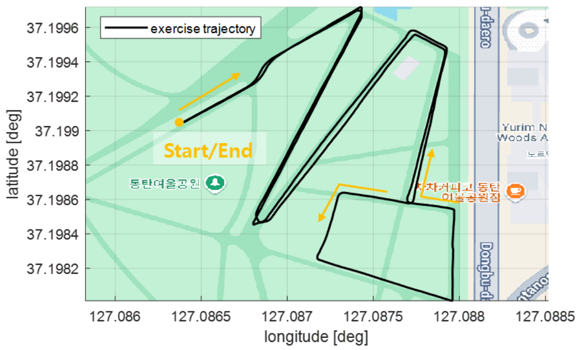

Figure 2: Exercise trajectory (walking)

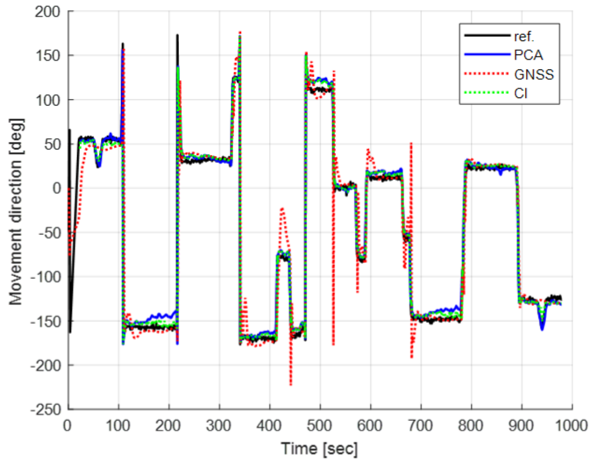

Figure 3: Estimated movement direction (walking)

4.2. Results

Throughout each trial, the fusion algorithm produced an MD estimate at the smartwatch's sampling rate. The instantaneous direction error (algorithm minus reference, unwrapped) was logged, and its root-mean-square error (RMSE) computed for each method. Table 3 provides a summary of the resulting direction RMSE for the inertial sensor only, GNSS only, and the proposed fusion approach.

1) Park (walking): With average HDOP < 3.9 and C/N_0>28 [dB-Hz], the user's path included several sharp turns (figures 2, 3). These turns degraded the GNSS-only direction, causing momentary spikes in error. The inertial PCA, however, remained stable and accurately tracked the overall direction. By blending GNSS and PCA, CI lowered error by 9 [deg] compared with GNSS alone and incurred only a small penalty relative to the inertial baseline. This demonstrates how CI adaptively trusts GNSS on straights but relies more on PCA during turns.

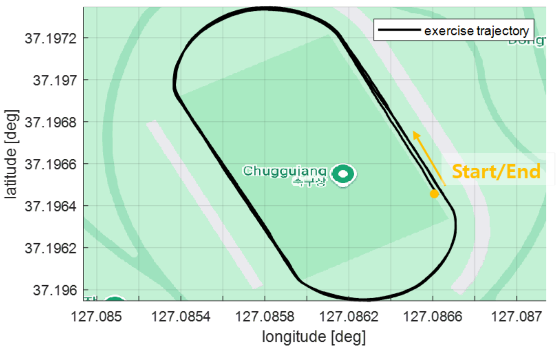

Figure 4: Exercise trajectory (running)

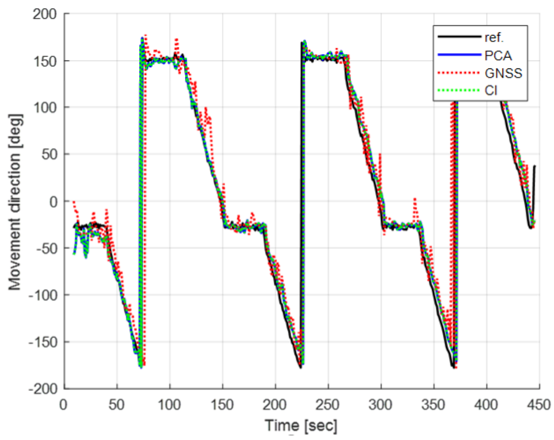

Figure 5: Estimated movement direction (running)

2) Track (running): In an open-sky stadium track (figures 4, 5), HDOP was below 3.8, and C/N_0 often exceeded 28.5 [dB-Hz]. Despite the relatively ideal conditions, GNSS position jitter introduced noticeable direction noise on the long straights. CI again outperformed GNSS-only and stayed within 0.6 deg of the PCA estimate. As before, this result shows how CI automatically down-weights GNSS data when it becomes noisy or inconsistent, preventing large fusion errors.

3) Riverside (cycling): In the 3 km cycling route (figures 6, 7), the participant passed under multiple bridges, causing intermittent satellite outages. Whenever C/N_0 was healthy, the algorithm updated the yaw-to-bearing offset; during outages, it relied on offset-compensated yaw. This significantly reduced direction error relative to uncompensated yaw and prevented large spikes when GNSS data were lost. The fusion method remained within 7 [deg] RMSE even through complete signal gaps, whereas yaw alone could drift by over 10 [deg]. Overall, this highlights the importance of periodic offset calibration in cycling contexts.

Across all exercises, the proposed fusion consistently delivered the lowest RMSE (see Table 3). CI leverages GNSS information when it is reliable (long straights, high C/N_0) yet defaults to PCA when satellites falter or the path turns sharply. During cycling, offset calibration was crucial for mitigating yaw drift and maintaining robust direction estimates. These findings validate the dual-mode framework of Sections 2 and 3, demonstrating robust smartwatch-based MD estimation under diverse urban conditions.

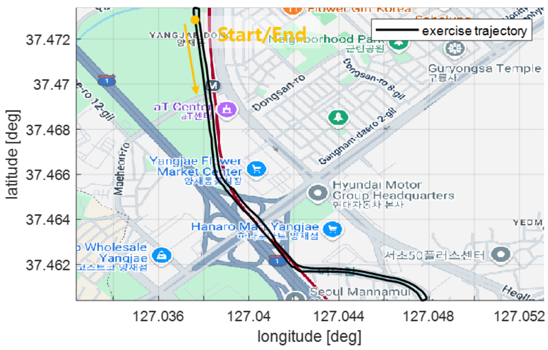

Figure 6: Exercise trajectory (cycling)

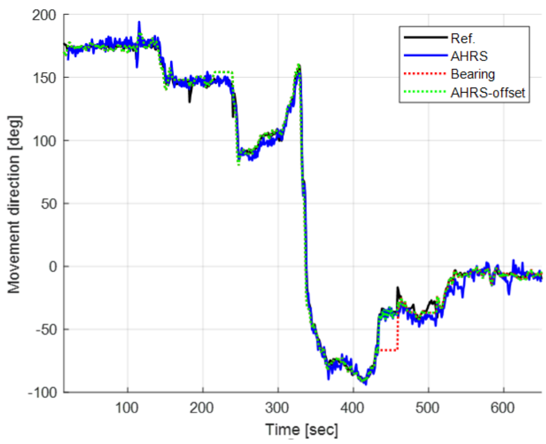

Figure 7: Estimated movement direction (cycling)

5. Conclusion

This paper presented a dual-mode framework for reliable smartwatch-based movement-direction tracking under walking, running, and cycling. For pedestrian motion, a PCA-based inertial direction and a GNSS-based direction are combined via Covariance Intersection to yield a statistically consistent estimate. For cycling, the framework periodically learns a yaw-to-bearing offset under favorable GNSS conditions, then applies the offset during GNSS outages.

Outdoor experiments revealed that this fusion consistently lowered RMSE compared to single-sensor baselines across three distinct scenarios, achieving average improvements of 47.9 % (walking), 28.2 % (running), and 34.8 % (cycling) relative to GNSS-only approaches. The proposed method maintained sub-12 [deg] RMSE across all test conditions while operating within a 1 [ms] computational budget per sample.

Future work will automate mode switching, address magnetometer bias for indoor usage, and examine long-term drift across multiple users and devices. By reducing direction errors under varied conditions, this approach promises more reliable navigation, coaching, and safety applications on everyday smartwatch platforms.

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Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT-4o in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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