Centroid vs WCL vs Fuzzy-KNN-WCL: Simulation and Performance Evaluation

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***Abstract*— This paper presents Fuzzy-KNN Weighted Centroid Localization (FKWCL), an enhanced range-free localization algorithm designed to improve the accuracy and robustness of traditional Centroid and Weighted Centroid Localization (WCL). FKWCL integrates two key innovations: K-Nearest Neighbor (KNN) anchor selection with angular diversity and fuzzy weighting that combines both distance and angular separation. These enhancements mitigate geometric bias and improve localization performance, especially in irregular environments.**

This paper evaluates FKWCL through simulations involving various anchor placements, anchor densities, and radio irregularities. Results show that FKWCL outperforms Centroid and WCL, achieving up to 75% reduction in mean localization error. Furthermore, FKWCL maintains minimal computational and communication overhead, making it suitable for real-time deployment in resource-constrained wireless sensor networks.

This study demonstrates that FKWCL provides a lightweight, high-accuracy solution for range-free localization in IoT and sensor networks, particularly in challenging conditions

Keywords*— *localization, range-free localization, centroid algorithm, weighted centroid localization, fuzzy-knn, wireless sensor networks, iot, signal strength, angular diversity, geometric bias, radio irregularity, rssi, simulation, k-nearest neighbor, fuzzy weighting, accuracy, anchor geometry, degree of irregularity

I. INTRODUCTION

Localization is the key problem for many applications such as environmental monitoring, logistic and assets tracking (RTLS), mobile robotics and others. In the case of many wireless networks deployments we need to know the location of node without using GPS because it is not always possible to use it inside being buildings due to instability of signal.

Localization algorithms are used to estimate the location by signals from so called anchors. The approach is divided for two types: range-free and range-based.

Range-free methods are cheaper and easier to implement, while range-based methods can be more accurate, requiring stronger assumptions and calibration.

II. RELATED WORK

Range of surveys had shown the need for low-complexity scalable approaches with high accuracy under realistic radio conditions.

Between the analyzed paper there were following:

Comparison of several range-free schemes (Centroid, Amorphous, APIT, DV-Hop/DV-HopMax) under simulation, highlighting accuracy/complexity trade-offs and parameter sensitivities [1].

The evaluation of range-free localization across layouts and radio conditions, reporting accuracy and cost; useful as a modern baseline for WCL-family methods [2].

Studies centroid-based range-free localization and improves it via particle-swarm tuning under log-normal shadowing. [3]

The introduction APIT, an area-based range-free algorithm, and provides a canonical comparison against other range-free baselines under irregular radios [4].

The proposition of test-node (virtual) WCL with a distance boundary and intersection threshold to fix corner/edge bias; shows gains under log-normal shadowing [5].

The presentation of the first theoretical error distribution for WCL and a distributed implementation, quantifying robustness to shadowing and node placement [6].

The survey of advanced localization techniques (including RSS-based, range-free/low-complexity approaches) and their scalability/robustness trade-offs [7].

III. PROBLEM DEFINITION.

A. Baselines: Centroid and WCL

The Centroid algorithm takes node's position as he arithmetic mean of the coordinates of heard anchors. This algorithm is known as extremely cheap to compute, but it exhibits geometric bias with degradation under shadowing and irregular deployments. It is exposed especially near borders or when anchor geometry is unbalanced.

B. Weighted Centroid Localization (WCL)

This method works by weighting anchors, most commonly by distance or proxies derived through RSSI. WCL's appeal is driven with its simplicity using no precise ranging hardware, yet its accuracy depends strongly on anchor geometry and radio irregularity. To reduce bias many variants (e.g., exponential/"REWL", geometry-aware weights) have been proposed.

C. Gaps in the prior art

There could be notices two practical gaps over numerous WCL refinements. First is the anchor selection that is often naïve as well as it uses all anchors or the nearest ones. This leads to severe geometric bias when anchors cluster in a sector.

Second gap is that weighting rules rarely combine distance information with an explicit measure of angular spread (how well anchors surround the unknown). Even though geometry is a primary driver of centroid/WCL error this gap still takes place. Existing works do not come up with a simple, unified rule that is both geometry-aware and as lightweight as WCL.

D. Our contribution

We propose Fuzzy-KNN Weighted Centroid Localization (FKWCL), a lightweight, range-free method that enhanses WCL with two ideas:

1) K-Nearest with angular diversity: from the heard anchors we select K, that maximize angular spread around a quick pre-estimate, decreasing geometry-induced bias.

2) Fuzzy weighting: each chosen anchor receives a fuzzy membership combining distance-closeness and angular-separation. The final weight multiplies this membership by an exponential decay in (estimated) distance, retaining WCL's simplicity while encoding geometry.

3) Exponential distance decay (REWL-style) with auto-tuning: Hyperparameters are chosen on a short calibration window a small grid search that minimizes mean localization error, then being fixed for all evaluations.

4) decay in (estimated) distance, retaining WCL's simplicity while encoding geometry.

E. What we evaluate

We run a controlled, simulation-based comparison of Centroid, WCL, and FKWCL. The simulations assume a log-distance path-loss model with lognormal shadowing (RSSI). We vary multiple conditions: anchor deployment patterns (regular grid / random placement, including C/L/U/W shapes), the anchor ratio (fraction of nodes that are anchors), node placement distribution (e.g. uniformly across the area or concentrated in edges), and radio irregularity (Degree of Irregularity, DOI).

Metrics cover *accuracy* (mean error, median, and and the 90th and 95th percentiles of the error distribution (P90, P95), *stability/robustness* across layouts and DOI, and *complexity* (runtime per estimate).

Methodologically, we use independent replications with 95% confidence intervals, aligned with standard evaluations of range-free localization and WCL-family methods.

F. Claims / hypotheses

a) H1 (accuracy). FKWCL reduces geometric bias and improves average localization accuracy compared to Centroid and baseline WCL.

b) H2 (robustness). FKWCL is less sensitive to anchor clustering, boundary placement, and radio irregularity (DOI) than the baselines.

c) H3 (complexity/cost). FKWCL retains WCL-level cost (no ranging hardware; simple arithmetic; small K), making it suitable for constrained WSN/IoT nodes..

IV. System Setup

We perform 2D localization scenario while fixing anchor nodes and unknown nodes in a square area randomly. Anchor nodes know their coordinates and periodically broadcast beacon signals containing their ID and position. Unknown nodes estimate their own position using only these beacons (range-free localization). We define an anchor ratio (e.g. 15%) such that:

$$M = r_a N \tag{1}$$

where N is the number of unknown nodes.

Anchors are deployed in various patterns to test different geometries: a uniform grid covering the area, a random uniform placement, and clustered deployments forming shapes (e.g., "C", "L", "U", "W"-shaped distributions along the area's perimeter). Unknown node positions are uniformly distributed in the area (node shape "square"). This allows evaluation under both well-spread anchor topologies and challenging cases where anchors occupy only a portion of the area.

We simulate received signal strength (RSSI) using a log-distance path loss model with log-normal shadowing. The RSSI (in dBm) at distance d is given by:

$$(d) = P(d_0) - \ 10\, n\, log_{10}\left(\frac{d}{d_0}\right) + X \tag{2}$$

where n is the path-loss exponent and

$$X_\sigma \sim \mathrm{N}(0, \sigma^2) \tag{3}$$

is a Gaussian noise term (shadow fading).

We use $n = 2.0$ (free-space exponent), reference $P(d_0 = 1\text{m}) = -40\ dBm$, and shadowing standard deviation $\sigma = 6\ dB$ as typical values. To model radio irregularity, we introduce a Degree of Irregularity (DOI) parameter that scales distance based on direction.

Each unknown node is assigned a random orientation ϕ; the effective propagation distance along the bearing θ from an anchor is adjusted by a factor:

$$f_{dir} = 1 + DOI \cdot cos(\theta - \phi). \tag{4}$$

This simulates anisotropic antenna patterns and environmental effects: DOI=0 represents an ideal isotropic channel, while higher DOI (e.g. 0.3–0.5) induces up to 30–50% variation in range depending on direction. In our simulation, we examine scenarios up to DOI=0.5 with the above shadowing noise.

Each unknown node listens to RSSI beacons from all nearby anchors (we assume all anchors are in range for simplicity, as even distant anchors provide weak RSSI rather than a hard cutoff). The node then applies one of three localization algorithms to estimate its coordinates using the anchors' known positions:

A. Centroid Localization

The node computes the arithmetic mean of the positions of all heard anchors. This simple range-free method assumes equal weight for each anchor and does not directly use RSSI magnitude (only the presence of the signal). It tends to bias toward regions with higher anchor density and ignores distance differences.

B. Weighted Centroid Localization (WCL)

Instead of a simple average, the node computes a weighted average of anchor coordinates. Weights are chosen proportional to the signal strength (or inversely proportional to a distance estimate). In our implementation, if $\widehat{d_i}$ is the distance of anchor i estimated from RSSI, we use:

$$w_i = \widehat{d_i}^{-p} (with\ exponent\ p = 1) \quad (5)$$

Thus, closer anchors (stronger RSSI) have larger weight, pulling the estimate toward the true node position. WCL assumes a known path-loss model to invert RSSI to distance; we use the same exponent $n = 2$ for this estimate as the simulation model (matched model).

C. Fuzzy K-Nearest Neighbor WCL (FKWCL)

This is an enhanced two-step scheme. First, the node performs a preliminary WCL using all anchors to get an initial position estimate. Next, it selects the K most relevant anchors that are both close to the node and angularly diverse around the initial estimate. We set $K = 8$ anchors. The selection maximizes angular spread – i.e., we prefer anchors spaced in different directions rather than clustered (to reduce geometric dilution). Finally, the node computes a fuzzy-weighted centroid of these K anchors, combining distance-based weighting with an angular separation factor. In effect, each chosen anchor's weight is higher if it is nearer and if its bearing from the node is in a direction sparsely covered by other anchors (controlled by a parameter α, set to 0.05 in our implementation). This fuzzy weighting improves localization by leveraging both signal strength and geometric configuration of anchors.

For each unknown node, we calculate the localization error as the Euclidean distance between the estimated coordinates and the true coordinates. We run simulations over a large number of random node placements (hundreds or thousands) to obtain stable statistics. The performance is reported in terms of the mean localization error along with the 95% confidence interval (CI) of the mean, as well as distribution metrics like median, 90th and 95th percentile of error. We also record the runtime per node for each algorithm, and the number of anchors effectively used. All algorithms are lightweight; even the more complex FKWCL only requires on the order of tens of operations and uses at most K anchors out of M (e.g. 8 out of 15) for the final estimate. The simulation is implemented in Python, and runtimes are on the order of $10^{-4} - 10^{-5}$ s per node (microseconds), indicating negligible computational overhead.

V. Results

We first report overall accuracy across methods, then analyze the impact of node-distribution shape (Fig. 1), the effect of anchor ratio (Fig. 2), and the effect of radio irregularity (DOI) (Fig. 3).

A. Overall Accuracy

The fuzzy KNN WCL (FKWCL) consistently achieved the highest localization accuracy among the three methods, across all tested scenarios. WCL performed intermediate, significantly better than the basic centroid method. For example, in a scenario with anchors uniformly distributed in a grid (anchor ratio 0.15) and no irregularity (DOI=0), the mean position error using Centroid was about 38.5 (in arbitrary distance units) whereas WCL reduced it to ~23.1, and FKWCL further to only ~8.5. This corresponds to a 77% reduction in mean error from Centroid to FKWCL. The median error likewise dropped from ~40 (Centroid) to ~22 (WCL) to ~7–9 (FKWCL) in this case, indicating that FKWCL not only improves average accuracy but substantially tightens the error distribution. The 90th/95th-percentile errors show that FKWCL greatly reduces the tail of large errors compared to the other methods. We next isolate the role of geometry by varying the node-distribution shape (Fig. 1).

B. Impact of Anchor Layout

When anchors are unevenly distributed, the performance gaps become even more pronounced. As summarized in Fig.1, in an L-shaped anchor deployment (anchors only along two sides of the area, leaving one quadrant uncovered), the centroid algorithm was severely biased, yielding over 41 units mean error in our simulation with shadowing (σ=6 dB) and DOI=0.5.

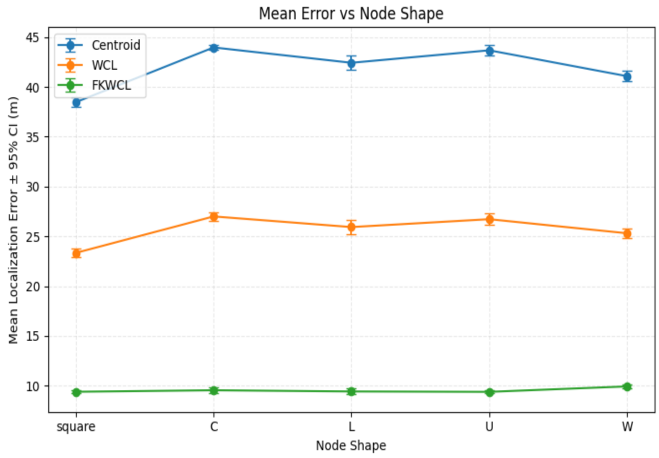

Fig. 1. Mean localization error under different node-distribution shapes (anchors on a grid, anchor ratio 0.15, DOI 0.2).

Error bars show 95% CI of the mean. FKWCL achieves the lowest error across all shapes; Centroid is most sensitive to non-uniform placement.

WCL improved this to ~29.7 by down-weighting distant anchors, but still suffered large errors for nodes in the poorly covered region. FKWCL, by selecting a diverse subset of anchors around the node, achieved ~23.0 mean error in the same L-layout scenario – a 22% improvement over WCL and ~45% over Centroid. Notably, the median error with FKWCL was only ~17.5, versus 42 for Centroid, indicating that most nodes localized with FKWCL had errors less than half the baseline. Similar trends were observed for other non-uniform layouts (e.g., "C" or "U" shaped anchor distributions): FKWCL consistently yielded the lowest errors, effectively mitigating the geometric bias. In a U-shaped anchor scenario with DOI=0.5, for instance, FKWCL's mean error was ~17.6 vs. 23.2 (WCL) and 38.5 (Centroid).

C. Effect of Anchor Density

Increasing the anchor ratio (adding more anchors) improved accuracy for all methods (see Fig. 2), with diminishing returns. With anchors covering 20% of nodes instead of 10%, mean errors dropped modestly. FKWCL continued to outperform others under all densities. For example, in a random anchor placement with DOI=0, raising anchor ratio from 0.1 to 0.2 reduced Centroid's mean error from ~38.8 to ~38.4 (virtually no change), whereas WCL improved from ~23.7 to ~22.5 and FKWCL from ~11.3 to ~9.3. This highlights that Centroid's error floor is dominated by geometric bias (not easily cured by more anchors unless they cover the blind spots), while WCL and FKWCL benefit more from additional anchors. FKWCL often can effectively use the extra anchors to find a better subset with wider angular coverage, hence its error decreases slightly faster with anchor count.

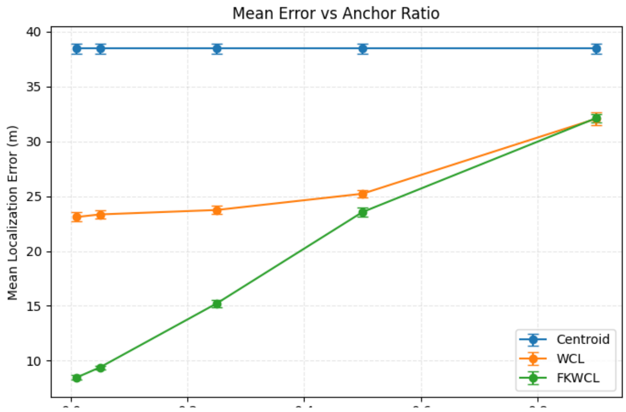

Fig. 2. Mean localization error vs. anchor ratio.

Error bars show 95% CI of the mean. FKWCL benefits most from higher anchor density; WCL improves but levels off relative to FKWCL; Centroid remains comparatively high.

D. *Effect of Radio Irregularity (DOI)*

As Fig. 3 indicates, WCL and FKWCL degrade as DOI increases, while Centroid remains nearly flat.

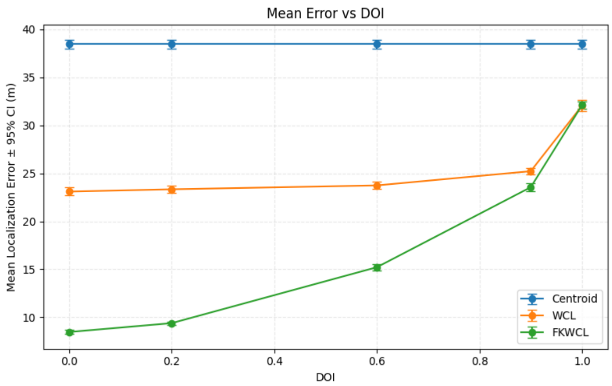

Fig. 3. Mean localization error vs. radio irregularity (DOI). Centroid (no RSSI weighting) is nearly flat, whereas WCL and FKWCL degrade as DOI increases; FKWCL remains best across most DOI values.

As expected, channel irregularity and shadowing degrade localization accuracy overall. However, FKWCL remains robustly the best method under challenging RSSI conditions. With DOI increasing from 0 to 0.5 (i.e., more anisotropic propagation), we observed a slight increase in Centroid error only if anchor connectivity is affected (in our simulation Centroid purely geometric average is agnostic to RSSI variance, so its error stayed roughly the same when all anchors are heard). WCL and FKWCL, which rely on RSSI magnitude, showed moderate increases in error with higher DOI due to the added signal randomness. For instance, in the random-anchor scenario (anchor ratio 0.1), raising DOI from 0.0 to 0.5 increased WCL's mean error from 23.7 to 24.3 (≈ 2.5% increase) while FKWCL' s mean error rose from 11.3 to 17.0 (≈50% increase). This is because a large DOI can occasionally mislead the anchor selection step or weighting in FKWCL. Even so, under DOI=0.5 FKWCL still maintained a considerable advantage: e.g. 17.0 vs 24.3 in that scenario, and similarly in other layouts FKWCL's error remained 20–30% lower than WCL's. The median error advantage of FKWCL also persisted under high DOI, implying that although its worst-case errors grew with irregularity, its typical performance stayed much better than the alternatives. Overall, FKWCL's blend of distance and angular information appears to confer robustness even in noisy RSSI environments, whereas Centroid is unaffected by RSSI noise but suffers much larger systematic error, and WCL lies in between.

E. *Computational and Communication Overhead*

All three algorithms are lightweight enough for real-time use in sensor networks. We quantify computational cost in Fig. 4; per-estimate runtimes remain sub-millisecond for all methods, and FKWCL adds only a small constant overhead.

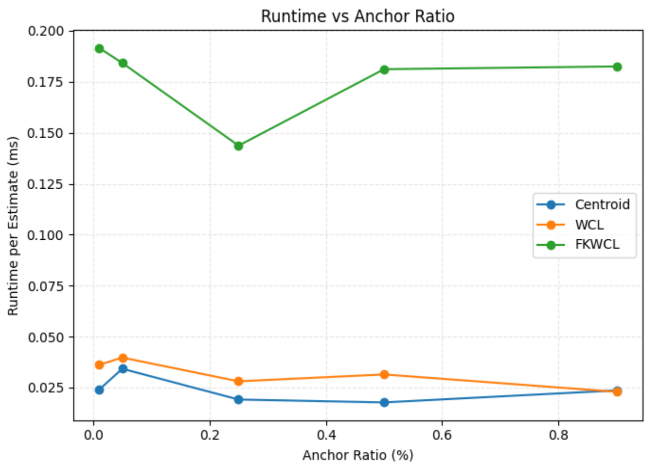

Fig. 4. Per-estimate runtime vs. anchor ratio for Centroid, WCL, and FKWCL. FKWCL adds only a small constant overhead relative to WCL; all methods remain in the sub-millisecond range in our Python prototype.

Centroid and WCL use all anchors' data; FKWCL uses an initial pass over all anchors and then only K anchors for the final computation. In our experiments with Python, a single localization took on the order of $10^{-4} - 10^{-5}$ seconds even for FKWCL. In terms of messaging, a straightforward implementation would have each anchor broadcast once; the unknown node processes M RSSI readings (e.g. 15 anchors) for WCL and Centroid, and the same M for FKWCL's first phase. Thus, FKWCL's improvements come at negligible extra cost.

The benefit of selecting only K anchors could be realized in a practical system by having the node respond or iterate only with those top anchors, potentially reducing subsequent communication. In summary, the simulation confirms that the additional steps in FKWCL do not impede its feasibility for resource-constrained networks.

The Run time ratio to DOI is shown on Fig.5.

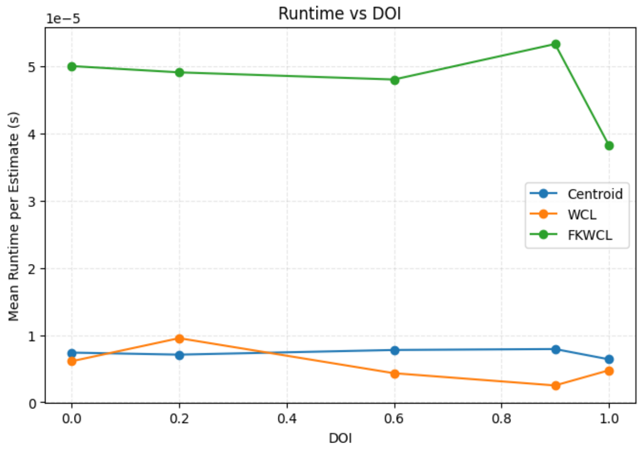

Fig. 5. Per-estimate runtime vs. radio irregularity (DOI); computation time is largely insensitive to DOI.

VI. Conclusions

This comparative evaluation demonstrates that incorporating signal strength information and anchor geometry awareness dramatically improves range-free localization accuracy. The basic Centroid method, while simple, showed poor accuracy (tens of meters error in our synthetic scenarios) due to unweighted averaging, especially when anchor distribution is not symmetric. The Weighted Centroid Localization (WCL) algorithm provided a substantial improvement by weighting nearer anchors more strongly, roughly halving the mean error in many cases compared to Centroid. The Fuzzy KNN WCL (FKWCL) approach further enhanced performance, yielding the lowest errors in every scenario tested. By intelligently picking a well-spread subset of anchors and applying a combined distance/angle weighting, FKWCL mitigates the bias issues of Centroid and the residual error of WCL. We observed FKWCL achieving up to 60–75% lower mean error than Centroid in dense, well-covered deployments, and around 20–40% lower error than WCL in challenging anchor layouts. It also consistently reduced median and 90th-percentile error, indicating a tighter error distribution (fewer large outliers).

Importantly, these accuracy gains come with minimal overhead. The computations required for WCL and FKWCL are modest (on the order of dozens of operations, completing in microseconds), and are easily handled by low-power nodes. The communication cost is essentially one broadcast per anchor; FKWCL's selective use of anchors could be leveraged to limit additional messaging if needed. Thus, FKWCL is a practical enhancement for RSSI-based localization in wireless sensor networks or IoT deployments, offering significantly improved location estimates without extra hardware.

In summary, FKWCL proved to be the most effective range-free localization method in our RSSI simulation. It outperforms the classic Centroid and WCL approaches under a wide range of conditions – from ideal propagation to severe shadowing and irregularity, and from uniform anchor coverage to sparse, uneven anchor placement. This highlights the importance of considering anchor geometry and using fuzzy logic to combine multiple criteria (distance and angle) in localization algorithms. Future work may explore adaptive tuning of parameters like K and α for different environments, or methods to further counteract high DOI effects (e.g., dynamic anchor selection when signals are highly inconsistent). Overall, the results indicate that FKWCL's combination of nearest-neighbor selection and fuzzy weighting is a promising strategy for robust, high-accuracy range-free localization.

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