Bridging Machine-Observation Gaps with Wearable Kinematics-Aided Worker Tracking for Construction Safety

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***Abstract*— This paper presents a wearable-aided worker tracking framework for maintaining worker–machine relative-position awareness when direct machine-based worker observations are temporarily unavailable. The framework combines wearable inertial navigation with lower-limb kinematic aiding (INS+LLK) and intermittent machine-based position corrections. When direct machine-based observation is available, it provides an external position correction to the wearable worker estimate. During an observation gap, INS+LLK continues to propagate the worker position, which is communicated to the machine and combined with the machine's own pose to maintain the worker–machine relative-position estimate. The framework is evaluated using controlled machine-observation gaps from 5 to 60 s. Mean end-of-gap relative-position error increased from 0.120 ± 0.131 m at 5 s to 0.632 ± 0.354 m at 60 s. For an experimentally defined 2-m machine-centered hazard region, recall decreased from 96.3% to 84.2%, while precision remained above 99%. These results demonstrate the feasibility of using wearable kinematics-aided navigation to bridge temporary machine-observation gaps and maintain safety-relevant worker–machine awareness.**

I. Introduction

Construction remains a high-risk industry, with approximately one in five workplace fatalities occurring among construction workers [1]. Struck-by incidents are a major contributor, with approximately 75% of struck-by fatalities involving heavy equipment such as trucks or cranes [2]. As mobile and increasingly automated machinery operates alongside workers, reliable awareness of nearby worker positions is therefore critical for collision prevention and safe human–machine interaction.

Worker-monitoring systems for construction safety have been developed using machine-mounted perception and site-based localization technologies. Vision and LiDAR can directly detect and localize nearby workers [3], [4], while technologies such as RFID and UWB use worker-worn devices and may require supporting readers, anchors, or other infrastructure [5]–[7]. However, continuous external worker observations cannot always be guaranteed in dynamic and cluttered construction environments. Machine-mounted perception can be affected by occlusion and limited sensor coverage, while wireless localization can experience obstruction and non-line-of-sight (NLOS) propagation [7]. Consequently, a worker may be physically close to a moving machine while temporarily unobservable to its onboard sensing. Maintaining worker–machine relative-position awareness during such observation gaps is therefore important for collision prevention, particularly when both the worker and machine continue moving.

Wearable inertial sensing provides a complementary source of worker-motion information because an inertial navigation system (INS), once initialized, can continuously propagate worker motion without requiring continuous external observations. Its primary limitation, however, is accumulated inertial drift. Pedestrian inertial-navigation methods exploit human locomotion to constrain this drift. Zhang *et al.* [8] used foot-kinematic information to construct quasi-zero-velocity observations under multiple motion modes, while Lee *et al.* [9] combined zero-velocity update (ZUPT)-based pedestrian dead reckoning with lower-body kinematic constraints to improve pedestrian position and heading estimation. These studies demonstrate that foot motion and lower-limb kinematics (LLK) can provide useful aiding information to constrain wearable INS drift. However, their primary objective is pedestrian self-localization rather than maintaining worker–machine relative-position awareness during temporary gaps in direct machine-based worker observations.

This work investigates wearable-aided worker tracking for construction safety. Rather than proposing a new inertial-navigation method, the proposed framework uses INS with lower-limb kinematic aiding (INS+LLK) to bridge temporary gaps in direct machine-based worker observations. Intermittent machine-based observations provide external position corrections to constrain accumulated worker-navigation drift. The framework is evaluated over increasing machine-observation gap durations in terms of worker–machine relative-position accuracy and machine-centered hazard-region awareness. The main contributions are: 1) a worker–machine tracking framework that uses continuous wearable INS+LLK to maintain worker-position estimates during machine-observation gaps and intermittent machine-based observations to constrain accumulated drift; and 2) a safety-oriented characterization of relative-position error and hazard-region awareness as functions of machine-observation gap duration.

II. Problem Formulation and Worker-Navigation Preliminaries

A. Problem Formulation

This work considers safety-relevant relative-position awareness between workers and mobile construction machinery when direct machine-based worker observations are intermittent. Figure 1 illustrates the considered scenario.

Let $\{\mathcal{W}\}$ denote a common local construction-site frame, and let $\{\mathcal{B}_m\}$ and $\{\mathcal{B}_{h_i}\}$ denote body-fixed reference frames

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attached to the machine and worker i, respectively, where $i \in \{1, \dots, N\}$ and N is the number of registered workers. The initial poses of the machine and workers are assumed to be registered in $\{\mathcal{W}\}$. Thereafter, the machine and workers may move independently. The machine pose in $\{\mathcal{W}\}$ is assumed available from its onboard localization or odometry system, and worker identity association is assumed known.

For worker i, the quantity of interest is the position of the worker reference point relative to the machine, expressed in the instantaneous machine frame:

$$ {}^{m}\mathbf{p}_{h_i,k} = {}^{w}\mathbf{R}_{m,k}^{\top} \left({}^{w}\mathbf{p}_{h_i,k} - {}^{w}\mathbf{p}_{m,k} \right), \tag{1} $$

where ${}^{w}\mathbf{p}_{h_i,k}$ and ${}^{w}\mathbf{p}_{m,k}$ denote the worker-reference and machine positions in $\{\mathcal{W}\}$ at time step k, respectively, and ${}^{w}\mathbf{R}_{m,k} \in SO(3)$ is the rotation matrix from the machine frame $\{\mathcal{B}_m\}$ to $\{\mathcal{W}\}$.

Direct machine-based observations of worker i may become temporarily unavailable. Let $[t_a, t_b]$ denote such an observation gap, with duration $T_{\text{gap}} = t_b - t_a$. Since the machine pose remains available, maintaining (1) during the gap primarily requires a continuous estimate of ${}^{w}\mathbf{p}_{h_i}$. The objective is therefore to maintain the worker-position estimate during T_{gap} so that worker–machine relative-position and machine-centered hazard-region awareness remain available even without direct machine-based worker observation.

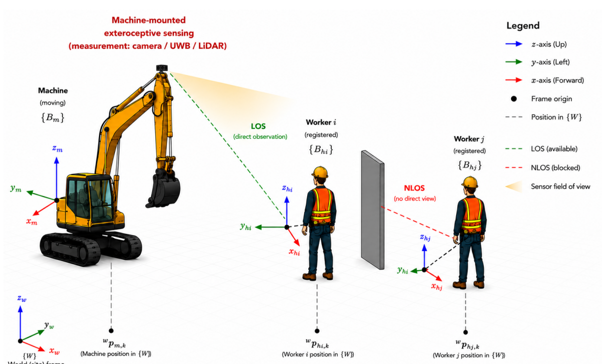


Fig. 1. Problem setup for worker–machine relative-position tracking under intermittent machine-based worker observations.

B. Worker Inertial Navigation

To maintain the worker position required by (1) independently of machine-based observations, we consider wearable inertial navigation. For clarity, the worker index i is omitted below; the same estimator is applied independently to each registered worker. A reference IMU mounted on the worker reference segment defines $\{\mathcal{B}_h\}$ and provides gyroscope and accelerometer measurements

$$ \boldsymbol{\omega}_{h,k}^{m} = \boldsymbol{\omega}_{h,k} + \mathbf{b}_{h,k}^{\omega} + \mathbf{n}_{h,k}^{\omega}, \tag{2a} $$
$$ \mathbf{a}_{h,k}^{m} = {}^{w}\mathbf{R}_{h,k}^{\top} \left({}^{w}\mathbf{a}_{h,k} - \mathbf{g} \right) + \mathbf{b}_{h,k}^{a} + \mathbf{n}_{h,k}^{a}, \tag{2b} $$

where ${}^{w}\mathbf{R}_{h,k} \in SO(3)$ maps vectors from $\{\mathcal{B}_h\}$ to $\{\mathcal{W}\}$. The angular velocity $\boldsymbol{\omega}_{h,k}$ is expressed in $\{\mathcal{B}_h\}$, while ${}^{w}\mathbf{a}_{h,k}$ and the gravity vector $\mathbf{g}$ are expressed in $\{\mathcal{W}\}$. The vectors $\mathbf{b}_{h,k}^{a}$ and $\mathbf{b}_{h,k}^{\omega}$ denote accelerometer and gyroscope biases, respectively, and $\mathbf{n}_{h,k}^{a}$ and $\mathbf{n}_{h,k}^{\omega}$ denote the corresponding measurement noises. The worker navigation state is

$$ \mathbf{x}_k^h = \begin{bmatrix} {}^{w}\mathbf{p}_{h,k}^{\top} & {}^{w}\mathbf{v}_{h,k}^{\top} & {}^{w}\mathbf{q}_{h,k}^{\top} & (\mathbf{b}_{h,k}^{a})^{\top} & (\mathbf{b}_{h,k}^{\omega})^{\top} \end{bmatrix}^{\top}, \tag{3} $$

where ${}^{w}\mathbf{p}_{h,k}$, ${}^{w}\mathbf{v}_{h,k}$, and ${}^{w}\mathbf{q}_{h,k}$ denote the position, velocity, and orientation of the worker reference frame in $\{\mathcal{W}\}$, respectively, with $\mathbf{R}({}^{w}\mathbf{q}_{h,k}) = {}^{w}\mathbf{R}_{h,k}$. The state and its uncertainty are propagated using strapdown inertial mechanization within an error-state extended Kalman filter (ESKF).

C. Lower-Limb Kinematic Aiding

To constrain accumulated inertial drift, lower-limb kinematic constraints are incorporated as aiding measurements [9]. The waist/pelvis IMU defines the worker reference segment, while IMUs on the bilateral thighs, shanks, and feet provide segment orientations and stance information.

For leg $\ell \in \{L, R\}$, let $\mathcal{C}_\ell$ denote the kinematic chain from the hip to the foot, and let ${}^{w}\hat{\mathbf{R}}_{B_j,k} \in SO(3)$ denote the orientation of segment $j \in \mathcal{C}_\ell$ in $\{\mathcal{W}\}$ after sensor-to-segment calibration and frame alignment. The foot-contact position is predicted from the worker reference state and lower-limb kinematics as

$$ {}^{w}\hat{\mathbf{p}}_{c_\ell,k} = {}^{w}\hat{\mathbf{p}}_{h,k} + {}^{w}\hat{\mathbf{R}}_{h,k} \boldsymbol{\ell}_{h \to hip_\ell}^{h} + \sum_{j \in \mathcal{C}_\ell} {}^{w}\hat{\mathbf{R}}_{B_j,k} \boldsymbol{\ell}_j^{B_j}, \tag{4} $$

where $\boldsymbol{\ell}_{h \to hip_\ell}^{h}$ is the fixed reference-segment-to-hip displacement and $\boldsymbol{\ell}_j^{B_j}$ is the corresponding link displacement expressed in the associated segment frame.

Under the no-slip stance assumption, the foot-contact position remains fixed during stance. At stance onset k_s^ℓ, the reference contact position is initialized as ${}^{w}\mathbf{p}_{c_\ell}^{\text{ref}} = {}^{w}\hat{\mathbf{p}}_{c_\ell, k_s^\ell | k_s^\ell - 1}$. The LLK residual is then

$$ \mathbf{r}_k^{\text{LLK},\ell} = {}^{w}\mathbf{p}_{c_\ell}^{\text{ref}} - {}^{w}\hat{\mathbf{p}}_{c_\ell,k|k-1}, \tag{5} $$

and is incorporated as an ESKF measurement update for each active stance leg. Although LLK constrains inertial drift, position error can still accumulate over extended periods.

III. Proposed Cooperative Worker–Machine Tracking

The proposed framework combines continuous wearable INS+LLK navigation with intermittent machine-based worker observations, as illustrated in Figure 2. Each worker is assumed to communicate its navigation estimate and associated uncertainty to nearby machines. A machine combines the communicated worker estimate with its own pose in the common site frame to maintain worker–machine relative-position awareness during temporary gaps in direct worker observation.

When a direct machine-based worker observation is available, it is transformed to the common site frame and used as an external position correction for the corresponding worker estimator. During a machine-observation gap, this correction is unavailable, and INS+LLK continues to propagate the worker state. Thus, cooperation is achieved through the exchange of wearable worker estimates and machine-based worker observations; the machine pose is assumed to be available independently. Communication latency, packet loss, and failures are outside the scope of this evaluation.

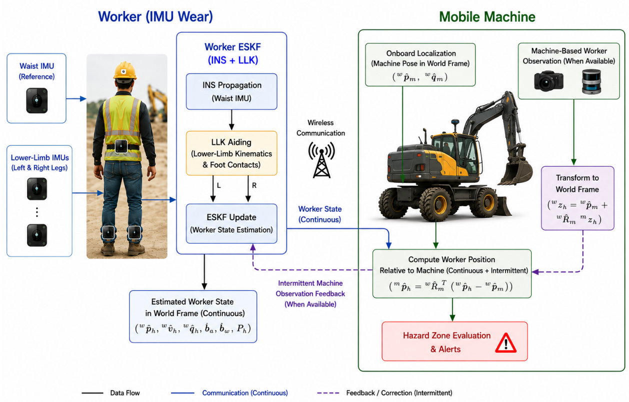


Fig. 2. Proposed cooperative worker–machine tracking framework.

A. Intermittent Machine-Based Position Correction

When worker i is directly observed by the machine-mounted sensing system, the measured worker position relative to the machine is modeled as

$$ {}^{m}\mathbf{z}_{h_i,k} = {}^{m}\mathbf{p}_{h_i,k} + \mathbf{n}^{m}_{i,k}, \qquad \mathbf{n}^{m}_{i,k} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}^{m}_{i,k}), \tag{6} $$

where ${}^{m}\mathbf{z}_{h_i,k}$ is the worker-position observation expressed in $\{\mathcal{B}_m\}$, ${}^{m}\mathbf{p}_{h_i,k}$ is the true worker–machine relative position from (1), and $\boldsymbol{\Sigma}^{m}_{i,k}$ is the observation covariance.

Using the available machine pose, the observation is transformed to the common site frame as

$$ {}^{w}\mathbf{z}_{h_i,k} = {}^{w}\hat{\mathbf{p}}_{m,k} + {}^{w}\hat{\mathbf{R}}_{m,k}\, {}^{m}\mathbf{z}_{h_i,k}, \tag{7} $$

where ${}^{w}\hat{\mathbf{p}}_{m,k}$ and ${}^{w}\hat{\mathbf{R}}_{m,k}$ are the estimated machine position and orientation in $\{\mathcal{W}\}$. The corresponding position innovation is

$$ \mathbf{r}^{\mathrm{MC}}_{i,k} = {}^{w}\mathbf{z}_{h_i,k} - {}^{w}\hat{\mathbf{p}}^{-}_{h_i,k}, \tag{8} $$

where ${}^{w}\hat{\mathbf{p}}^{-}_{h_i,k}$ is the INS+LLK worker-position prediction before correction. The innovation is incorporated through the ESKF position-measurement update.

B. Worker–Machine Safety Awareness

At each time step, the communicated worker estimate and available machine pose are used in (1) to compute ${}^{m}\hat{\mathbf{p}}_{h_i,k}$. This relative-position estimate remains available during machine-observation gaps through wearable INS+LLK propagation. Let $\mathcal{Z}_m$ denote a machine-centered hazard region defined in $\{\mathcal{B}_m\}$. The estimated hazard state of worker i is

$$ \hat{s}_{i,k} = \begin{cases} 1, & {}^{m}\hat{\mathbf{p}}_{h_i,k} \in \mathcal{Z}_m, \\ 0, & \text{otherwise}, \end{cases} \tag{9} $$

where $\hat{s}_{i,k} = 1$ indicates that the worker reference point is estimated to lie within the hazard region. The experimental evaluation therefore examines relative-position accuracy and hazard-region awareness as functions of machine-observation gap duration T_{gap}.

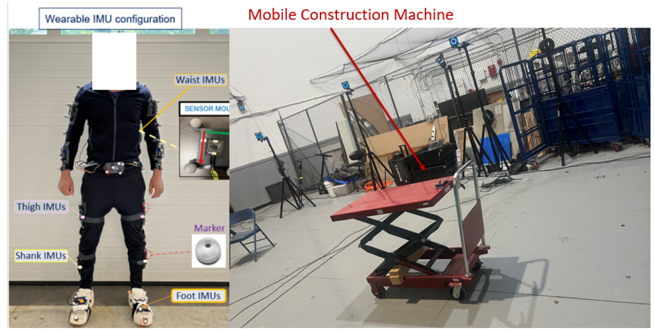


Fig. 3. Experimental setup with the wearable-instrumented worker and representative mobile machine moving in a shared workspace.

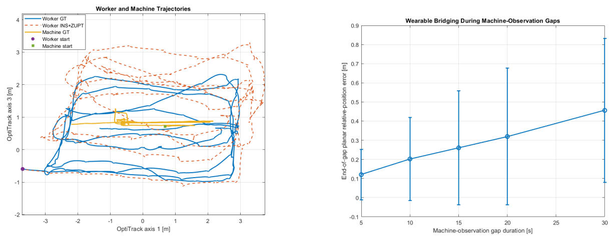
IV. Experimental Evaluation

A. Experimental Setup and Protocol

The proposed framework was evaluated in a controlled shared-workspace experiment, as shown in Figure 3. The worker wore a reference IMU at the waist and additional IMUs on the bilateral thighs, shanks, and feet for lower-limb kinematic aiding. A movable platform served as a representative mobile construction machine. OptiTrack markers were attached to both the worker and machine to provide synchronized ground-truth poses.

During the 391.4-s evaluation period, the worker and machine moved independently through the shared workspace, including changes in worker travel direction and machine heading and multiple transitions through the machine-centered hazard region. The wearable measurements were registered to the OptiTrack world frame through initial calibration, and the worker position was continuously estimated using INS+LLK. OptiTrack was used independently as ground truth and, offline, to generate idealized intermittent machine-based worker observations. Worker–machine information exchange was represented by synchronized data in the offline evaluation; a physical wireless communication system was not evaluated. The resulting worker and machine trajectories are shown in Fig. 4(a).

To evaluate tracking when direct machine-based worker observations are temporarily unavailable, controlled observation gaps of $T_{\text{gap}} \in \{5, 10, 20, 30, 60\}$ s were introduced offline. Each gap began with an idealized machine-based worker-position correction. Direct worker observations were then withheld, and INS+LLK continued to propagate the worker position. The machine pose remained available throughout, allowing continuous worker–machine relative-position estimation from the communicated wearable estimate. The end-of-gap error, evaluated immediately before the next machine observation, therefore represents the drift accumulated during the observation gap. Non-overlapping gap windows were evaluated using planar end-of-gap relative-position error, gap RMSE, and maximum gap error. Hazard-region awareness was evaluated using recall, precision, and



(a) (b)

Fig. 4. Experimental results: (a) worker and machine trajectories over the 391.4-s evaluation period, with OptiTrack providing ground truth; and (b) planar worker–machine relative-position error during controlled machine-observation gaps, showing the mean end-of-gap error and one standard deviation across gap windows.

TABLE I
WORKER–MACHINE TRACKING PERFORMANCE DURING CONTROLLED MACHINE-OBSERVATION GAPS.

T_{gap} [s]	N	End Error [m]	RMSE [m]	Max. [m]	Recall [%]	F1 [%]
5	72	0.120 ± 0.131	0.086	0.155	96.3	98.0
10	37	0.202 ± 0.218	0.134	0.248	94.5	96.9
20	19	0.320 ± 0.358	0.245	0.414	92.0	95.6
30	12	0.456 ± 0.377	0.325	0.550	87.8	93.4
60	6	0.632 ± 0.354	0.492	0.828	84.2	91.1

F1 score for an experimentally defined 2-m-radius region centered on the moving machine. This radius serves only as an experimental evaluation region and does not represent a regulatory safety distance.

B. Results and Discussion

Figure 4(b) shows the mean planar worker–machine relative-position error at the end of each machine-observation gap, with error bars indicating one standard deviation across the evaluated windows. Because each gap begins from a corrected worker position, this metric characterizes the relative-position error accumulated during INS+LLK propagation while direct machine-based worker observations are unavailable.

As summarized in Table I, the mean end-of-gap relative-position error increased from 0.120 ± 0.131 m at 5 s to 0.632 ± 0.354 m at 60 s, showing increasing accumulated error with machine-observation gap duration. Hazard-region recall decreased from 96.3% to 84.2% over the same range, while precision remained above 99% for all evaluated gap durations. Because non-overlapping windows were used, the number of evaluated windows decreased with gap duration; the 60-s result ($N = 6$) should therefore be interpreted with caution.

These results demonstrate the complementary roles of wearable and machine-based information in the proposed framework. INS+LLK maintains continuous worker-position information during machine-observation gaps, enabling the moving machine to retain worker–machine relative-position and hazard-region awareness. However, accuracy degrades as the gap duration increases, highlighting the role of intermittent machine-based observations in periodically constraining accumulated navigation drift.

The machine-based worker observations were generated offline from OptiTrack ground truth; thus, this proof-of-concept evaluates observation-gap bridging under idealized corrections rather than actual onboard perception. Future work will consider real perception and communication uncertainties and reduced-IMU configurations.

V. CONCLUSIONS

This paper presented a wearable-aided worker tracking framework for construction safety. The framework combined continuous wearable INS+LLK with intermittent machine-based position corrections to maintain worker–machine relative-position awareness. During temporary gaps in direct machine-based worker observations, the wearable estimate was combined with the machine's own pose to maintain relative-position and hazard-region awareness. When machine-based observations became available again, they provided external position corrections to constrain accumulated navigation drift. Mean end-of-gap relative-position error increased from 0.120 ± 0.131 m at 5 s to 0.632 ± 0.354 m at 60 s. Over the same range, hazard-region recall decreased from 96.3% to 84.2%, while precision remained above 99%. These proof-of-concept results demonstrate the feasibility of wearable kinematics-aided navigation for bridging temporary machine-observation gaps under idealized machine-based position corrections.

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