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# Mobile Radio Access Network Monitoring Using the Self-Organizing Map

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**Abstract**. In this study, a method for process clustering and visualization using the Self-Organizing Map (SOM) is described. The presented method is applied in clustering and monitoring of mobile cells of a Mobile Radio Access Network (RAN).

## 1 Introduction

The wide range of services provided by the third generation mobile networks will set new challenges for radio network planning and optimization. In order to meet the quality of service (QoS) requirements set for each service, more advanced analysis methods to support mobile cell parameter configuration is needed.

In this paper, the Self-Organizing Map (SOM) in clustering and visualization of mobile cell data to support radio network optimization is described. The SOM implements a nonlinear topology preserving mapping from multi-dimensional input space into a low-dimensional grid of map units, making it especially suitable for visualization of high-dimensional data [4]. The SOM has previously been used in mobile cell clustering in [5].

## 2 Mobile network

The data set used in this work has been generated using wideband code division multiple access (WCDMA) radio network simulator [3]. The WCDMA radio network was planned to provide 64-kbps service with 95% outdoor coverage probability with reasonable (2%) blocking. The network configuration consisted of 46 omnidirectional antennas in the Helsinki city area (see Fig. 1). The users of the network were circuit-switched with 64-kbps and the admission control was parameterized so that uplink interference had no impact on the admission process.

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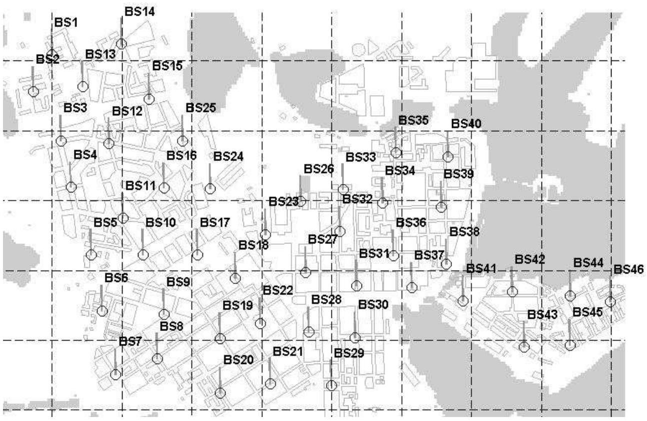


Figure 1: Helsinki city area and the mobile network.

The state of the network is characterized by 17 variables measured every 100 ms in each mobile cell. In this work, the downlink direction was analyzed using the three most relevant parameters: the number of users (nUsr), average transmission power (dlTxp) and frame error rate (dlFER).

# 3 Visualization of cluster and density structures

In this section a method for visualization of measured process data is described. The method consists of several phases as illustrated in Fig. 2. Quantization for the data set is performed using SOM in order to approximate the original data set by a smaller amount of reference vectors (codebook) and to form a mapping from multidimensional measurement space into a 2-dimensional grid for data visualization. Quantization also decreases the computational cost of clustering carried out in the next phase of the visualization process.

Clustering of the codebook vectors of SOM is performed in order to obtain qualitative information about cluster structures in the data [7]. Several clusterings of the codebook vectors into different number of clusters can be performed and the best can be selected, for example, by finding the one with lowest Davies-Bouldin index [1].

In order to obtain quantitative information about cluster properties, a set of descriptive rules is computed. Rules describe clusters in terms of value ranges for each measured variable. Single descriptive rules and their combinations for each cluster can be computed by maximizing the significance measure $S_r(i,r)$ of a rule $r$ for cluster $i$:

$$S_r(i,r) = P(i|r)P(r|i) = \frac{n_{r\&i}^2}{n_r n_i},$$

where $n_r$ is the number of data samples in the data set for which the rule $r$ is

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true, $n_i$ is the number of data samples in cluster $i$, and $n_{r\&i}$ is the number of data samples in the cluster $i$ for which the rule $r$ is true [6].

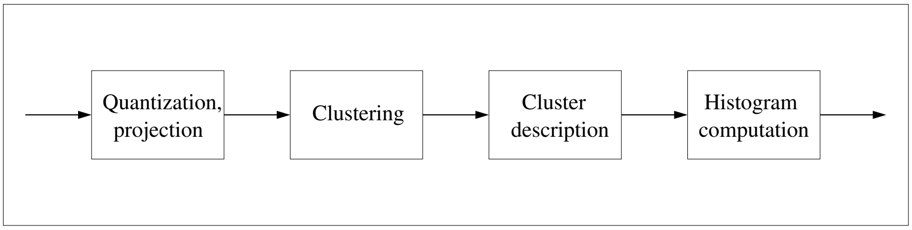


Figure 2: Block diagram describing the different phases of data analysis procedure.

In addition to the cluster structure visualization, the densities of each cluster can be computed in order to further visualize the properties of the data. This can be established by computing a hit-histogram from data: the number of data samples that belong to each cluster is computed. The computed densities can effectively be visualized as a data histogram on the trained map.

# 4 SOM of density structures

For the process monitoring purposes it is important to detect changes in the statistics of the measured data. In order to gain insight into the process variations, a visualization of density structures of consecutive, possibly overlapping subprocesses can be obtained. This can be performed by dividing the data set into fixed length subprocesses and computing the hit-histograms for each subprocess separately using previously computed clustering. The set of computed hit-histograms is used as a training data for a SOM. Each map unit of the trained SOM describes a possible distribution of data samples between data clusters in the measurement space.

A clustering for the codebook vectors of the histogram-map can be performed in similar fashion as described in Sec. 3 to separate areas on the map with different properties. Clustered histogram-map can be used for subprocess clustering by computing hit-histograms from each subprocess separately and finding the corresponding best-matching units on the map. The subprocesses are clustered based on cluster memberships of the corresponding best-matching map units.

# 5 Experiments

## 5.1 Visualization of mobile network data

In order to visualize the structure of the data measured from the mobile network in Fig. 1, quantization and projection into a 2-dimensional grid was performed

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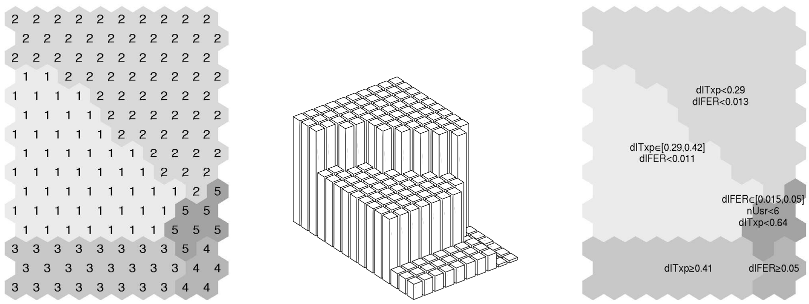
using SOM. Then, the codebook of SOM was clustered into five clusters using k-means clustering algorithm [2]. Fig. 3(a) shows the data set after quantization and clustering.

For visualization of density structure of the data set, the amounts of data samples in each data cluster, that is, the hit-histogram was computed. The computed hit-histogram visualized on top of the trained map is shown in Fig. 3(b), indicating that most of the data samples were distributed in data clusters 1 and 2.

The rules describing the clusters in the measurement space are shown in Fig. 3(c). From the rules it easy for application domain expert to assess the properties of each data cluster. For example, cluster 4 represents data samples with unacceptable high downlink frame error rate (dlFER $> 0.05$).




(a) (b) (c)

Figure 3: (a) Visualization of data clusters, (b) their densities and (c) their properties using SOM.

## 5.2 The histogram-map

In order to analyse the behavior of mobile cells of the network, a histogram-map was trained using the network data as described in Sec. 4. Then, the trained histogram-map was clustered into seven clusters using k-means clustering algorithm in order to separate dissimilar areas on the map. Fig. 4(a) shows the clustered histogram-map.

In Fig. 4(b) the properties of each cluster on the histogram map are shown. Each cluster represents differently distributed data samples in the measurement space. These distributions are visualized as a data histogram in which each bar represents the density of the corresponding data cluster in the measurement space. For example, cluster 6 on the histogram-map represents density structures in which most of the data samples are located in data cluster 4 as indicated by the height of the 4th bar of the histograms. As mentioned earlier, the data cluster 4 represents data samples with unacceptable high downlink

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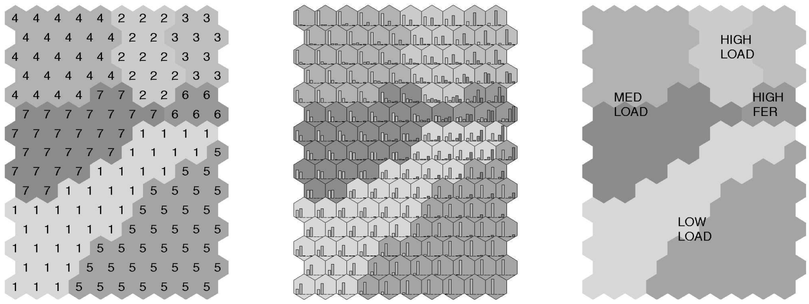
FER, indicating that cluster 6 on the histogram-map describes undesired data distribution and thus it should be avoided by making corrections to the process configuration parameters.




(a) (b) (c)

Figure 4: (a) Clusters on the histogram-map and (b) their properties visualized by histograms. (c) Properties of clusters are manually labeled on top of SOM.

### 5.3 Monitoring mobile cells using histogram-map

In order to monitor the operation of a mobile cell, the best-matching map units on the histogram-map for consecutive subprocesses was computed. The best-matching map units form a trajectory on the histogram-map. By following the trajectory, the changes in cell behavior are easily detected. Fig. 5 illustrates this monitoring process for mobile cells 8, 14 and 44. For example, cell 8 starts from low load state, visiting medium load and high load areas before settling back to medium load area. Mobile cell 14 operates on low load, except a small peak in dlFER in the beginning of the data set. Cell 44 operates exclusively on high load and dlFER area.

## 6 Conclusion

In this study, a method for visualization and clustering of process data using two clustered SOMs was described. The presented method can be used to monitor the behavior of mobile cells and to form clusters of similar mobile cells, providing tools to move from time consuming per cell optimization to cell cluster optimization.

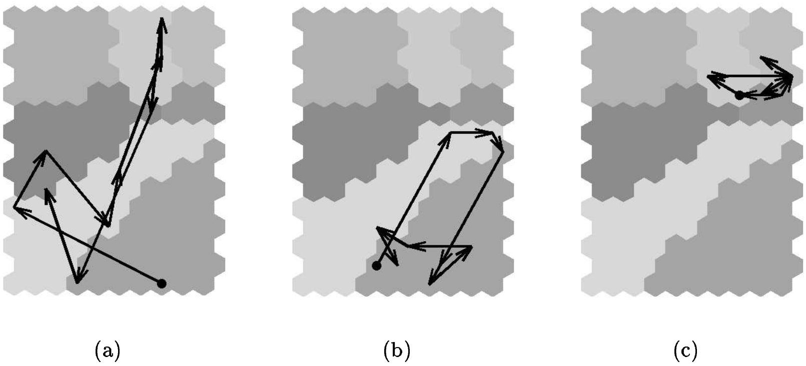



Figure 5: Trajectories of mobile cells (a) 8, (b) 14 and (c) 44 of the mobile network on the histogram-map.

## Acknowledgment

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