Postprint: Wi-Fi Indoor Positioning Algorithm Based on PDR Feedback

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Abstract

Wi-Fi fingerprinting localization is susceptible to environmental influences and exhibits poor stability; pedestrian dead reckoning (PDR) positioning requires the initial position of the target to be localized and is prone to cumulative errors. To address these issues, a Wi-Fi indoor localization algorithm based on PDR feedback is proposed. The algorithm consists of three main stages: an initial position localization stage based on relevance vector regression (RVR), a feedback stage based on PDR positioning, and a fingerprint localization stage based on K-nearest neighbor (KNN). Experimental results demonstrate that the proposed algorithm achieves significant improvements in localization accuracy and stability compared to other localization algorithms, and the algorithm reduces time complexity compared to Wi-Fi localization, exhibiting good real-time performance.

Full Text

Preamble

Title: Research on Wi-Fi Indoor Positioning Algorithm Based on PDR Feedback

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Abstract: Wi-Fi fingerprint positioning is susceptible to environmental influences and suffers from poor stability, while Pedestrian Dead Reckoning (PDR) positioning requires an initial position of the target and is prone to cumulative errors. To address these issues, this paper proposes a Wi-Fi indoor positioning algorithm based on PDR feedback. The algorithm consists of three main stages: an initial position localization stage based on Relevance Vector Regression (RVR), a feedback stage based on PDR positioning, and a fingerprint localization stage based on K-Nearest Neighbor (KNN). Experimental results demonstrate that the proposed algorithm significantly improves positioning accuracy and stability compared to other localization algorithms, while reducing time complexity relative to Wi-Fi positioning alone and achieving better real-time performance.

Keywords: fingerprint positioning; pedestrian dead reckoning; relevance vector regression

1 Design and Implementation of Fusion Positioning Structure

This section introduces the fundamental principles of Wi-Fi fingerprint positioning and PDR positioning, analyzes their respective advantages and limitations for independent localization, and thereby establishes the necessity of fusion positioning. Based on this analysis, we propose a fusion positioning scheme and architecture.

1.1 Wi-Fi Fingerprint Positioning and PDR Positioning

In complex indoor propagation environments, Wi-Fi positioning typically employs location fingerprint matching to establish a correspondence between physical coordinates and signal strength, thereby achieving target localization. Fingerprint positioning consists of two phases: offline database construction and online localization. During the offline phase, RSS values from various Access Points (APs) are collected at reference points to build a location fingerprint database. In the online phase, real-time RSS signals are matched against this database to determine user position.

PDR positioning is a trajectory estimation method based on the following principle: after obtaining the target’ s initial position, accelerometer sensors and related algorithms are used to determine the user’ s step length, while direction sensors calculate the pedestrian’ s movement orientation, ultimately estimating the next position coordinate. If the target’ s coordinates at time k are (x_k, y_k), step length is d_k, and orientation angle is θ_k, then the position coordinates at the next time instant are calculated as:

$$\begin{cases} x_{k+1} = x_k + d_k \cdot \cos\theta_k \\ y_{k+1} = y_k + d_k \cdot \sin\theta_k \end{cases}$$

Analysis of these two positioning algorithms reveals inherent limitations. In Wi-Fi fingerprint positioning, RSS signals exhibit temporal variability—even at the same location, RSS values differ across time—leading to unstable positioning results with large error variance. In PDR positioning, each localization step relies on the previous step’ s result, making long-term positioning susceptible to cumulative errors. Moreover, PDR requires known initial coordinates and cannot operate independently. However, both methods possess distinct advantages: Wi-Fi fingerprinting provides relatively accurate absolute positioning without cumulative error and can localize targets independently, while PDR offers stable positioning by effectively utilizing smartphone built-in sensors to provide orientation information. Therefore, fusing these two positioning modalities is essential.

1.2 Fusion Positioning Structure Based on PDR Feedback

In conventional fusion structures (shown in [Figure 1: see original paper]), Wi-Fi and PDR positioning are simply combined through a filtering algorithm without effectively leveraging respective feedback information. To address this limitation, we propose a fusion positioning structure based on PDR feedback, illustrated in [Figure 2: see original paper]. This architecture comprises three stages: initial position localization based on Relevance Vector Regression, feedback correction based on PDR positioning, and fingerprint localization based on K-Nearest Neighbor.

For Stage 1, considering the critical importance of initial position accuracy and RSS signal temporal variability, we propose an initial position localization algorithm based on RVR. Unlike traditional machine learning algorithms, RVR requires no penalty factor setting, and its kernel function selection is unrestricted by Mercer’ s theorem, yielding superior regression performance and more precise initial coordinates. This stage significantly reduces errors introduced by RSS temporal variability, enhancing initial position accuracy and providing more reliable input for Stage 2.

For Stage 2, addressing Wi-Fi positioning’ s instability and large error variance, we propose a positioning algorithm based on PDR feedback. This stage primarily feeds PDR positioning results back into the final Wi-Fi localization. Employing a PDR feedback-based structure not only effectively mitigates complex indoor environmental impacts but also substantially narrows the localization scope, satisfying real-time user requirements.

For Stage 3, the final localization result is obtained by leveraging PDR positioning results and real-time RSS signals. The step length parameters in PDR positioning are corrected to reduce cumulative errors. The complete system localization flow proceeds as follows: first, RVR algorithms compute the target’ s initial position coordinates; then PDR positioning estimates the next position, feeding this result into the final Wi-Fi localization; finally, online RSSI fingerprint vectors are collected, and KNN algorithms match real-time RSSI vectors against fingerprint information from coordinates physically adjacent to the PDR-estimated position, yielding the system’ s final localization result while simultaneously correcting PDR step length parameters based on the final coordinates.

2 Algorithm Implementation

2.1 Initial Position Localization Algorithm Based on RVR

Relevance Vector Machine is proposed within a Bayesian framework, sharing the same functional form as SVM. Like SVM, it transforms low-dimensional nonlinear problems into high-dimensional linear problems through kernel mapping. In Wi-Fi fingerprint positioning, establishing a mapping relationship between localization features and physical positions is challenging, and reducing complex indoor environmental impacts is crucial. Therefore, we employ an initial position localization algorithm based on RVR.

SVM regression constructs learning machines based on structural risk minimization principles. In contrast, RVR' s Bayesian framework yields more accurate predictions. RVM offers two major advantages: no penalty factor requirement and unrestricted kernel function selection by Mercer' s theorem, enabling probabilistic predictions that further enhance learning capability.

We employ RVR to establish the mapping between localization features and physical positions. During the offline phase, signal fingerprints are collected and trained via RVR; during the online phase, real-time signal fingerprints undergo regression analysis through RVR to obtain specific coordinates. Given training data $\{(x_i, z_i)\}_{i=1}^{N}$, where x_i is the i-th input localization feature sample and z_i is the corresponding output position coordinate, input features are mapped to a high-dimensional nonlinear space via kernel methods to construct the regression function:

$$z_i = y(x_i; w) + \varepsilon_i$$

where ε_i represents Gaussian noise. The probability density function of position coordinates can be rewritten as:

$$p(z_i|x_i) = \mathcal{N}(y(x_i; w), \sigma^2)$$

Assuming training samples are independent and derived from the model $y(x_i; w) = w_0 + \sum_{i=1}^{N} w_i k(x, x_i)$, where $k(x, x_i)$ is the kernel function (single or composite), w_i are kernel weights, $\mathbf{w} = [w_0, w_1, ..., w_N]^T$ is the weight vector, and σ^2 is noise variance. To prevent overfitting, we impose a zero-mean normal distribution on $\mathbf{w}$, yielding:

$$p(\mathbf{w}|\alpha) = \prod_{i=0}^{N} \mathcal{N}(w_i|0, \alpha_i^{-1})$$

where α represents hyperparameters. According to sparse Bayesian learning theory, through Markov properties and simplification, the integral term (product of Gaussian functions) yields an approximate solution:

$$p(\mathbf{z}|\alpha, \sigma^2) = \int p(\mathbf{z}|\mathbf{w}, \sigma^2)p(\mathbf{w}|\alpha)d\mathbf{w}$$

The posterior distribution over weights is Gaussian: $p(\mathbf{w}|\mathbf{z}, \alpha, \sigma^2) = \mathcal{N}(\mu, \Sigma)$, where:

$$\begin{cases} \mu = \sigma^{-2}\Sigma\Phi^T\mathbf{z} \\ \Sigma = (\sigma^{-2}\Phi^T\Phi + \mathbf{A})^{-1} \end{cases}$$

Here $\mathbf{A} = \mathrm{diag}(\alpha_0, \alpha_1, ..., \alpha_N)$, and Φ is the design matrix with elements $\Phi_{ij} = k(x_i, x_j)$. Hyperparameters are estimated by maximizing the marginal likelihood:

$$\alpha_{\mathrm{MP}}, \sigma^2_{\mathrm{MP}} = \arg\max_{\alpha,\sigma^2} p(\mathbf{z}|\alpha, \sigma^2)$$

With initial values for α and σ^2, iterative training proceeds via:

$$\begin{cases} \alpha_i^{\mathrm{new}} = \frac{\gamma_i}{\mu_i^2} \\ (\sigma^2)^{\mathrm{new}} = \frac{\|\mathbf{z}-\Phi\mu\|^2}{N-\sum_i \gamma_i} \end{cases}$$

where μ_i is the i-th posterior mean weight and $\gamma_i = 1 - \alpha_i\Sigma_{ii}$.

Appropriate kernel function selection critically impacts RVR performance. In this work, RSS signal distribution statistics and nonlinearity directly determine kernel selection. For RVR, Gaussian kernels exhibit strong learning capability but weak generalization, while spline kernels show the opposite characteristics. Therefore, we construct a composite multi-kernel function combining Radial Basis Function (RBF) and Spline Function:

$$k(x, y) = \eta L(x, y) + \delta S(x, y)$$

where $S(x, y)$ is the spline kernel:

$$S(x, y) = 1 + xy + xy\min(x, y) - \frac{x+y}{2}\min(x, y)^2 + \frac{1}{3}\min(x, y)^3$$

and $L(x, y)$, $G(x, y)$ are Laplace and Gaussian kernels respectively:

$$L(x, y) = \exp\left(-\frac{\|x-y\|}{\eta}\right), \quad G(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\delta^2}\right)$$

This composite kernel maximizes learning capability while improving generalization performance, effectively addressing Gaussian kernel weaknesses. The Laplace kernel, as a harmonic function, further enhances learning ability. RVR' s kernel selection freedom reduces complexity, enabling optimal regression for precise initial positioning.

2.2 Improved PDR Localization Algorithm

After obtaining the target' s initial position, PDR estimates the post-movement location based on pedestrian step length and direction. PDR' s key components are: gait detection, step length calculation, and motion direction determination. Gait detection and direction can be obtained via smartphone sensors (accelerometer, gyroscope, magnetometer), while step length estimation critically impacts PDR accuracy.

PDR' s first step is gait detection. Human walking is periodic with minimal inter-individual variation. Since walking is periodic, accelerometer data also exhibits periodicity, enabling step counting through acceleration analysis. We collect accelerometer values every 200ms, producing the curve shown in [Figure 3: see original paper]. Raw signals contain noise requiring Gaussian smoothing with window $N = 10$:

$$a_k^{\text{filtered}} = \frac{1}{N}\sum_{i=0}^{N-1} a_{k-i}$$

Filtered signals show prominent peaks, each corresponding to one step. Step detection occurs when a peak is identified.

Step length estimation accuracy directly affects PDR precision. Traditional step length models include artificial intelligence models, biomechanical models, linear models, nonlinear models, and constant/pseudo-constant models. Nonlinear models are relatively simple and smartphone-implementable but perform poorly during fast walking. To accommodate various walking states, we improve the nonlinear step estimation model.

The nonlinear model establishes a mathematical relationship between step length and acceleration extrema. Given maximum and minimum acceleration within one step, step length L is calculated as:

$$L = H \cdot \sqrt[4]{a_{\max} - a_{\min}}$$

where H is a model coefficient. However, this model ignores walking time, reducing accuracy at high speeds. Our improved model incorporates temporal factors:

$$L = H_1 \cdot \frac{a_{\max} - a_{\min}}{a_{\text{avg}}} + H_2 \cdot T \cdot (a_{\max} - a_{\min})$$

where H_1 and H_2 are model parameters initialized with preset values and subsequently corrected via fusion localization results.

Experiments using a Huawei Nova 2 compared traditional and improved models at 1.42 steps/s and 2.20 steps/s walking speeds. At 1.42 steps/s over 48m, the improved model outperformed the traditional model in 7 of 8 trials ([Figure 4: see original paper]). At 2.20 steps/s over 78m, the improved model consistently performed better with smaller errors ([Figure 5: see original paper]), demonstrating superior robustness across walking speeds.

2.3 Fingerprint Localization Algorithm Based on KNN

The final stage employs KNN for fingerprint matching. After obtaining PDR position estimate (x_0, y_0), we identify fingerprint information from physically adjacent coordinates in the database. Real-time RSSI fingerprint vectors are collected, and Euclidean distances D_i between online fingerprints and adjacent coordinate fingerprints are computed:

$$D_i = \sqrt{\sum_{j=1}^{n}(RSS_j^{\text{online}} - RSS_j^{\text{ref}})^2}$$

The K nearest neighbors are selected, and the final position (x, y) is obtained via weighted KNN:

$$(x, y) = \sum_{i=1}^{K} w_i(x_i, y_i)$$

where w_i is the weight of the i-th reference point. K depends on the number of adjacent coordinates. With 1m reference point spacing on a square grid, we select adjacent coordinates within radius $r = 2$m of the PDR estimate (x_0, y_0), as illustrated in [Figure 6: see original paper].

3 Algorithm Validation and Analysis

Experiments were conducted on the second floor of the USTC library (30m × 40m) using a Huawei Nova 2 smartphone running Android.

3.1 Experimental Analysis of RVR-Based Wi-Fi Positioning

Before fusion localization experiments, we validated RVR' s regression effectiveness through simulation. Using the same fingerprint dataset, we compared single-kernel RVR, composite-kernel RVR, and SVR regression training. To simulate indoor environments, fingerprint samples were generated via the empirical propagation loss model:

$$P(d) = P(d_0) + 10n \log \frac{d}{d_0} + X_\sigma$$

where d is the actual distance between AP and reference point, $d_0 = 2$m is the reference distance with RSSI $P(d_0) = -35$dB, $n = 3.5$ is the path loss exponent, and X_σ is environmental noise (Gaussian white noise with 4dB intensity). Using 200 sample points from this model, regression training simulations were performed, with results shown in [Figure 7: see original paper]–[Figure 9: see original paper].

[Figure 7: see original paper] and [Figure 8: see original paper] show that SVR' s trained propagation loss model exhibits poor fitting at multiple ranges (2.5–8m, 30–40m). In contrast, [Figure 9: see original paper] demonstrates that our composite kernel RVR controls error within 7dB (average ~1.5dB), producing a smoother regression curve that improves positioning accuracy.

To verify RVR' s feasibility for indoor positioning, Matlab simulations were performed on a PC (Intel i5 2.30GHz dual-core CPU, 3.8GB RAM). The simulation emulated a 16.15m × 3.77m laboratory corridor with 8 wireless APs spaced 4m apart. The offline phase collected RSS samples at 48 points (1m spacing), while the online phase randomly selected test positions. Using the propagation loss model with $d_0 = 2$m and $n = 3.5$, we implemented RVR (composite kernel), SVR (Gaussian kernel) [12], and KNN ($K = 5$). Results are shown in [Figure 10: see original paper].

At 1.5m positioning error, RVR-based localization achieves 89.6% probability, surpassing SVR' s 73.5%. KNN only reaches 86.7% probability at 3m error. The proposed RVR-based algorithm achieves 1.42m average error, significantly narrowing the error range and meeting precise initial positioning requirements for fusion localization.

3.2 Experimental Analysis of PDR Feedback-Based Fusion Localization

We conducted positioning experiments in the library corridor comparing PDR feedback fusion localization, RVR-based Wi-Fi localization, and PDR localization alone. [Figure 11: see original paper] shows the trajectories, with the leftmost point as start and rightmost as end. The path traversed a 10m × 10m square corridor in 46 steps at constant speed.

Wi-Fi positioning exhibits instability and jumping due to environmental influences, with large errors and low trajectory matching. PDR matches well in the first half but diverges later due to cumulative error. The PDR feedback fusion localization shows highest trajectory matching, maintaining high accuracy even in regions with large individual positioning errors.

[Figure 12: see original paper] shows cumulative probability distributions of positioning errors. Fusion localization achieves 1.24m average error, compared to 1.82m for PDR and 2.64m for Wi-Fi alone. The fusion approach stabilizes errors, with Wi-Fi corrections mitigating PDR cumulative drift. Additionally, fingerprint matching count per step is greatly reduced compared to pure Wi-Fi positioning, improving real-time performance.

4 Conclusion

This paper proposes a PDR feedback-based fusion localization algorithm to address Wi-Fi positioning' s environmental sensitivity and PDR' s requirements for initial position and susceptibility to cumulative errors. By incorporating PDR information into Wi-Fi localization, the approach achieves superior performance. Specifically:

1. An RVR-based initial positioning stage reduces average error to 1.42m, addressing the common problem of low initial position accuracy in existing fusion methods.
2. In the KNN-based fingerprinting stage, PDR information not only overcomes Wi-Fi instability but also narrows the search region, dramatically reducing fingerprint matching time.
3. These improvements enhance both accuracy and real-time performance, reducing average positioning error from 2.64m to 1.24m.

Experimental results validate that the proposed algorithm effectively resists complex indoor environmental effects while simultaneously improving positioning accuracy and real-time performance.

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Note: Figure translations are in progress. See original paper for figures.