Neural Network with Plural Voting for Wi-Fi Fingerprinting-based Indoor Localization Algorithm

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SURF 2018 4th meeting

Outline

1. Previous research
   - Method
   - Limitations
2. Proposed Wi-Fi Fingerprinting System
   - System architecture
   - Data collection and features extraction
   - Structure of the proposed neural networks and training
3. Performance evalution
   - Simulation
   - Experimentation

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- Collect Receiver Signal Strength Indicator (RSSI) to construct a radio map.

Previous research

Method

- Collect Receiver Signal Strength Indicator (RSSI) to construct a radio map.
- Use Support Vector Machine (SVM) and Multi-Class SVM (MCSVM) to extract best features.

Previous research
Method

- Collect Receiver Signal Strength Indicator (RSSI) to construct a radio map.
- Use Support Vector Machine (SVM) and Multi-Class SVM (MCSVM) to extract best features.
- Use K-Nearest Neighbor (KNN) to find the best matching point from radio map.

Previous research

Limitations

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- The significant variation of RSSIs degrade the performance of KNN method.

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- Didn't perform generalization very well (radio map).

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New features

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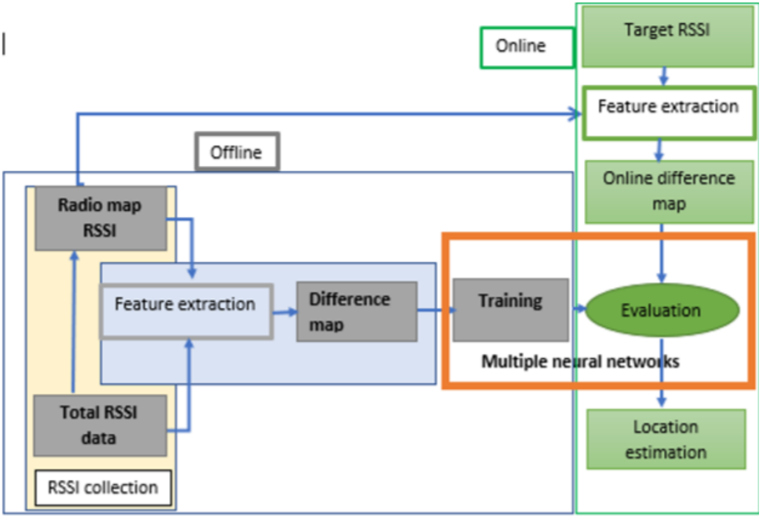
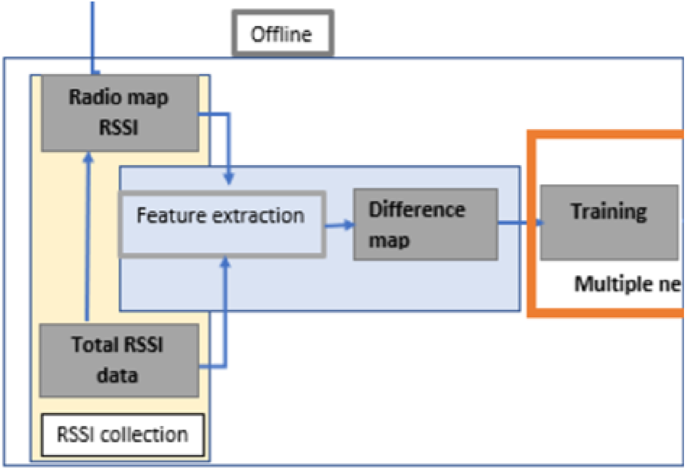
New features

- Not only focus on single neural network but apply **multiple neural networks** with plural voting based Wi-Fi ngerprint algorithm
- Extract novel feature to construct a reliable feature map (**difference map**)

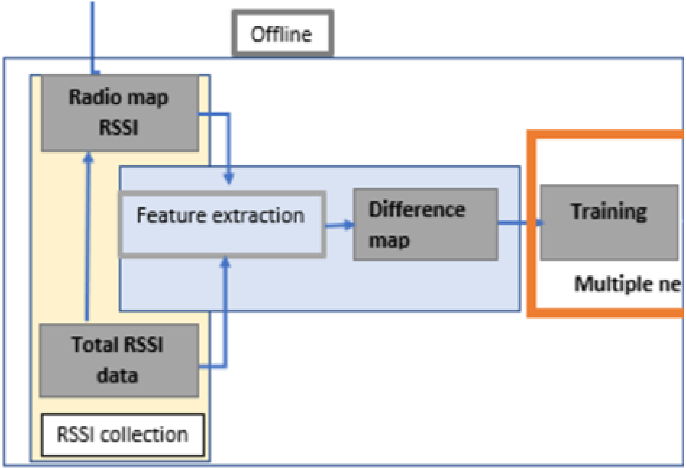
System architecture





Offline
Radio map RSSI
Feature extraction
Difference map
Training
Multiple ne
Total RSSI data
RSSI collection

System architecture
Offline phase



- **RSSI data collection**

System architecture

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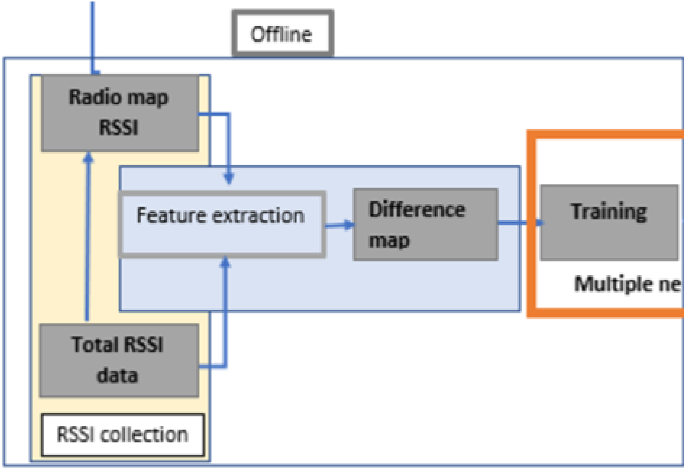
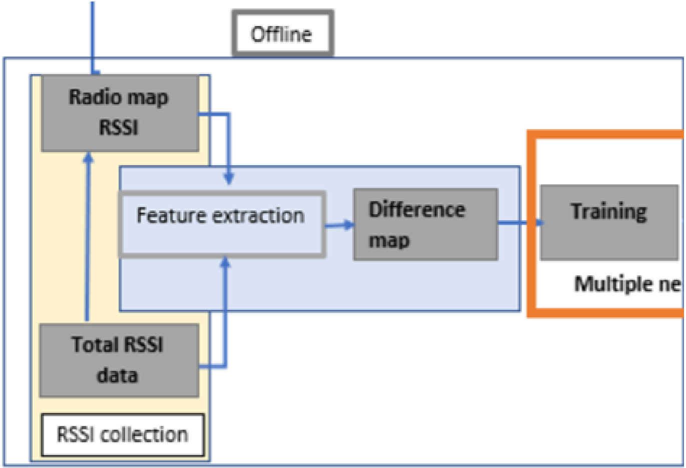


- **RSSI data collection**
- **Feature extraction**

System architecture

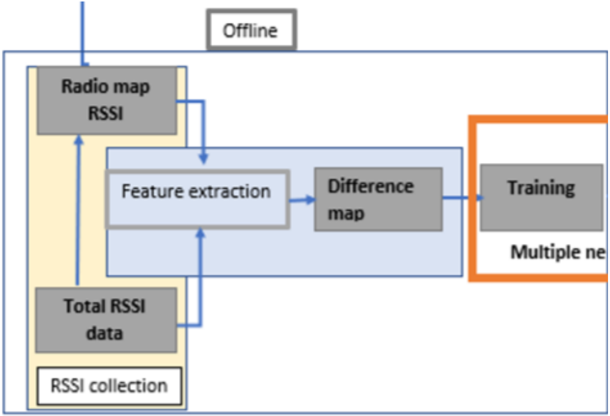
Offline phase



- RSSI data collection
- Feature extraction
- Training

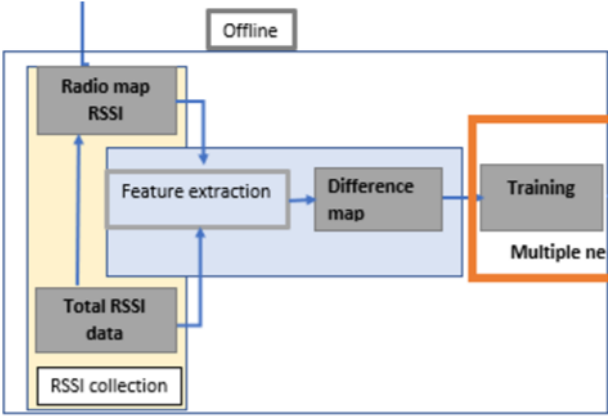
Offline phase

RSSI data collection



Offline phase

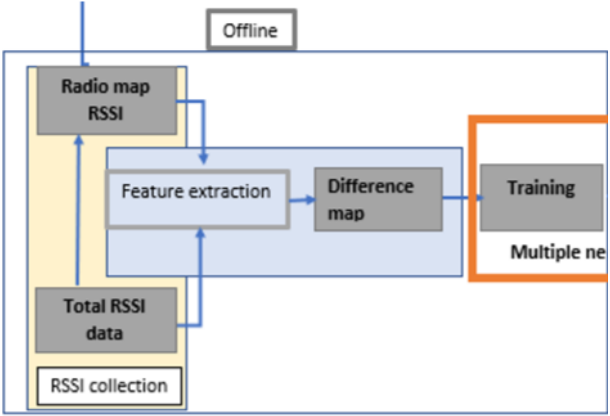
RSSI data collection



- Each Reference Point (RP) needs multiple-scan and saved as **Total RSSI Data**

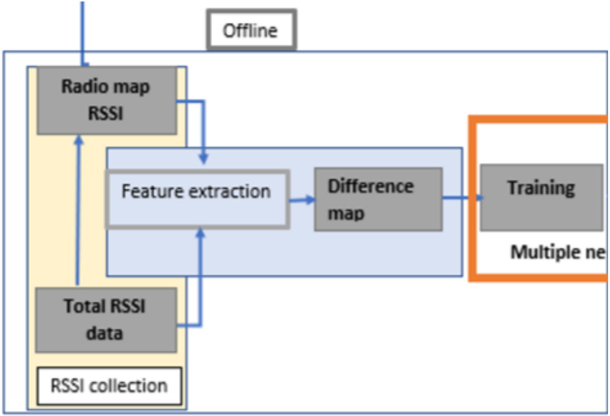
Offline phase

RSSI data collection



- Each Reference Point (RP) needs multiple-scan and saved as **Total RSSI Data**
- Use first record to construct **Radio Map RSSI**

Offline phase
Feature extraction



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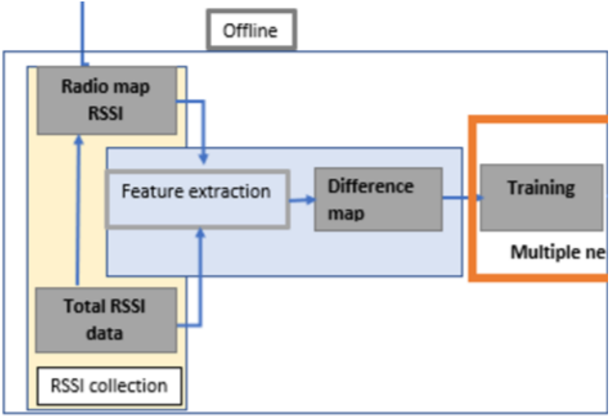
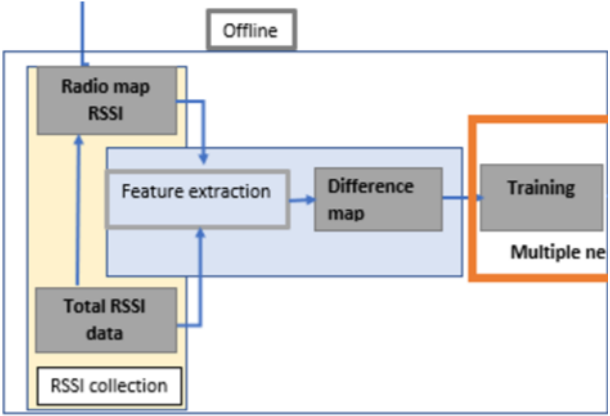
Feature extraction



- Take absolute value of the difference of each AP's RSSIs in **Total RSSI Data** and **Radio Map RSSI**

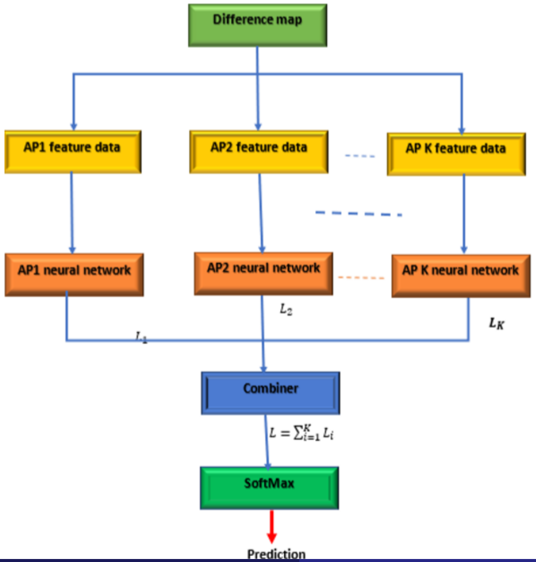
Offline phase
Feature extraction



- Take absolute value of the difference of each AP's RSSIs in **Total RSSI Data** and **Radio Map RSSI**
- Build a feature map database (**difference map**)

Offline phase

Training



Offline phase
Training

- Split the **difference map**'s data according to different APs and used as inputs for each independent neural network

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- Split the **difference map**'s data according to different APs and used as inputs for each independent neural network
- Combine the last layer's output and pass through **SoftMax Function**

Online phase

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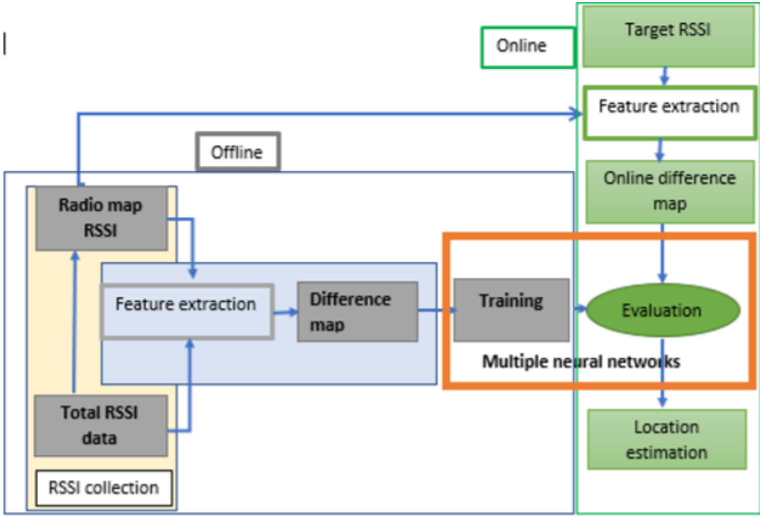
Data collection and features extraction

A typical scenario:

Parameters	Meaning
K	number of APs
R	number of RPs
N	measure N samples at each RP

System architecture



Data collection and features extraction

Total RSSI Data: $A \in \mathbb{R}^{NR \times (K+1)}$

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$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1(K+1)} \\ a_{21} & a_{22} & \cdots & a_{2(K+1)} \\ \vdots & \vdots & \ddots & \vdots \\ a_{R1} & a_{R2} & \cdots & a_{RK} \\ a_{(R+1)1} & a_{(R+1)2} & \cdots & a_{(R+1)(K+1)} \\ a_{(R+2)1} & a_{(R+2)2} & \cdots & a_{(R+2)(K+1)} \\ \vdots & \vdots & \ddots & \vdots \\ a_{(NR)1} & a_{(NR)2} & \cdots & a_{(NR)(K+1)} \end{bmatrix}$$

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- Column 1 to k represents different APs

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- Column k+1 represents the MAC address for each AP

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- Column 1 to k represents different APs
- Column k+1 represents the MAC address for each AP
- Row number (1 to NR) represents different samples at different RPs

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Data collection and features extraction

Radio Map RSSI: $B \in \mathbb{R}^{R\times(K+1)}$

(The first part of **A**)

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Data collection and features extraction

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Dimensions	Meaning
1	number of APs (neural networks)
2	data size
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Aim at transform RSSI data into independent input data for each neural network.

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Data collection and features extraction

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Algorithm 1: Difference map construction

---

create $D[K, (NR), R]$
n = length of A
K = number of AP in B
for $i = 0$ to $n - 1$ **do**
  $C = |A[i,:] - B|^T$
  for $j = 0$ to $K - 1$ **do**
    concatenate$C[j,:]$ to $D[j]$
  end for
end for
$returnD$

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- The column k+1 (MAC address) will be concatenated on D(i) at last.

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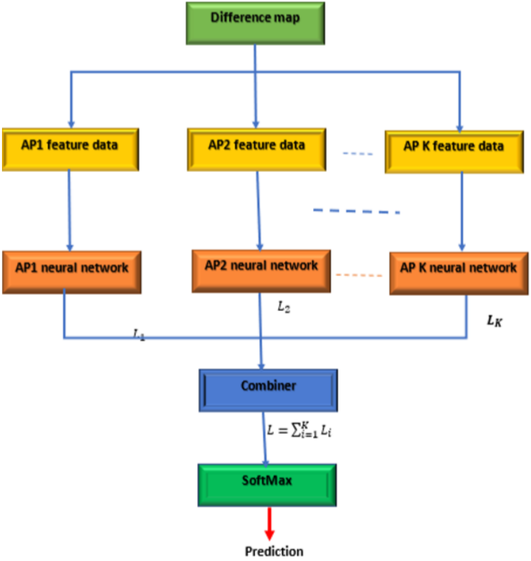
Outline

Structure of the proposed neural networks and training



$$
\begin{aligned}
L_k &= {W^T}_{k,n} * h_{k,n} \\
L &= \sum_{k=1}^{K} L_k
\end{aligned}
\tag{1}
$$

Parameters	Meaning
$h_{k,n}$	output of the last hidden layer of the k^{th} network
$W_{k,n}$	associated weights for its output layer
L_k	output for each independent network
L	element-wise summation of the outputs

The prediction probability for each reference point RP_i :

$$p_i = \frac{e^{L(i)}}{\sum_{i=1}^{r} e^{L(i)}}$$

Structure of the proposed neural networks and training

In online phase

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- Apply Algorithm 1 to a new measured RSSI

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- Restore the model to predict the probable positions

Structure of the proposed neural networks and training

In online phase

- Apply Algorithm 1 to a new measured RSSI
- Restore the model to predict the probable positions
- Apply the following function where $pi \geq 0.2$ and $k \leq 3$

$$T(x_t, y_t) = \frac{\sum_{i=1}^{k} p_i * RP(x_i, y_i)}{\sum_{i=1}^{k} p_i}$$

Parameters	Meaning
$T(x_t, y_t)$	position of test point
$RP(x_i, y_i)$	$i^{th} mostprobableRPforatestpoint$
p_i	prediction probability for RP_i

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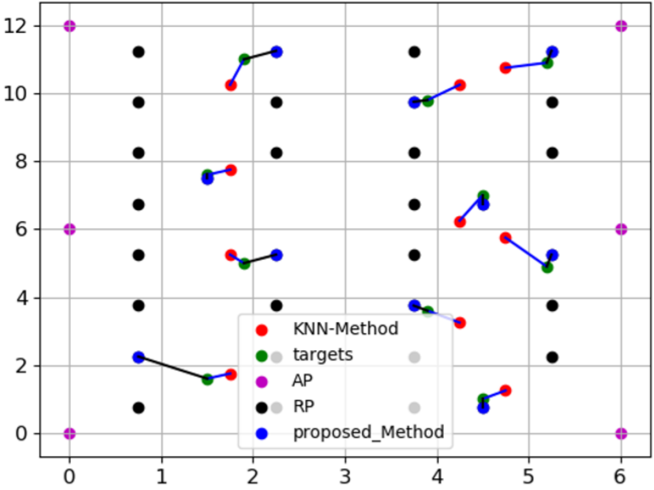
Performance evaluation
Simulation results



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Performance evaluation
Experimentation results

Model	Root Mean Square Error(RMSE) in meter(m)
Scenario1 (proposed method)	5.001
Scenario2 (proposed method)	0.960
Scenario1 (KNN method)	7.28
Scenario2 (KNN method)	10.92

Fig.: Using corridor dataset

Model	Root Mean Square Error(RMSE)
Scenario1 (proposed method)	1.74
Scenario2 (proposed method)	0.907
Scenario1 (KNN method)	2.38
Scenario2 (KNN method)	2.09

Fig.: In Office environment

Thanks for listening!
Any questions?