Analysis of Soft Handover Measurements in 3G Network

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ABSTRACT

A neural network based clustering method for the analysis of soft handovers in 3G network is introduced. The method is highly visual and it could be utilized in explorative analysis of mobile networks. In this paper, the method is used to find groups of similar mobile cell pairs in the sense of handover measurements. The groups or clusters found by the method are characterized by the rate of successful handovers as well as the causes of failing handover attempts. The most interesting clusters are those which represent certain type of problems in handover attempts. By comparing variable histograms of a selected cluster to histograms of the whole data set an application domain expert may find some explanations on problems. Two clusters are investigated further and causes of failing handover attempts are discussed.

Categories and Subject Descriptors

H.4.3 [**Information Systems Applications**]: Communications Applications—*Information browsers*; I.5.3 [**Pattern Recognition**]: Clustering

General Terms

Algorithms, Management, Performance

Keywords

3G network, soft handover, mobility management, data mining, hierarchical clustering, neural networks

1. INTRODUCTION

Mobility management is a great challenge in current and future radio access networks. In third generation (3G) networks user experienced quality of service (QoS) under a move of mobile station (MS) from one mobile cell to another cell has been improved by implementing soft handover (SHO). Soft handover makes it possible to have connections on several base stations (BS) simultaneously.

In this paper, a set of measurements which can be used for soft handover decision making are analyzed and compared with other measurements in which statistics of successfulness of handover attempts have been collected. We do not know exactly the parameters of used SHO algorithm. SHOs are investigated only on basis of data set and some general knowledge of 3G systems. Mobile cell pairs with handovers (HO) are divided in groups using clustering algorithm. Cell pairs in which SHOs are similar with each other fall in same group. Different types of SHO failures are analyzed using clustering information and distributions of measurements in each cluster.

In Section 2 the soft handover concept, the measurements and used neural network algorithm are shortly introduced. Analysis methods which have been used are described in Section 3. Preliminary results are shown and discussed in Section 4. Finally, some conclusions are drawn in the last section.

2. BACKGROUND

In this section, the basics of soft handover in 3G network is explained and the available data set is introduced. Neural network algorithm used in data clustering is also presented.

2.1 Soft handover

Soft handover is a state of MS being connected to several BSs simultaneously. In GSM networks, a fixed threshold for handover from one cell to another is used. In 3G networks, each MS is connected to a network via a set of BSs called active set. Members of active set are updated on basis of measurements made by MS. The advantage of having connections on several BS simultaneously is realized when MS is moving towards another BS, the MS should have a connection at least on one BS all the time. In GSM system, the older connection has to be terminated before the new one can be setup. The connection setup phases are the most vulnerable steps in a call. The connection between MS and BS is setup in a beginning of a call or later when handover occurs. If the setup is not successful, it is useful to have an existing connection to another BS or otherwise the call will be abnormally terminated.

Handover can occur due to signal quality reasons or when the traffic capacity in a cell has reached its maximum or is approaching it. In the latter case, traffic load in the network can be distributed more uniformly by handing over some users from the most crowded cells. The above method is

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MSWiM'06, October 2–6, 2006, Torremolinos, Malaga, Spain.
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called cell breathing. Use of cell breathing without giving the information to the analyzer increases the complexity of the analysis and can mix up a lot in the analysis process.

For a user soft handover means power saving (in uplink) and less abnormally terminated calls. For an operator lower MS transmitting powers mean less interference. When MS is in SHO, several BSs listen the same uplink channel, but all BSs have their own downlink channel. The offered diversity is resource consuming in downlink direction. There is a tradeoff between better QoS in mobility management and consumption of resources.

Decision of soft handover is made in mobile station by comparing the signal-to-noise ratios of active and candidate BSs Common Pilot Channel (CPICH) [2]. Members of active set are selected on basis of powers of this pilot signal [5, 12, 16].

BSs which are not in the active set but next from it in the sense of measured quantity are in candidate set. Candidate set BSs are constantly monitored whether their offer better connection than cells in active set. Cells not in active or candidate set are monitored less frequently whether their can enter the candidate set. Cell is either added to the active set if the maximum amount of cells in the active set is not reached or cell replaces the cell which offers the lowest quality connection. Cells which are no more able to offer a connection which is good enough are removed from the active set.

Thresholds are used in adding, replacing and removing BSs from active set by BSs in candidate set to avoid ping pong effect. This means that a value of measured quantity should be with a certain threshold better than the old one for changing cells in active set. If measurement which is only slightly better (i.e. with zero threshold) is enough for changing cells in sets, it is quite possible that the same change is performed in opposite direction very soon. Thus, the original update of the set was useless and resource consuming in the sense of all required signaling.

2.2 Data

Three data sets of Key Performance Indicator (KPI) level measurements related on handover events are saved. Each set consists of measurements collected during one hour. KPI is considered as an important measure to be followed. It can be a measurement by itself or it has been computed from a group of raw counters [10]. One data vector consists of probabilities, means, sums and counters computed over one hour of one source target cell pair. Here, source refers on cell in active set and target on another cell which is measured and possibly added in active or candidate set. Measurements of target cell are compared with those of source cell. Handover decisions are made in MS on basis of measured and computed base stations received signal signal-to-noise ratios (E_c/N_0). For each source and target cell pair mean of signal-to-noise ratio differences is computed using

$$\text{EcnoDiffMean} = \text{mean}\left\{[E_c/N_0]_{target} - [E_c/N_0]_{source}\right\}.$$

Mean value and number of made comparisons (EcnoDiffNum) are saved. Four bin pdfs of these measurements are also stored with bin centers in -6, -3, 0 and 3dB, correspondingly.

In addition to E_c/N_0 measurements, averages of received pilot signal power ratios between BS pairs (av_rscp_ratio) have been computed and stored in database. The time and probability of being in SHO with each other have also been measured. Time of target and source cell being in SHO with each other simultaneously is counted in variable t_act. Then, at least one MS is in SHO having both source and target cell in its active set. The measurement is symmetric for a switch of source and target cells. Time of target cell being in SHO with source cell is stored in t_act_dir. Cell total time in SHO is saved in tot_time_sho. It has been counted over all the targets of fixed source cell. Probability of target and source being in same active set is stored in variable p_act.

Total number of SHO attempts to add target to active set is stored in SHO_total_att. Ratio of successful SHO attempts which lead to addition of target cell in active set is saved in add_ratio. In addition to those above, the number of SHO failures is stored in pfail_total and ratios of four different failure causes are saved. Failure occurs in setup or active time phase of SHO and it is either radio channel problem or not. Probability of cell being in monitored state is also measured (p4th_5th). All the measurements used in the analysis are shortly described in Table 1.

A lot of data has been saved in data sets, but also some very important information is missing. Due to missing information on cell capacities, their locations and performed manual and automatic tuning operations on network configuration between successive data set saves, only preliminary analysis can be performed. The rest of the analysis process is described on theoretical level.

2.3 Self-Organizing Map

Self-Organizing Map (SOM) [8] is an unsupervised neural network algorithm which adapts the codebook vectors of neurons so that they approximate the input data distribution. When the training has converged topological areas or domains corresponding to certain types of inputs can be found from the map. The topology and the size of the network is fixed before adaptation.

In the SOM algorithm, the codebook vectors w_j of the SOM are at first initialized. Then, the following steps are repeated for each input vector x: Find the index of best-matching or nearest codebook vector using

$$i(x) = argmin||x - w_j||,$$

in which j goes through all the neurons in the map. Next, the codebook vectors of winner neuron and its neighbors are updated using

$$w_j(t+1) = w_j(t) + \alpha h_{ij}(x)(x(t) - w_j(t)).$$

Here, α is the learning rate and $h_{ij}(x)$ is the neighborhood function centered around the winner neuron. Input sample x defines the winner neuron and the topological distance between indexes i and j defines how much the neuron is updated. Neighborhood function is typically Gaussian or bubble function i.e. function which decrease monotonically and even goes to zero when the distance increases.

In this paper, a batch version of the SOM algorithm is used. In batch SOM, all codebook vectors of the SOM are computed after the best-matching units of all input data vectors have been found. The same data set is used several times.

3. METHODS

Handover related measurement from 3G network can be analyzed using standard data mining methods [1]. In this

Table 1: **Measurements in the analysis. Data set has one sample vector for each source target cell pair.**

Variable	Explanation	Type
EcnoDiffNum	Computed E_c/N_0 differences	number
EcnoDiffMean	Computed E_c/N_0 differences	mean
EcnoDiffPdf-6.0	-6 dB bin of E_c/N_0 difference pdf	ratio
EcnoDiffPdf-3.0	-3 dB bin of E_c/N_0 difference pdf	ratio
EcnoDiffPdf0.0	0 dB bin of E_c/N_0 difference pdf	ratio
EcnoDiffPdf3.0	3 dB bin of E_c/N_0 difference pdf	ratio
t_act	Target and source simultaneously in SHO	mean
t_act_dir	Time of target being in SHO with source	mean
tot_time_sho	Cell total time in SHO	sum
p_act	Target in active set of source	ratio
SHO_total_att	SHO attempts to add Target to active set	number
add_ratio	Successful attempts leading to addition	ratio
pfail_total	Failures	number
pfail_ini	Setup phase failures due to non-radio	ratio
pfail_ini_radio	Setup phase failures due to radio	ratio
pfail_act	Active time failures due to non-radio	ratio
pfail_act_radio	Active time failures due to radio	ratio
p4th_5th	Cell is in monitored state (=4th or 5th)	ratio
av_rscp_ratio	Target / Source Received power ratio	mean
r_fail	Ratio pfail_total / SHO_total_att *	ratio
r_EcnoDNum	Ratio EcnoDiffNum / SHO_total_att *	ratio

* Variable defined in the analysis.

study, methods presented in Figure 1 are used. At first, the miner have to decide what could be interesting in this data. The analysis task has to be defined. On basis of that the first choice of variables will be done. Next, the selected variables are preprocessed, in order to be able to use them in later analysis.

In data mining tasks, variable selection and preprocessing are the most critical phases, because in this step the miner decides which variables are important and how should they be processed. The whole data mining process consists of several cycles performed repeatedly. The cycles include testing how different variable selections and preprocessing methods effect on final results. The process has inner loops in which some tasks or parameters are fixed on basis of selections made in outer loop. The inner loops are performed more frequently. Loops with more general task like the definition of mining task are repeated less frequently. When the mining task is defined the analyzer should be able to decide what is (s)he looking out for.

Now, the analysis task is defined as finding groups of similarly behaving cell pairs in SHO situations. Importance of measurements can also be highlighted using proper weighting of variables. In addition to clustering, also other tasks for data analysis can be defined. One possibility is to try to find cells or cell pairs with anomalous behavior. Anomalies can also be found by clustering, but expert knowledge in variable selection and preprocessing steps are very important.

Using different variables, preprocessing methods and weighting of variables different clustering results can be found. To find out which of them is useful, interpretation of clusters is needed. This can be done using histograms or rules defined by data samples falling in clusters. The results which have been found using clustering methods should be visualized together with spatial locations to be able to understand the usefulness of results. Methods should be performed repeatedly to analyze successive data sets under the knowledge of performed tuning operations. Thus, there is a possibility to find explanations to changing results. In this study, results of only one data set are shown, because more information on application domain is needed to be able to combine and compare successive clustering results.

3.1 Preprocessing

Different preprocessing methods have been tested. The final method was selected on basis of histograms and the clusters which were found using the selected method. At the first step, the distributions are truncated. Outliers in the selected variables were replaced by their maximum permitted values. Two variables, pfail_total and EcnoDiffNum, were scaled using the number of performed soft handover attempts (see Table 1). Logarithms of some of the variables were taken, but finally only scaled EcnoDiffNum was preprocessed with logarithmic function. Sample vectors with high amount of undefined measurements were canceled. Used clustering method (see section 3.2) allows using sample vectors in which some variables are undefined. However, they are not so useful when the rate of undefined values increases. Here, sample vectors with 15 or more missing values in 20 variables are canceled.

In Figure 2 the histograms of the most interesting variables preprocessed using selected methods are visualized. Some of the variables have quite high peaks in distributions, but due to the origin of variables no other preprocessing have been performed. For example, handover failure reasons pfail_ini, pfail_ini_radio, pfail_act_radio and pfail_act sum up to unity. However, pfail_act is not analyzed because it is zero all the time in the first data set.

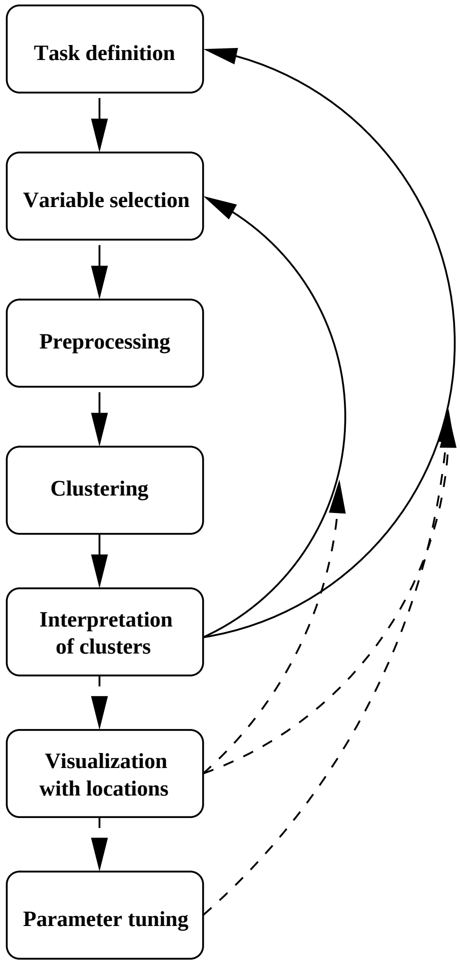


Figure 1: Used data analysis method. Steps connected with solid arrows have been performed.

3.2 Clustering

Cluster analysis is used to divide data vectors in groups. Data vectors falling in same cluster are similar with each other. Here, clustering is performed using a two-phase method [15]. In this method, data vectors are at first used to train a Self-Organizing Map. Neurons of the SOM adapt to incoming data so that the input data can in later analysis be represented by the codebook vectors of neurons. Number of these codebook vectors is much smaller than the number of original data vectors. Thus, computational complexity of the final crisp clustering algorithm is decreased. Another advantage of using a SOM based two-phase method instead of direct clustering of data vectors is the visualization capability of SOM.

In addition to preprocessing, SOM algorithm provides another possibility to emphasize important properties of data. Larger weights in distance computation are given to the most important properties defined by the analyzer. Smaller or even zero weight can be given to those variables which are not used in organization of the SOM i.e. in building clusters. However, values of them can be compared to those with larger weights using various visualization methods. Weighting by variable importance can also be built into SOM training algorithm by utilizing learning distance metrics [7].

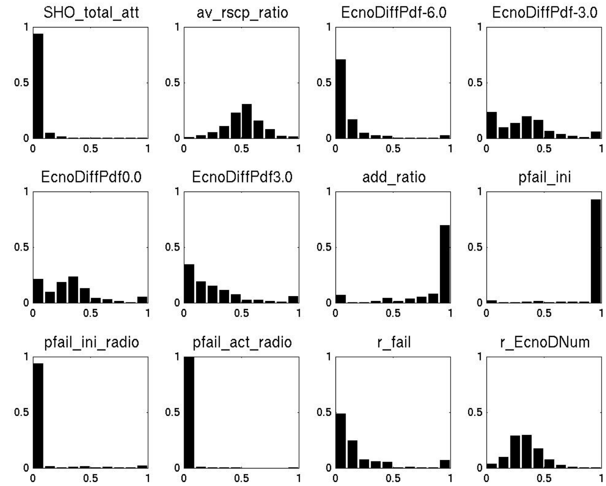


Figure 2: Logarithmic histograms after distribution cuts, logarithmic preprocessing of r_EcnoDNum and scaling of all variables between [0,1]

The codebook vectors are further clustered using k-means or some hierarchical clustering method. In this paper, Ward agglomerative clustering method has been used [4]. In the beginning of hierarchical clustering, each codebook vector is a cluster of its own. In the next step, the most similar clusters are combined and this is continued until all vectors are in same cluster. The clustering results form a tree structure called dendrogram. In visualization of a dendrogram, the clusters combined in each step and the distance between them are shown. Final clustering is selected by cutting this tree at certain level. The number of clusters can be selected manually or some cluster validation index can be utilized to find the optimum. In this paper, Davies-Bouldin validation index has been used [3]. Similar clustering methods have earlier been used in the analysis of both GSM and 3G network BTSs [9, 11, 13].

As a result of clustering, each data vector is represented by index of one neuron or by the codebook vector stored in that neuron. Furthermore, the neuron and the data vectors the neuron represents belong to same cluster. On basis of the clustering result, some clusters can be selected for more specific analysis. Cluster selection is usually done on basis of found higher values of some critical variables. It is possible to build a system in which rules are found for clusters [14, 9] and these are used to select interesting clusters automatically. Here, interesting clusters are selected manually on basis of clusterwise variable mean values and histograms.

4. RESULTS

In this section, handover measurement data is used to train a Self-Organizing Map of size 17×12. Then, the codebook vectors of the SOM are clustered using hierarchical Ward method. Results of clustering are described and two clusters are then selected for more specific analysis. Characteristics of sample vectors falling in those clusters are studied using histograms.

Only the most interesting variables are used to find the nearest neuron of input data vector. These variables have nonzero mask which can also be considered as a weighting factor in a search for the best-matching neuron. Rest of the variables have zero mask, which means that they can be visualized and updated using SOM algorithm, but they do not have an effect on organization of the SOM and on selection of the cluster in which the sample belongs to.

In Figure 3 all other component planes of SOM with positive mask are shown, except E_c/N_0 difference distributions which are shown in Figure 6. In component plane visualization, distributions of components (or variables) of SOM codebook vectors are shown. Component values of one codebook vector are visualized using grayscaling and their locate in the same position at each plane. For example, values of one codebook vector are shown at upper right corner in each plane.

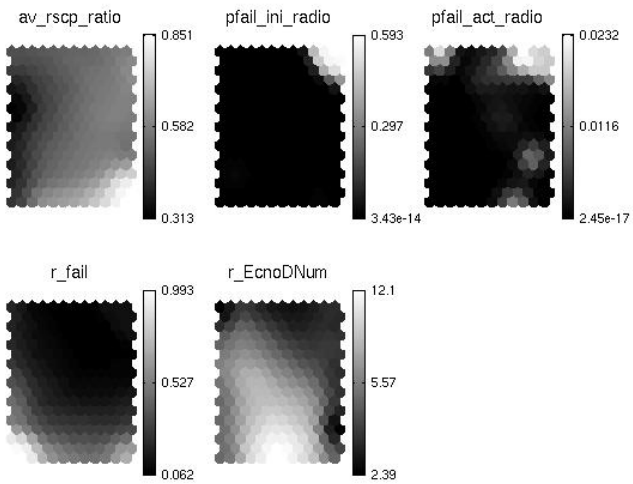


Figure 3: Component planes of SOM with denormalized scales. Shown variables have nonzero mask and they are not describing E_c/N_0 difference distributions.

Some component values which were not used in SOM training (i.e. they were masked out) are shown in Figure 4. Although, they have no effect on SOM organization, they are adapted to be able to compare their distributions even with those used in organizing the SOM.

By visual comparison of variables in Figures 3 and 4, it can be seen that the total number of SHO attempts (SHO_total_att) and E_c/N_0 difference measurements (EcnoDiffNum) is higher in upper part of the SOM. However, when the latter is scaled by total number of attempts, higher rate of measurements (r_EcnoDNum) is in lower part of the map. Also, the total number of failuring SHO attempts (pfail_total) is high in upper right corner, but scaling this by number of attempts tells us that the failure rate (r_fail) in upper right corner is quite moderate. Instead, higher failure rates exists in both lower corners i.e. in clusters 5 and 8 (see Figure 5).

Trained SOM codebook vectors are clustered using hierarchical Ward algorithm. The clustering result selected by Davies-Bouldin index is shown in Figure 5. Four bin E_c/N_0 difference histograms are visualized on top of clustered SOM

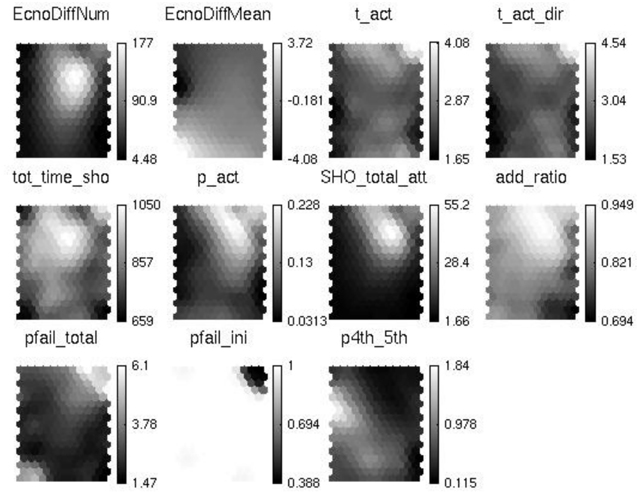


Figure 4: Denormalized component planes of variables which were not used in SOM training.

in Figure 6. When component values of SOM (see Figures 3, 4 and 6) are compared with clustering result (see Figure 5) several types of source target pairs can be found. Most of them are behaving as expected, but some of them represent handover attempts with certain type of problems.

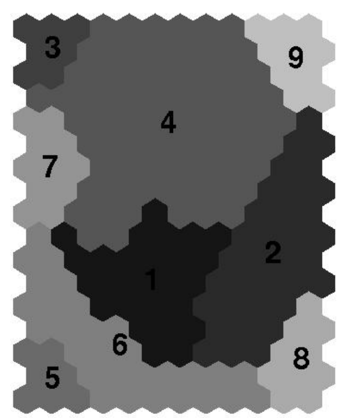


Figure 5: SOM which is clustered using hierarchical Ward method and Davies-Bouldin validation index.

To find out the most interesting clusters of the SOM for further investigations, distribution of data samples on SOM is visualized. In Figure 7a hits of all samples on SOM nodes are visualized and in Figure 7b hits of samples with SHO failure rate (r_fail) larger than 22% are shown. Samples are distributed all over the map, only some edge nodes have slightly larger hit rate. Lower part of the map has more hits when samples with increased failure rate are considered.

In Figure 8 hits of samples which represent two differ-

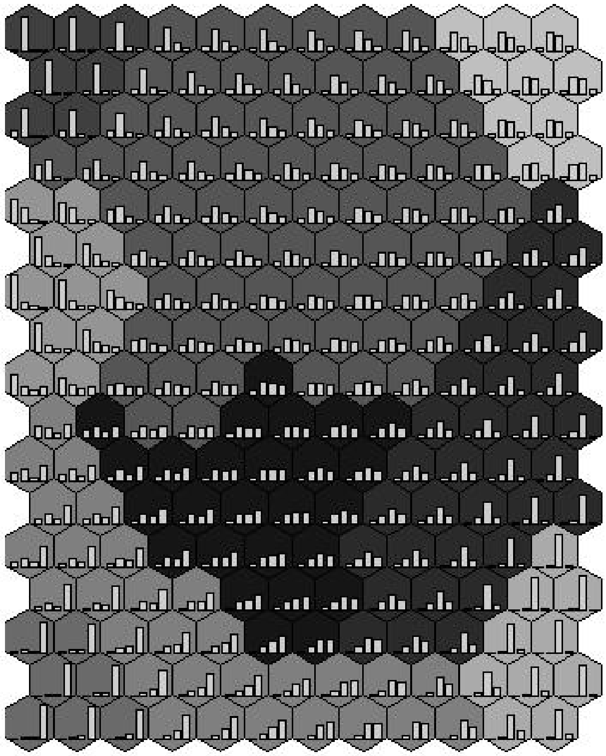
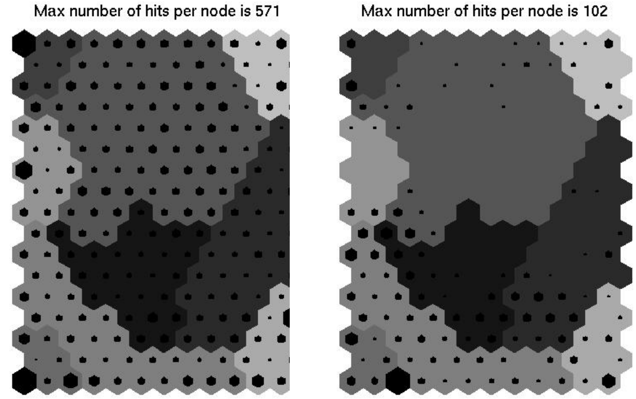


Figure 6: EcnoDiff distributions on top of clustered SOM. In each SOM node a four bin E_c/N_0 histogram is shown.

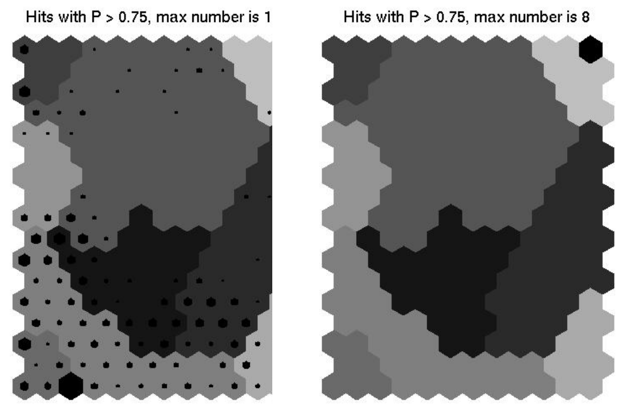
ent types of SHO failures are shown. Samples are from cell pairs in which the rate of selected type of failures is larger than 75%. However, handover initialization failures due to some other reason than radio channel resources (i.e. pfail_ini type failures) are obviously more frequent than failures due to radio channel initialization problems (pfail_ini_radio type failures). Cell pairs with SHO failures originating mainly from these two reasons are mapped on separate clusters. All SHO failures due to radio channel initialization are in cluster 9 (see Figures 5 and 8b) and most of all other initialization failures are in cluster 5 (see Figures 5 and 8a). In the following, these two clusters are studied in more detail.

In Figures 9 and 10 histograms of samples which belong to clusters 5 and 9 are shown. These histograms should be compared with histograms of whole data set which were shown in Figure 2. In histograms of cluster 5 (see Figure 9), the average received signal power ratio (av_rscp_ratio) is slightly lower than in general. Distributions of three largest E_c/N_0 difference measurement bins are completely different than corresponding distributions from the whole data set. In cluster 5 most of the samples have about 3dB E_c/N_0 difference (EcnodiffPdf3.0) which means that at least this measurement makes successful SHOs possible and SHO should be performed. Exceptional E_c/N_0 difference measurements



(a) All (b) SHO failure rate > 22%

Figure 7: Sample vector hits on SOM nodes. Size of black hexagonal on SOM node denotes the number of hits. Maximum number of hits per node is shown above the plot.



(a) pfail_ini (b) pfail_ini_radio

Figure 8: Hits of samples of two failure types. Samples of which more than 75% are failuring due to selected cause are counted.

of this cluster can also be seen in Figure 6. All the failing cell pairs fail in initialization due to other than radio channel reasons (pfail_ini). Total rate of failures is very high (r_fail). One reason for high rate of failures can be that all the capacity is in use.

In histograms of cluster 9 (see Figure 10), the average received power ratios are a bit higher than usual, but there are no samples with high rate of 3dB E_c/N_0 differences (EcnoDiffPdf3.0). However, in such a situation it should be possible to perform successful SHOs. The rate of initialization failures in radio channels (pfail_ini_radio) is higher than usually, but because only a small part of samples in this cluster have above mentioned problems the total SHO failure rate is not higher than usually. The total number of samples or cell pairs with high rate of initialization failures in SHO is so small, that it is impossible to make any further inferences from these clusters. It is possible to check histograms of only those samples which fulfill the failure rate criteria, but the number of samples is anyway quite low.

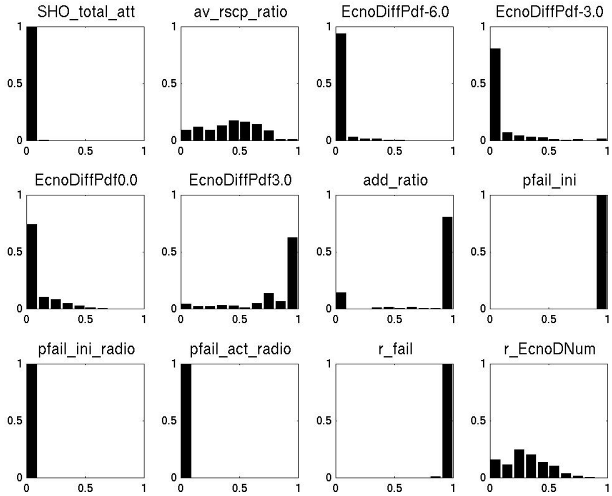


Figure 9: Histograms of data vectors of cluster 5.

Cell pairs with high rate of radio channel initialization failures in SHO attempts vary from data set to another, but without any information on network topology and with uncomplete information on performed tuning operations, it is impossible to make any further inferences.

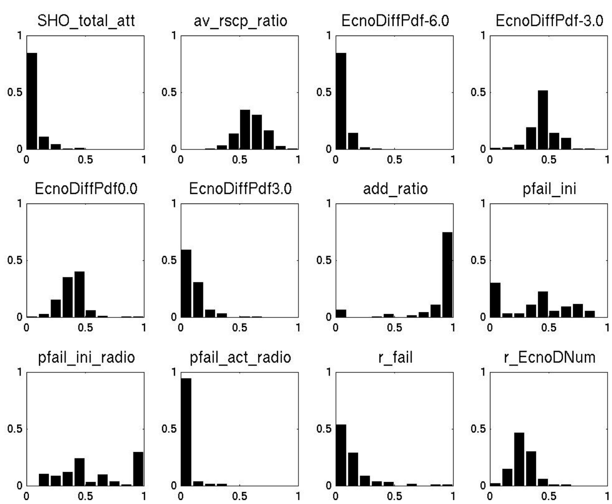


Figure 10: Histograms of data vectors of cluster 9.

5. CONCLUSIONS

In this paper, a data analysis method based on a neural network has been presented. The method is utilized in data visualization and clustering. The presented method is only one possibility for finding data clusters. However, the benefits of the proposed method are the decrease in computational complexity due to used two-phase clustering algorithm and the visualization capability of the method. Thus, it is well suitable for this kind of explorative data analysis.

It is desirable to find clusters with characteristics which differ from one cluster to another. In the presented method, selection of variables and variable weighting factors have been used to find interesting clusters. In the preprocessing phase, also the number of permitted undefined measurement values in sample vector has an effect on found clusters. Sample vectors with high rate of missing values are not so usable and describable as samples without them. Vectors with missing values can be used in the SOM training but the benefit of using them decreases when the rate of undefined values increases.

In this study, histograms are used both when preprocessing methods are decided and when an interpretation for the found clusters are looked for. However, clusters can also be compared using other visual methods, finding limiting rules for variable values in clusters or comparing distributions of variable values in clusters using more sophisticated distribution comparison measures like Kullback-Leibler divergences [6].

The results which have been obtained using all available data sets differ slightly from each other, but due to uncomplete information on network configuration and parameter tuning, further inferences cannot be made. However, adding this information would offer interesting possibilities to continue this study.

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