A Weighted Kernel-based Hierarchical Classification Method for Zoning of Sensors in Indoor Wireless Networks

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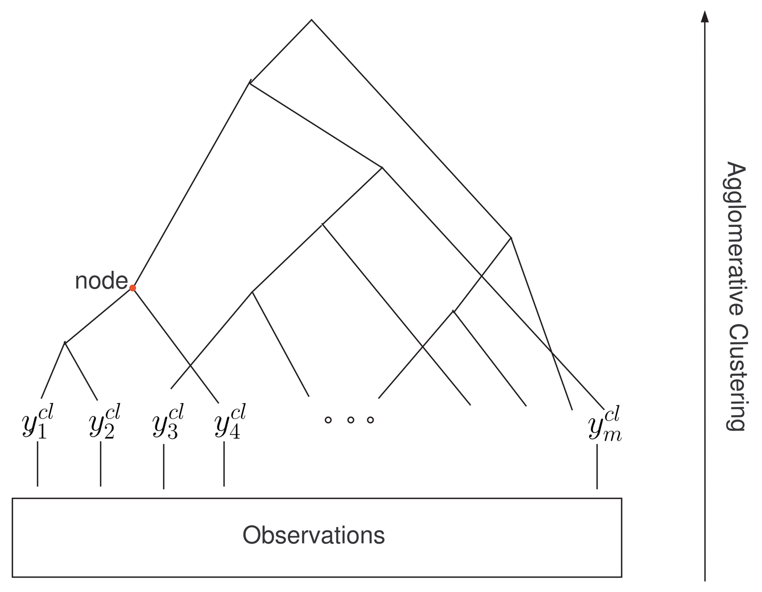
Abstract

This work presents a solution for localization of sensors by zoning, in indoor wireless networks. The problem is tackled by a classification technique, where the objective is to classify the zone of the mobile sensor for any observation. The kernel density estimation is used first to model the features observations. The algorithm then uses hierarchical clustering and similarity divergence to create a two-level hierarchy. At each level of the hierarchy, a feature selection technique is carried to optimize the misclassification rate and feature redundancy.

Classification method

Problem statement

- $y_j^{cl}, j \in \{1, \ldots, m\}$, are m competing classes;
- $F = \{f_1, \ldots, f_p\}$ is a set of p features;
- $\mathbf{x}_{j,r} = (x_{j,1,r}, \ldots, x_{j,p,r}), r \in \{1, \ldots, \ell_j\}$, are offline training observations taken in y_j^{cl}, with respect to F;
- $\bar{\mathbf{x}} = (\bar{x}_1, \ldots, \bar{x}_p)$ is a new observation.
- The aim is to find a function $\mathbf{h} : \mathbb{R}^p \rightarrow [0,1]^m$, such that $\mathbf{h}(\bar{\mathbf{x}}) = (\mathcal{C}f(y_1^{cl}), \ldots, \mathcal{C}f(y_m^{cl}))$.
- $\mathcal{C}f(y_j^{cl})$ is the level of confidence assigned to y_j^{cl}.



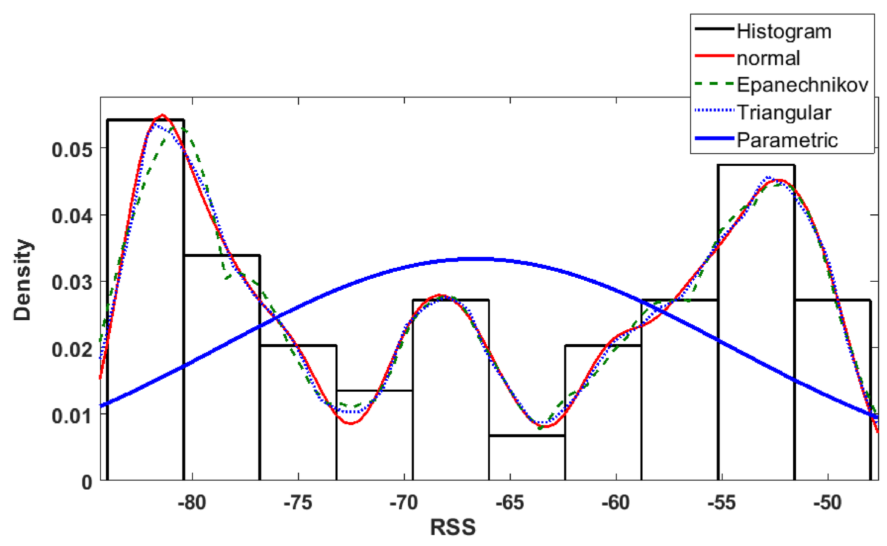
Kernel density estimate

- The KDE in the multivariate case is defined as,

$$Q_j(\tilde{\mathbf{x}}) = \frac{1}{\ell_j} \sum_{r=1}^{\ell_j} \frac{1}{h_1 \ldots h_p} \prod_{k=1}^{p} \mathcal{K}\left(\frac{\tilde{x}_k - x_{j,k,r}}{h_k}\right).$$

- The bandwidth h_k is equal to $\arg\max_{h_k} ML(h_k)$, such that $ML(h_k)$ is defined as,

$$ML(h_k) = \ell_j^{-1} \sum_{r=1}^{\ell_j} \log\left[\sum_{r' \neq r} \mathcal{K}\left(\frac{x_{j,k,r'} - x_{j,k,r}}{h_k}\right)\right] - \log[(\ell_j - 1) h_k].$$

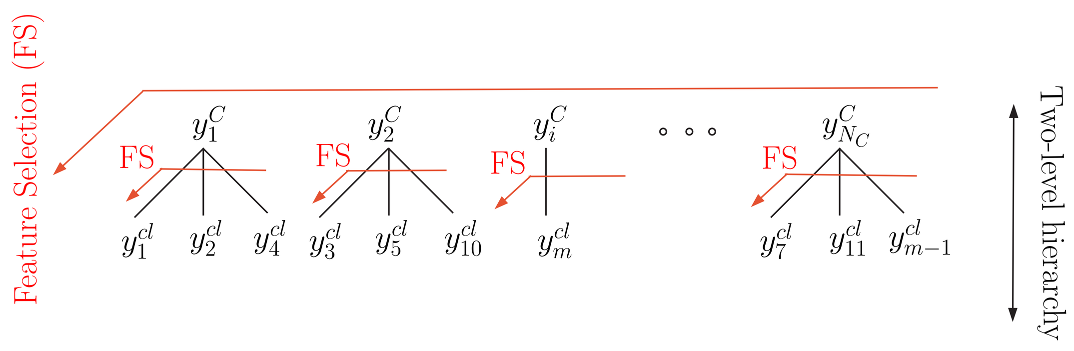


Clustering

- Reducing the number of classes to be classified.
- Merging classes using a hierarchical technique.
- Using similarity measure for this aim.
- The Kullback-Leibler divergence is defined by,

$$D_{KL}(Q_j || Q_{j'}) = \int_{\mathbf{x}} \log\left(\frac{Q_j(\mathbf{x})}{Q_{j'}(\mathbf{x})}\right) Q_j(\mathbf{x}) d\mathbf{x}$$
$$\approx \frac{1}{\ell_j} \sum_{r=1}^{\ell_j} \log Q_j(\mathbf{x}_{j,r}) - \log Q_{j'}(\mathbf{x}_{j,r}).$$

- Reformation of dendrogram into a two-level hierarchy.
- Classification of clusters then classes in each cluster.



Feature selection technique

The feature selection technique aims at determining the best subset of features.

Discriminative capacity

- The discriminative capacity of a subset $F' \subseteq F$ is defined as,

$$DisC(F') = \sum_{u=1}^{m} \sum_{v=1}^{m} D_{KL}(Q_{F',u} || Q_{F',v}).$$

- The error associated to F' is thus,

$$\mathcal{E}(F') = 2^{-DisC(F')}.$$

Redundancy

- The coefficient of multiple correlation of a feature f_k is defined as,

$$R_k^2 = c_k^T R_{xx,k}^{-1} c_k.$$

- The redundancy associated to F' is

$$\mathcal{R}(F') = \frac{\sum_k (R_k)}{|F'|}.$$

$$g_k(F_k^{(\ell)}) = \alpha \frac{\mathcal{E}(F_{k-1}) - \mathcal{E}(F_k^{(\ell)})}{\max(\mathcal{E}(F_{k-1}), \mathcal{E}(F_k^{(\ell)}))} + (1-\alpha) \frac{\mathcal{R}(F_{k-1}) - \mathcal{R}(F_k^{(\ell)})}{\max(\mathcal{R}(F_{k-1}), \mathcal{R}(F_k^{(\ell)}))}.$$

Weighted decisions using belief functions

- $2^Y = \{\emptyset, \{y_1\}, \ldots, Y\}$ is the set of all subsets of Y, y being a cluster or a class.
- All observations related to $A \in 2^Y$ are represented by Q_A.
- Having an observation $\bar{\mathbf{x}}$, a mass is assigned to each subset A,

$$m(A) = \frac{Q_A(\bar{\mathbf{x}})}{\sum_{A' \in 2^Y} Q_{A'}(\bar{\mathbf{x}})}, \quad A \in 2^Y.$$

- For decision making, the pignistic transformation is used,

$$BetP(A) = \sum_{A \subseteq A'} \frac{m(A')}{|A'|}.$$

- The pignistic levels of classes and clusters are combined as follows,

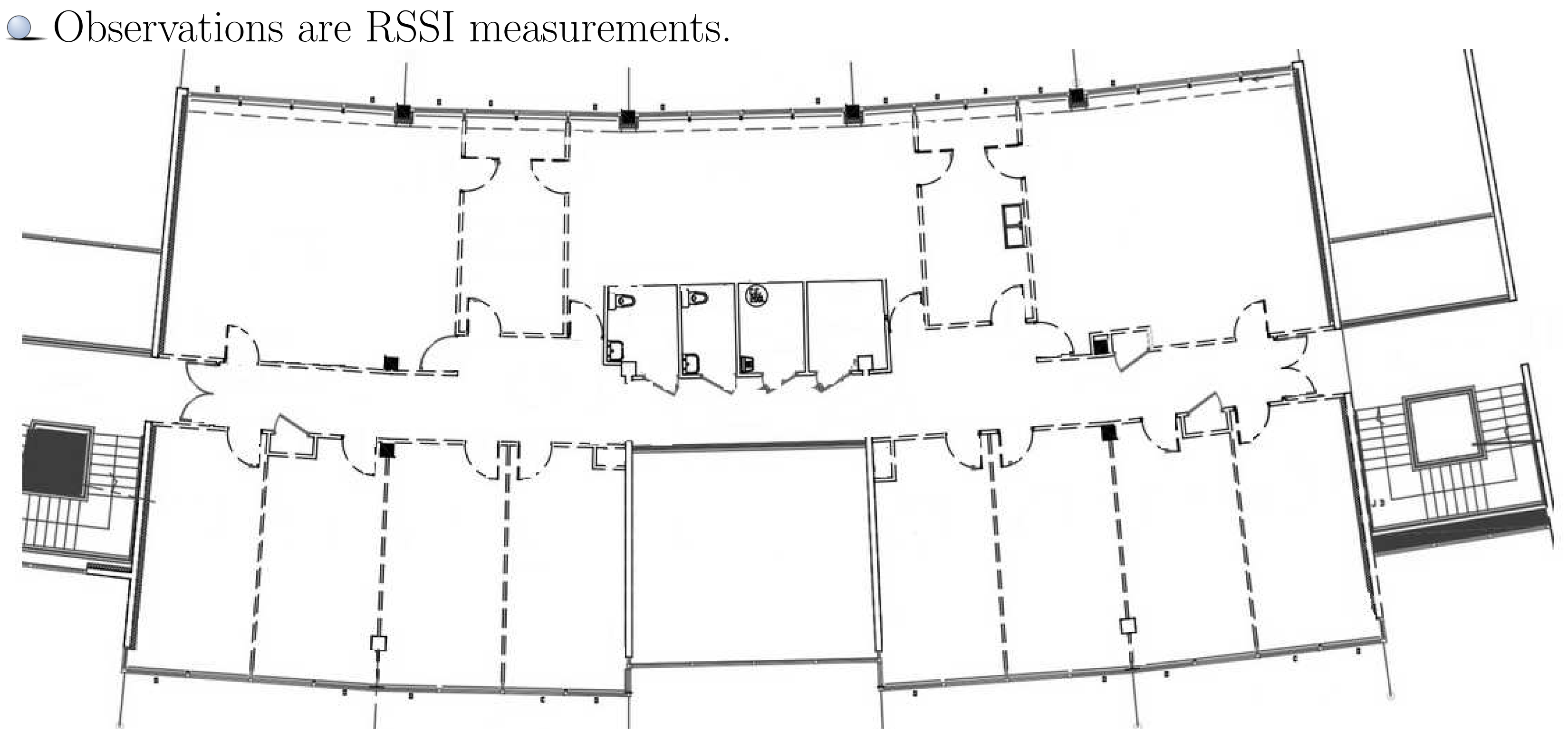
$$\mathcal{C}f(y_j^{cl}) = BetP^C(\{y_i^C\}) \times BetP^{cl,i}(\{y_j^{cl}\}),$$

such that $j \in J_i, i \in \{1, \ldots, N_C\}$, J_i being the set of indices of zones in cluster C_i.

Experiments

Zoning of sensors in indoor wireless networks

- Classes are zones;
- Features are Access Points;
- Observations are RSSI measurements.



Parameter α	accuracy (%)	online time (s)
-	89.44	0.3168
0.25	83.89	0.2117
0.5	86.11	0.2619
0.75	92.78	0.2955

Technique	accuracy (%)	online time (s)
KNN	83.33	0.1289
NB	81.66	0.1018
MLR	82.78	0.1498
NN	84.72	0.1866
SVM	85.55	0.1859
RF	86.66	0.4077
HSVM	86.38	0.4667
Parametric	87.77	0.2508
Proposed method	92.78	0.2955

This project is funded by the European Regional Development Fund and the Grand Est region in France.