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IMPLEMENTATION OF SMART RSSI CLUSTERING FILTER IN DUAL-BAND WI-FI INDOOR POSITIONING SYSTEM

ASIM ABDULLAH[1], OMAR ABDUL AZIZ[2,*], MUHAMMAD HARIS[3], ROZEHA A. RASHID[4], AHMAD SHAHIDAN ABDULLAH[4]

[1]Centers of Excellence in Science and Applied Technologies, H-11/4, Islamabad, Pakistan
[2]Wireless Communication Centre, Universiti Teknologi Malaysia, 81310, Johor Bahru, Johor, Malaysia
[3]Department of Computer Science and Bioinformatics, Khushal Khan Khattak University, Karak, Pakistan
[4]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310, Johor Bahru, Johor, Malaysia
*Corresponding Author: omar@utm.my

Abstract

The prospect of providing precise location-based services motivates fingerprinting exercises for indoor positioning systems (IPS). Large-scale IPS installations necessitate the use of algorithms that are quick, precise and robust. Although algorithms that are facilitated by data analytics has greater precision, incorporating them into scalable plus real-time systems is highly dependent on computation complexity. This paper presents computationally efficient Smart Received Signal Strength Indicator (RSSI) Clustering Filter or SRCF, to improve IPS's performance based on Wi-Fi fingerprinting. The proposed filter algorithm was implemented on various clustering techniques when filtering data to mitigate real-time data fluctuations. Based on performance evaluations carried out, SRCF showed computational time enhancement from 22% up to 47 %. The reduction in computation complexity corresponds to estimated localization compromise of only 10 cm and less from RSSI clustering benchmark approach in all investigated scenarios. From the analysis benchmarks, hierarchical clustering based SRCF algorithm was shown to provide best accuracy while Fuzzy C-Means clustering based SRCF algorithm demonstrated least computational time requirement. The designed algorithm could potentially improve IPS for diverse purposes including tracking of assets as well as navigation within indoor setting.

Keywords: Asset tracking, Data filtering, Indoor positioning system, Machine learning, RSSI clustering, Wi-Fi.

1. Introduction

Continuing attention given to the study of Wi-Fi-based fingerprinting [1-4] for indoor positioning systems (IPS) is driven by very promising localization performance, a wide range of applications and the ubiquity of Wi-Fi network [5]. In addition to ubiquitous wireless signal coverage for internet connectivity [6], IPS-based tracking systems are considered essential for smart industrial plants [7, 8]. Since IPS leveraging on Wi-Fi fingerprinting have an array of applications, augmenting their reliability in terms of accuracy and processing time is critical [9].

Data filtering techniques estimate the appropriate Received Signal Strength Indicator (RSSI) value across numerous instantaneous samples to offer necessary processed data to the positioning algorithm for high precision localization. Many filtering processes have been proposed in the literature for this purpose. Conventional windowed filters were proposed to improve positioning accuracy by examining unprocessed RSSI data [10]. In order to smooth data that is considered noisy, Savitzky-Golay filter has been highlighted [11].

Gaussian filtering was proposed to present RSSI data that is cleaned to improve the accuracy of IPS [12]. Isolation Forest (IF) technique targeted performance enhancement by anomaly detection-based data filtering [13]. A filter that employs RSSI Clustering (RC) and adopts clustering process with k-means could improve accuracy via better initialization of the clustering procedure [14].

Although the windowed and Savitzky-Golay filtering techniques are computationally efficient, their susceptibility to no line-of-sight (NLOS) scenarios limits the utility of the algorithms under dynamic multipath circumstances. Since the IF data filter is based on offline training, the algorithm lacks adaptability to real-time fluctuations. The Gaussian and RC filters exhibit high processing requirements, due to the computation intensive processes of matrix convolution and k-means clustering respectively.

To enable large-scale deployments, scalable and real-time data filtering algorithms that possess low computational cost, better accuracy and strong robustness must be developed. This paper addresses the highlighted gap by presenting a computationally efficient algorithm that is robust for scalable and real-time Wi-Fi fingerprinting. While aiming to improve computing efficiency, the approach reduce possible accuracy compromise, hence results in a stable IPS solution. From real-time data, the filtering algorithm efficiently determines suitable RSSI level. Clustering process for the data filter is statistics-driven to ensure computational cost reduction. The primary contributions of our work could be concisely described as:

- Introducing real-time data statistics driven clustering execution for computational enhancement.
- Design plus implementing smart clustering-based data filter algorithm to enhance IPS's performance.
- Comprehensive evaluation of various clustering algorithms for efficient implementation of data filtering.

2. Methods and Materials

To improve the efficiency of indoor positioning systems, a robust data filtering approach that minimizes computing complexity without significant accuracy degradation was developed. Details of the utilized dataset and algorithm design methodology are reported in this section.

2.1. Dataset and indoor environment

Wireless communication system operating at diverse frequency bands could complement coverage issues due to interior building structures [15]. With reduced inconsistency examined in dual-band Wi-Fi's Received Signal Strength Identifier (RSSI) data, contemporary studies have advocated relying on dual-band instead of single-band data for better precision in Wi-Fi indoor positioning [16]. The proposed algorithm in this paper was implemented and evaluated using UTMInDualSymFi dataset [17]. This dataset provides extensive dual-band Wi-Fi data at 2.4 GHz and 5 GHz, recorded in multi-buildings with LOS, NLOS and multipath settings. The UTMInDualSymFi dataset contains dual-band Wi-Fi RSSI data that were collected using two different devices. Complete dataset details and related works are provided in [18].

2.2. Smart RSSI clustering filter (SRCF)

The proposed SRCF filtering technique from this study calculates suitable RSSI based on real-time and dynamic Wi-Fi data samples. An enhanced variety of the RC filter [14] was designed to lower computational cost without accuracy degradation. The computation enhancements are primarily based on statistics driven smart clustering. The architectural schematic of proposed IPS integrated with SRCF is illustrated in Fig. 1.

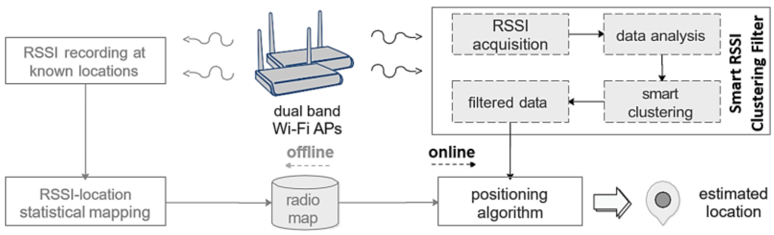


Fig. 1. Schematic architecture of proposed indoor positioning system integrated with SRCF.

In the offline phase from Fig. 1, k-means clustering implements cluster initialization based on quantile estimation of sample windows containing equal number of dual-band Wi-Fi RSSI samples to form the radio map. The indoor environment is divided into labelled sub-areas defined by locations having common three strongest Wi-Fi Access Points (APs) measurement data. Whereas, in the online phase, SRCF clusters raw RSSI data based on real-time statistics, and provides the positioning algorithm with filtered data. The positioning algorithm completes the localization using filtered data and the radio map. SRCF estimates the appropriate RSSI level ρ_i (in dBm) from η consecutive samples. Considering a total of n_{ap} APs, the input vector r_i for SRCF is defined in Eq. (1),

$$r_i = \{r_{1,i}\ r_{2,i}\ \dots\ r_{\eta,i}\}^{\mathrm{T}} \tag{1}$$

where, $r_{a,b}$ is the a-th RSSI (dBm) sample from the b-th AP, $1 \le a \le \eta$, $1 \le b \le n_{ap}$. As suggested in [16], $10 \le \eta \le 60$, and in this study $\eta = 10$. Firstly, the data within $\mathbf{r_i}$ is sorted to form $\mathbf{s_i}$. Then the standard deviation is measured as in Eq. (2),

$$\sigma_i = \sqrt{\sum_{p=1}^{\eta}\left(r_{p,i} - \mu_i\right)^2 \Big/ \eta} \qquad 1 \le i \le n_{ap} \tag{2}$$

where $\mu_i = 1/\eta \sum_{p=1}^{\eta} r_{p,i}$; $1 \le i \le n_{ap}$. Since clustering is computationally intensive, two parameters are introduced namely ϵ_l and ϵ_h ; $\epsilon_l < \epsilon_h$, which SRCF smartly control for clustering execution. If the calculated standard deviation is lower than ϵ_l, SRCF's output filter is simplified to only be the mean. The condition signifies low RSSI variations, in which mean filtering is accurate and efficient. If σ_i is higher than ϵ_h, it indicates very high RSSI variations and outliers. Under such conditions clustering accuracy degrades and therefore it is not executed.

Alternatively, SRCF output is declared as mean of ω ($\omega = 4$, in this work) samples within $\mathbf{s_i}$, as an efficient outlier removal approach. The k-means clustering ($k = 3$) as in [14], is executed when σ_i lies between the two control parameters (ϵ_l, ϵ_h). Three cluster centres are initialized with the lowest, highest, and average values of $\mathbf{r_i}$. The clustering algorithm outputs three final cluster centres, $\mathbf{c_i}$, and the middle one is declared as SRCF output. The SRCF algorithm is designed to be readily implementable with various clustering techniques other than k-means [19] such as k-medoids [20], fuzzy c-Means (FCM) [21], hierarchical [22], and spectral clustering [23].

Hierarchical clustering creates a dendrogram to visualize nested clusters, which is appropriate for small datasets [24, 25]. Spectral clustering is effective in handling complex shapes and graph-structured data with dimensionality reduction but is computationally expensive owing to eigenvalue decomposition [23, 26]. FCM allows for soft, elastic clustering by giving membership degrees to points, but it is potentially initialization-sensitive [27, 28]. K-medoids is outlier and noise resilient with the employment of real data points as centres but is more computationally expensive compared to k-means [29]. Each algorithm is better suited for some data and clustering requirements than the other.

In Eq. (3), the SRCF output under parametric circumstances is defined as,

$$\rho_i = \begin{cases} \frac{1}{\eta}\sum \mathbf{r_i} & \sigma_i < \epsilon_l \\ \frac{1}{\omega}\sum_{p=c_a}^{c_a+\omega} \mathbf{s_i}(p) & \sigma_i < \epsilon_l \quad c_s + \omega < \eta \\ \mathbf{c_i}(2) & otherwise \end{cases} \tag{3}$$

where $c_s = \lfloor 0.5(\eta - \lfloor 0.5\,\omega \rfloor) \rfloor$. The pseudocode for implementing the SRCF algorithm with k-means clustering is presented in Algorithm 1 below.

Algorithm 1 SRCF algorithm pseudocode

Require: $k = 3$, $n_{ap} > 0$, $0 < \epsilon_l < \epsilon_h$, $10 \le \eta \le 60$

while $i = 1$ *to* n_{ap} **do**

$\mathbf{r_i} = \{r_{1,i}, r_{2,i}, \dots, r_{\eta,i}\}^T$

  $\mathbf{s_i} \leftarrow \mathrm{sort}(\mathbf{r_i})$

$\sigma_i \leftarrow \sqrt{\frac{1}{\eta}\sum_{p=1}^{\eta}\left(r_{p,i} - \mu_i\right)^2}$
if $\sigma_i < \epsilon_l$ **then**
  $\rho_i \leftarrow \frac{1}{\eta}\sum \mathbf{r_i}$
else
  if $\sigma_i > \epsilon_h$ **then**
    $c_s \leftarrow \lfloor 0.5(\eta - 2) \rfloor$
    $\rho_i \leftarrow \frac{1}{4}\sum_{p=c_s}^{c_s+3} \mathbf{s_i}[p]$
  else
    $\mathbf{c_{en}} \leftarrow \{\min(\mathbf{r_i}), \text{mean}(\mathbf{r_i}), \max(\mathbf{r_i})\}$
    $\mathbf{c_i} \leftarrow \text{kmeans}(\mathbf{r_i}, k, \mathbf{c_{en}})$
    $\triangleright$ *d* (k-means with k clusters, $\mathbf{c_{en}}$–initial cluster centres)
    $\rho_i \leftarrow \mathbf{c_i}[2]$
  endif
endif
endwhile

3. Results and Discussion

The performance evaluations of the proposed data filtering algorithm are described in this section. The SRCF data filter was implemented in multiple versions, with each leveraging k-means, k-medoids, FCM, hierarchical, and spectral clustering. For comparative analysis, the same clustering techniques were incorporated in multiple versions of the RC filter [14]. The performance of SRCF was evaluated based on location errors (meters) at the 75th percentile as well as execution time (seconds) averaged over 100 repetitions. The 75th percentile was selected based on comparison metrics adopted by many indoor navigation recent works and competitions [30-32].

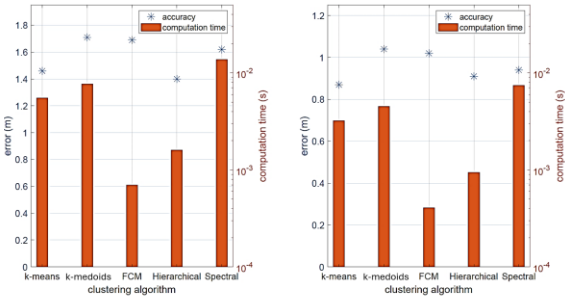
3.1. Benchmark positioning algorithm

The SRCF needs to be executed together with a standard IPS algorithm. Hence, k-Nearest Neighbors (kNN)-based IPS algorithm [33] that has been commonly benchmarked in IPS's fingerprinting [30, 34] was implemented along with the SRCF algorithm. It should be noted that the UTMInDualSymFi dataset was also benchmarked pertaining to accuracy with the kNN algorithm for various values of (k = 3, 4, 5, 6, 7, 8). The reported accuracy results for all values of k were calculated by averaging errors at the 75th percentile.

3.2. Performance baseline of RC filtering

Firstly, the performance baselines were established by evaluation of RC filtering algorithm as in [14]. The RC filtering algorithm is chosen as the baseline due to its good performance in indoor scenario with strong accuracy [35, 36]. The RC data filter performs clustering with k-means and its accuracy and computational cost were adopted as the performance baseline. The results of RC filtering implemented along with kNN positioning are reported for two multi-floor buildings as per the dataset, namely block CX1 and F04, as shown in Fig. 2. In terms of accuracy, RC filtering with k-means and hierarchical clustering showed the best performance across buildings. The accuracy in building F04 was comparable for both clustering techniques, whereas in building CX1, hierarchical performance performed around

2.5% better than k-means. FCM and k-medoids clustering provided the lowest accuracy at 5-6% below the k-means benchmark.



(a) CX1 **(b) F04**

Fig. 2. Accuracy and computation time of RC filtering based on various clustering techniques in building (a) CX1 and (b) F04

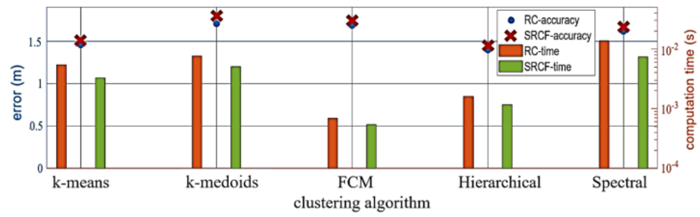
On the other hand, FCM and hierarchical clustering provided around 20% and 25% computational enhancement respectively, in comparison to k-means. The k-medoids and spectral clustering increased the computational cost roughly by 18% and 130% respectively as compared to the k-means baseline. Overall, the hierarchical clustering provided computational improvement over k-means in addition to providing high accuracy performance.

3.3. Performance evaluation of SRCF algorithm

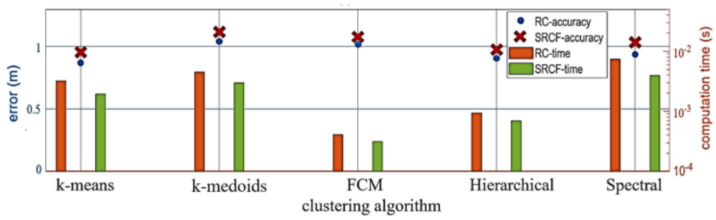
The proposed SRCF algorithm was implemented in multiple versions, each corresponding to the k-means, k-medoids, FCM, hierarchical and spectral clustering implementation. The performance evaluation results of SRCF and kNN localization are reported in Fig. 3. The reported results demonstrates that SRCF provided computational improvement for all clustering techniques across block CX1 and F04 buildings.

The extent of computation enhancement in addition to subsequent accuracy compromise, is ascertained by results reported in Table 1. Across buildings and clustering techniques, the accuracy compromise with SRCF was limited to 10 cm, in comparison to the RC filtering baseline. The accuracy degradation is not absolute and refers to the difference in 75th percentile of errors.

When implemented in SRCF, FCM and hierarchical clustering exhibited from 22% to near 27% computational improvement respectively relative to RC filtering. Since k-means, k-medoids, and spectral clustering are naturally computation-intensive in comparison to FCM and hierarchical techniques, computational time improvements exceeding 40% were exhibited when applying SRCF filter. The results show that SRCF could significantly decrease the computational cost of the computation-expensive clustering approaches examined. Additionally, the results also indicate that FCM clustering based SRCF performed the best pertaining to computation time performance while hierarchical clustering based SRCF performed the best in terms of accurate positioning.



(a) CX1



(b) F04

Fig. 3. Accuracy and computation time of filtering algorithms based on various clustering techniques in building (a) CX1 (b) F04.

Table 1. Accuracy and computational evaluation of SRCF. All reported results are in comparison to RC filtering.

Clustering algorithm	Block CX1 Computation enhancement (%)	Block CX1 Increased error (m)	Block F04 Computation enhancement (%)	Block F04 Increased error (m)
k-means	40.2	0.06	40.6	0.09
k-medoids	44.3	0.10	43.8	0.08
FCM	22.3	0.03	22.7	0.04
Hierarchical	26.7	0.05	26.9	0.07
Spectral	46.3	0.05	47.1	0.10

4. Conclusions

For an IPS, data filtering techniques facilitates positioning algorithm to match RSSI values with precise localization. This paper proposes SRCF algorithm for Wi-Fi fingerprinting-based IPS that could minimize computing complexity while maintaining localization accuracy. The proposed SRCF algorithm was assessed using dual-band Wi-Fi data and different positioning devices inside multi-building setups data, implemented to k-means, k-medoids, FCM, hierarchical as well as spectral clustering techniques. It has been demonstrated that SRCF successfully achieved accurate real-time RSSI estimation for the investigated scenarios with strong computational time improvement from 22.3% up to 47.1% across evaluation scenarios and clustering technique implementations. The reduction in computing complexity corresponds to compromise in localization estimation accuracy of only 10 cm or less based on the benchmarked RSSI clustering performance.

From the performed analysis, the hierarchical clustering based SRCF algorithm showed the highest precision accuracy. On the other hand, FCM clustering based SRCF algorithm demonstrated the lowest computational cost. With the presented results, the SRCF algorithm has been shown to offer potential solution in reducing the computational cost of IPS that can be applied for tracking of assets and inbuilding navigation. Prospective associated study would involve optimizing the handpick of algorithmic factors to permit smooth deployment across different datasets.

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Nomenclatures

k	k-means clustering value
n_{ap}	Number of AP
r_i	Input vector

Greek Symbols

μ_i	RSSI mean value
σ_i	Standard deviation
ϵ_h	High threshold of standard deviation
ϵ_l	Low threshold of standard deviation
η	Consecutive received samples
ω	Four central RSSI received samples
ρ_i	RSSI value

Abbreviations

AP	Access Point
FCM	Fuzzy c-means
IPS	Indoor Positioning System
kNN	k-Nearest Neighbours
NLOS	None line-of-sight
RC	RSSI clustering
RSSI	Received Signal Strength Identifier
SRCF	Smart RSSI clustering filter

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