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Dempster-Shafer Theory-Based Indoor Region Prediction With Single Wi-Fi Access Point for Static Object Localization

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Session #XXXX

Outline

1. Introduction
2. Related Work
3. Data collection of Single Access Point
4. Dempster- Shafer theory
5. Proposed algorithm
6. Future Work and Motivation

1.1 Background

- Indoor positioning systems (IPS) fill the gap where GPS falls short, especially in complex areas like multistory buildings and underground parking. Using networks of devices, they enable precise tracking of people and objects in such environments.
- Businesses increasingly adopt indoor location systems for precise tracking and space optimization.

(a) Warehouse Management

(b) Indoor localization

1.2 Existing Technologies

There are several technologies have been used in indoor localization as follows:

- Radio Frequency
- Ultrawideband (UWB)
- Bluetooth
- Vision
- Infrared
- Wi-Fi
- Acoustic Signal

1.3 RSSI-based indoor localization

In general, Wi-Fi has been a popular technology because of its ubiquitous, low cost and does not require infrastructure development. But there are several issues:

1. Signal Fluctuations
2. Low Accuracy
3. Interference and Noise
4. Path Loss Variability
5. Device Heterogeneity
6. Calibration Effort

1.4 Our Contribution

Our main contributions are summarized as follows:

1) The proposed algorithm works in a single Wi-Fi access point, requiring fewer fingerprints.

2) The dataset was recorded using a smartphone in a laboratory of 154 sq meters for a Single Access Point (AP).

3) This paper uses the Dempster Shafer-Theory (DST) approach to predict the regions.

4) The proposed approach is compared with the machine learning algorithms

2.1 Related Work

[1] **Indoor localization via wlan path-loss models and dempster-shafer combining**

An innovative approach that integrates path loss algorithms with non-Bayesian data fusion based on DST. In this approach, belief masses are assigned to different positions within the localization area based on RSS signals from anchor nodes and the likelihood of the target node's presence at these positions.

The Log-Distance Path Loss Shadowing (LDPLS) model, which models RSS noise as a Gaussian distribution, is used to compute these probabilities. Additionally, the Design Rule (DR) is employed as a decision-making framework to iteratively combine information, thereby enhancing the overall believability of the localization estimate.

[1] Kasebzadeh, G.-S. Granados, and E. S. Lohan, "Indoor localization via wlan path-loss models and dempster-shafer combining," pp. 1–6, 2014.

2.2 Related Work

[2] A Soft Range Limited K-Nearest Neighbors Algorithm for Indoor Localization Enhancement.

The SRL-KNN algorithm [23] addresses the challenge of limited mobility indoors by incorporating a penalty function that accounts for the physical distance between a user's current and previous positions when calculating fingerprint distances. This method effectively reduces spatial ambiguity and improves performance.

[2] M. T. Hoang *et al.*, "A Soft Range Limited K-Nearest Neighbors Algorithm for Indoor Localization Enhancement," in *IEEE Sensors Journal*, vol. 18, no. 24, pp. 10208-10216, 15 Dec.15, 2018

2.3 Related Work

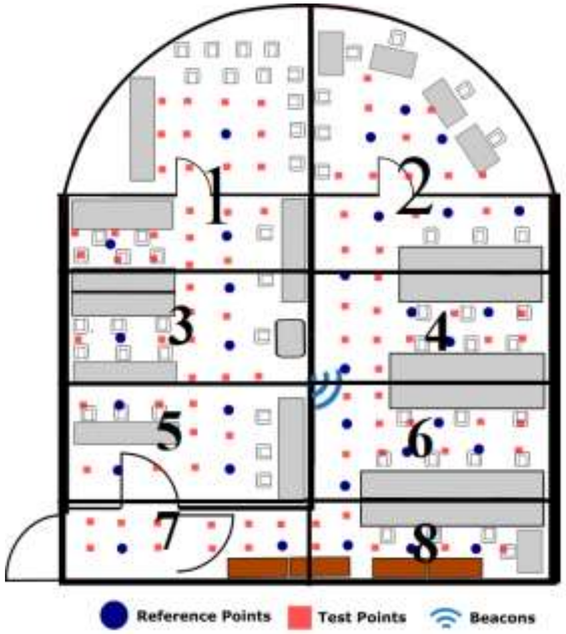
[3] A Low-Cost and Efficient Spatial-Temporal Model for Indoor Localization “H-LSTMF”

The H-LSMTF approach improves localization accuracy by removing outliers from the training data to reduce output fluctuations caused by noise. It then uses locally weighted regression (LWR) to further reduce uncertainty and integrate an encoder LSTM-encoder model. Evaluation of two datasets—one in a 10m x 5m room (Dataset I) and another in a 35m x 16m laboratory (Dataset II)—showed improvements in localization accuracy of 20% and 60% for Dataset I and Dataset II, respectively, compared to existing state-of-the-art algorithms.

[3] R. Kumar, S. Singh and V. K. Chaurasiya, "A Low-Cost and Efficient Spatial-Temporal Model for Indoor Localization “H-LSTMF”," in *IEEE Sensors Journal*, vol. 23, no. 6, pp. 6117-6128, 15 March15, 2023

3 Data Collection of a Single Access Point

- The dataset was recorded in the CoRDIoT Lab at IIIT Allahabad. It is a complex space with furniture, equipment, and computers.
- The dataset was recorded in two ways as Reference points and Test points in four directions (RIGHT, LEFT, UP and DOWN)
- **Reference points**: 32 points for 2 minutes each.
- **Test points:** 90 points for 1 minute each.



[1] Datasets for Indoor Positioning with Single-AP Wi-Fi Fingerprinting: CEUR Workshop Proceeding

4 Dempster-Shafer Theory

Dempster (1967) developed a method to combine the degree of beliefs derived from independent items of evidence. Later, **Glenn Shafer (1976)** developed a method for obtaining degrees of belief for one question from subjective probabilities for related questions. It is an evidence theory and combines all possible outcomes of a problem.

Uncertainty in this model:

1) Consider all possible outcomes
2) Belief will lead to belief in some possibility by bringing out some evidence.
3) Plausibility will make evidence compatible with possible outcomes.

https://bennycheung.github.io/dempster-shafer-theory-for-classification

4.1 Dempster-Shafer Theory

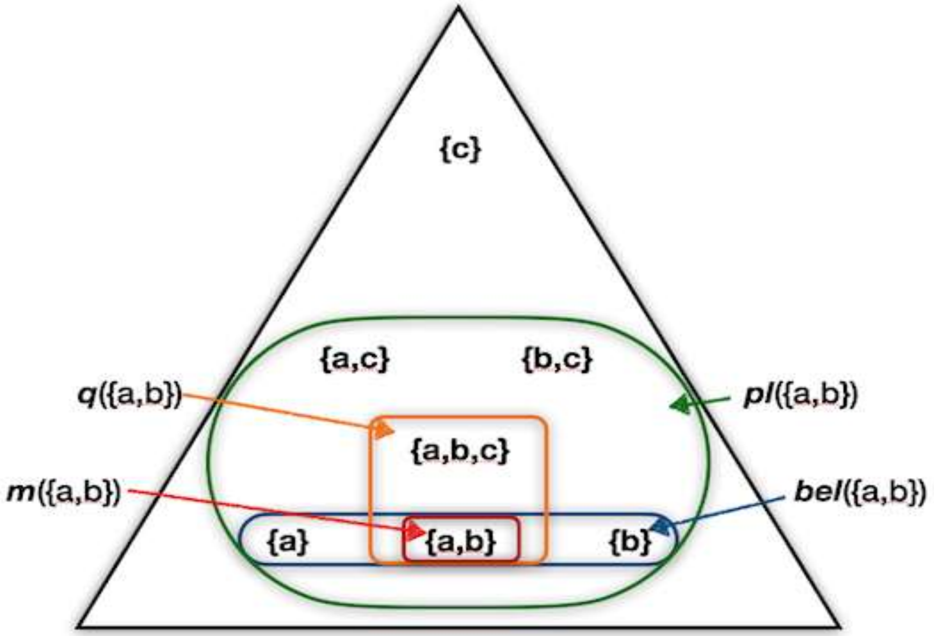


Figure. *Illustration of different belief function representations. In this example, the frame of discernment Θ consists of three elements: a, b and c. The triangle contains all subsets of Θ except for ∅. The indicated sets correspond to the mass of the different belief representations* **m, bel, pl** *and* **q** *associated with the set* **{a, b}.**

- **Mass functions denoted by m:** A mass function, also known as a basic belief assignment, is a fundamental way to represent beliefs in Dempster-Shafer's theory. A mass function m maps subsets A of the frame of discernment U to values between 0 and 1. The value m(A) indicates the amount of belief committed to the hypothesis A. All other belief representations can be derived from this foundational concept.

- **Belief functions denoted by bel:** The total belief committed to hypothesis A and its subsets is denoted by bel(A). This function, bel: $P(U)\rightarrow[0,1]$, is called a belief function and can be derived directly from a mass function m. It is often interpreted as defining a "lower bound" for an unknown probability function P.

- **Plausibility functions denoted by pl:** The plausibility pl(A) measures the belief not committed to the complement ¬A, indicating how much belief supports hypothesis A. While the belief function bel(A) serves as a lower bound for an unknown probability P, and plausibility can be viewed as an upper bound.

- **Commonality functions denoted by q**: The commonality q(A) indicates the total mass committed to hypothesis A and all its supersets, reflecting how much mass potentially supports the entire set.

https://bennycheung.github.io/dempster-shafer-theory-for-classification

4.2 Dempster's Rule of Combination

To solve inference problems, we must meaningfully combine belief functions representing different pieces of evidence. Combination rules are a key component of Dempster-Shafer's (D-S) evidence theory, allowing us to fuse individual belief functions into a single representation of all available evidence.

The joint mass is calculated from two sets of masses, m1m_1m1 and m2m_2m2, to achieve this integration:

$$m_{1,2}(\emptyset) = 0$$

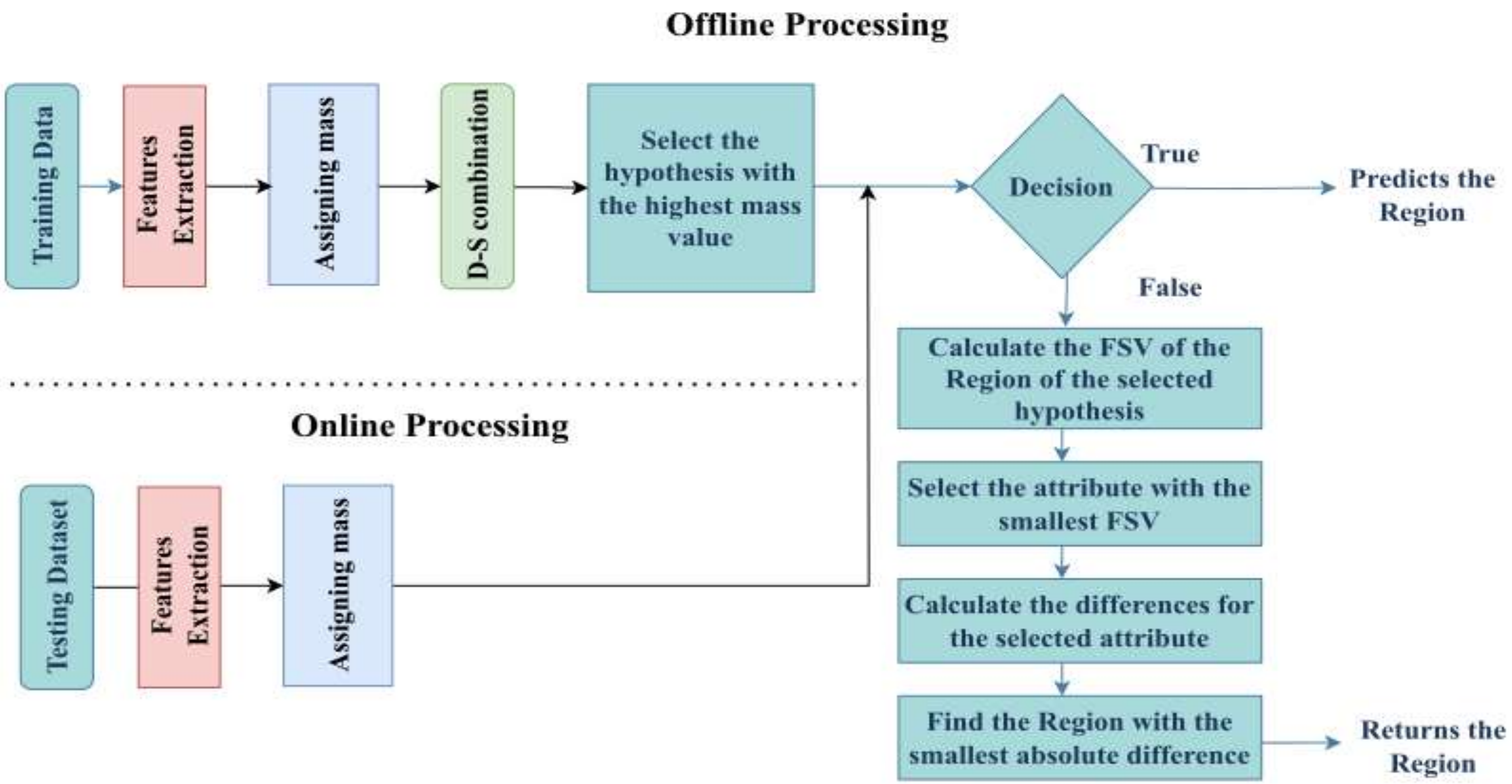
$$m_{1,2}(A) = (m_1 \oplus m_2)(A) = \frac{1}{1-K} \sum_{B \cap C = A \neq \emptyset} m_1(B) m_2(C)$$

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C)$$

K is a measure of the amount of conflict between the two mass sets.

https://bennycheung.github.io/dempster-shafer-theory-for-classification

5 Proposed Algorithm



5.1 Results

TABLE I: Performance (Accuracy) of different approaches in single feature and multiple feature values of RSSI Datasets

Dataset	Features	Proposed-DST	H-LSTMF	Decision Tree	Random Forest	XGBoost
ESP32 Dataset	5	**0.35**	0.26	0.23	0.23	0.17
Smartphone Dataset	5	**0.34**	0.28	0.29	0.29	0.19

6 Future Work and Motivation

- This work will be extended for Three-dimensional based indoor localization. It can be used for micro drones where heavy components cannot be equipped
- Improving Accuracy through Signal Processing
- Handling Multipath Effects
- Dynamic Environments
- Integration with Other Sensing Technologies
- Practical Deployment and User Studies
- Security and Privacy Considerations

Reference

- https://www.geospatialworld.net/blogs/indoor-positioning-indoors-gps-stops-working/
- https://www.gep.com/blog/technology/guide-to-inventory-and-warehouse-management-what-why-and-how
- Kasebzadeh, G.-S. Granados, and E. S. Lohan, "Indoor localization via wlan path-loss models and dempster-shafer combining," pp. 1–6, 2014.
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Thank you!