Chapter 14

Process monitoring and visualisation using self-organizing maps

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1. Overview

Analysis and control of complex nonlinear processes constitutes a difficult problem area. In complicated systems, as in chemical processes, it is not possible to predict all possible error types in advance. The self-organizing map algorithm can be used to investigate complex dependencies between various process parameters as well as input and output variables. It can also be utilised to create systems to monitor complicated, dynamical processes and to visualise the process development.

2. Introduction

The self-organizing map (SOM) algorithm [8][9] creates a mapping from input patterns to map units. The key point in the applicability of the SOM algorithm is the topological nature of the mapping; similar signal patterns are mapped to nearby locations on the map. Such a mapping can be applied to pattern sequence analysis by finding the mapping locations of subsequent patterns and observing the trajectory, that is the curve of the locations in time. The pattern sequence in multi-dimensional input space can in that way be transformed into a two dimensional trajectory which can be used, for example, in process monitoring applications.

In the following, the use of the self-organizing map in process state monitoring is described. Some applications in visualisation of the process operation are presented. In addition to visual monitoring, the SOM algorithm can be applied in fault detection and analysis. Examples of fault diagnosis of devices and processes are presented.

The self-organizing map algorithm can also be applied to other signal analysis tasks to provide the visualisation of certain signal characteristics. Applications where the SOM algorithm has been used in visualisation of speech signals and speech signal variations in time are also described. Finally, other applications of the SOM algorithm in monitoring and signal analysis are shortly covered. More detailed review of the use and application of the SOM algorithm will be found in [6].

3. Process state monitoring

In process state monitoring applications, the problem is to analyse and visualise the typically complex relations between various system parameters in an efficient and understandable way. The online process status measurements should be converted to some simple displays that, despite the dimensionality reduction, preserve the relationships between states. Simultaneously, it should be possible for the user to follow the process state development. Furthermore, process monitoring is often carried out in order to estimate the future behaviour. Reliable prediction of the future behaviour could result in efficient fault diagnosis. In practical applications, also the online process control based on the state analysis is an important aspect.

The self-organizing map method makes a mapping from a multi dimensional space to two dimensional surface of the processing units. The mapping is, furthermore, done in such a way that the topological relations between the input feature vectors are preserved. In monitoring applications, the self-organizing map algorithm can easily be used to analyse the complex relations between the various process parameters.

In complex processes, e.g. in chemical engineering, there are usually three types of variables or process parameters that must be considered: (1) input variables or data, (2) the process parameters, and (3) outputs of the process. All these parameters can be concatenated to form a feature vector which is used as an input to the self-organizing map, as shown in Figure 1. Due to the topology preserving property of the map, similar features corresponding to similar states of the process are mapped close to each other resulting in clusters on the map.

The mapping is created in an unsupervised way from the measured data and parameters, i.e. no knowledge of the process behaviour is required during this learning phase. The physical interpretation of the map can be obtained by labeling the nodes of the map according to the known process behaviour. The nodes corresponding to similar features are merged in the labeling process. Thus, each cluster on the labeled map corresponds to a certain state or operation point of the process. This is depicted in the lower part of Figure 1. Only a limited number

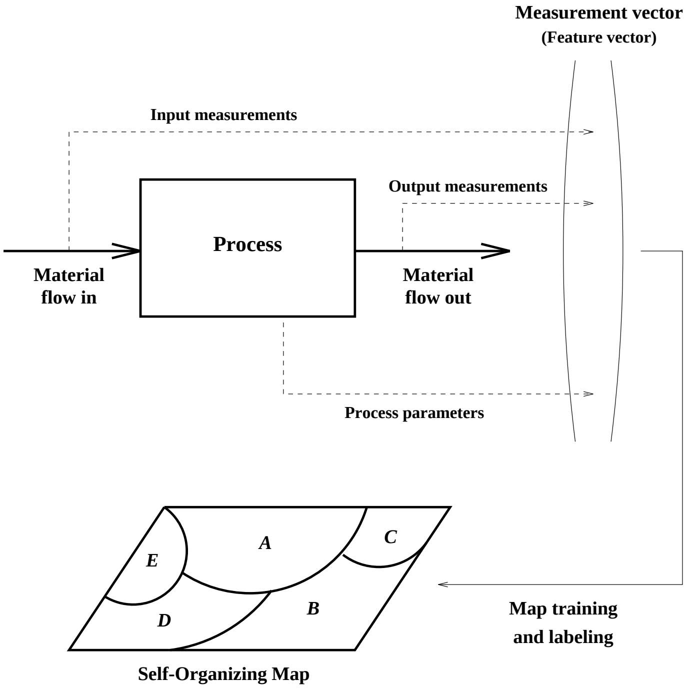


Figure 1. Feature vector obtained from process parameters and data (above). Physical interpretation of the self-organizing map by labeling the clusters of similar features to corresponding process states (below).

of preclassified samples are required in the labeling phase. Using the labeled map in monitoring, we can now identify the state of the process corresponding to a certain operation point.

3.1. Visualization

The self-organizing map is an efficient tool for visualising the process behaviour [7]. The parameter of interest can be extracted from the feature vector by displaying its value as a gray level on the map. Following the trajectory of the operation point, we can easily monitor the parameter value. An example is shown in Figure 2.

In this example, measurements of the process parameters have been analysed during a period of 24 hours. The trajectory is drawn on the map displaying one of the temperatures. Dark gray tones correspond to low and light tones to high temperatures, respectively. It can be seen that the operation point has moved from dark to light and back again corresponding to the daytime operation of the system. The trajectories of the successive days were very similar during normal operation.

Simulated data and process parameters can also be used in the learning phase. The self-organizing map can, thus, be used in process modeling. Various parameter dependencies and their effect on process behaviour can easily be investigated. For instance, the effect of certain process parameters on process state or output can be visualised on the map.

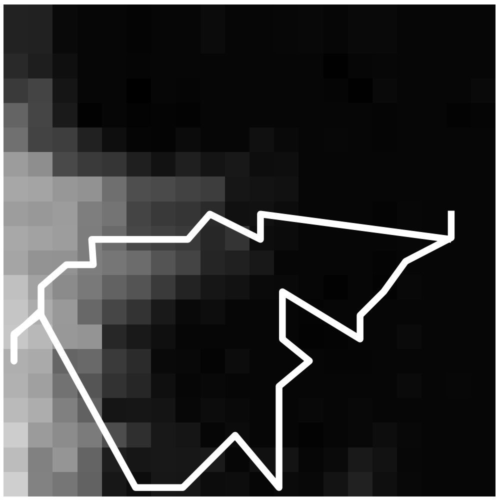


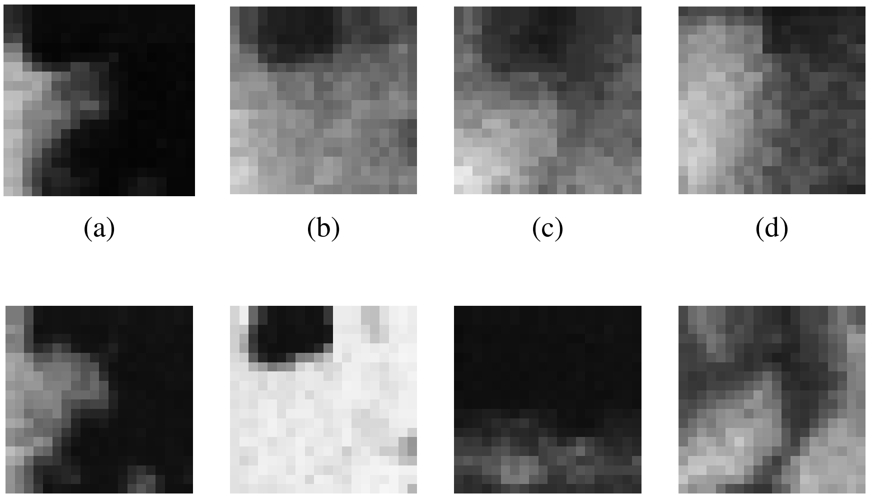
Figure 2. Example trajectory of a process state during 24 hours.

Several parameters can be visualised simultaneously by using a set of maps. In Figure 3, eight different parameters of interest have been extracted from the feature vector. The parameter values and their dependencies can be analyzed directly by comparing the gray levels of corresponding map units. The trajectory of the operating point can also be displayed on each separate map giving thus the parameter values corresponding to the state of the process.

In evaluating the quality of complex processes, various characteristic figures are often calculated. Using these figures of merit as parameters in the feature vector it is possible, for instance, to make overall comparisons of different processes. The effect of various parameters to the process behaviour can be analyzed and to some extent even "optimised". As an example, the SOM algorithm is currently being applied in the analysis of a pulp process, where especially the air and water emissions of the process are of interest.

3.2. Fault diagnosis

Another important application of the self-organizing map is in fault diagnosis. The map can be used in two ways: (1) to detect the fault and (2) to identify the fault. In practical applications, we can distinguish between two



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 3. A set of maps corresponding to different parameters.

different situations; either we have no prior measurements of the faulty situations or we have been able to record also faults.

In the learning phase, the map is trained to recognise only those states of the process that are covered by the measurements. Thus, the state space will be divided into two parts: (1) The possible operation space and (2) its complementary space. Therefore, only the situations included into the training data can be recognised by the labeled map.

In case the training data has contained no measurements from faulty situations, the operation space on the map covers only normal situations. Fault detection can now be based on the so called quantisation error. The feature vector corresponding to the measurement is compared to the weight vectors of all the map units. If the difference exceeds a predetermined threshold the process is in a faulty situation. This conclusion is based on the assumption that due to the large distance of the feature vector from all the map nodes the operation point must belong to the complementary space, not covered by the training data. Therefore, the situation has not occurred before and something is possibly going wrong.

In fault identification, the training data must contain samples of faulty situations. In this case, clusters corresponding to certain faults are created on the map and these clusters can be considered as "forbidden" areas. The fault can now be easily identified by following the trajectory of the operating point. If the trajectory moves to a forbidden area the fault will be identified. An example of the map including one forbidden area is shown in Figure 4. In this particular example, the trajectory passes the forbidden area and the fault corresponding to too high temperature in certain part of the process is identified.

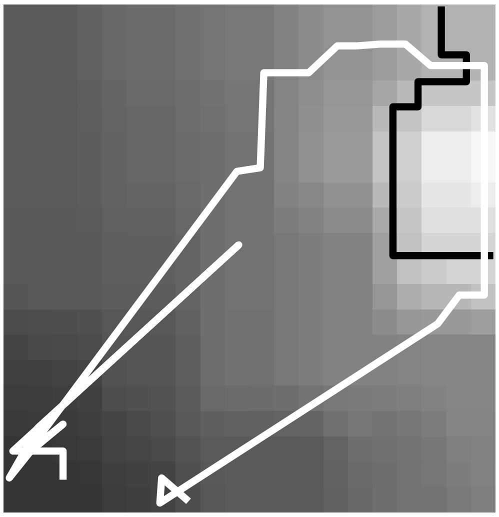


Figure 4. Forbidden area on the map corresponding to a faulty situation.

In fault analysis, simulated data can also be used. Forbidden areas corresponding to various faults can be created on the map. This is possible if faulty situations and their reasons are known well enough so that simulated data can be produced. This is especially important in situations where faults are rare and true measurements are thus not available.

3.3. Fault detection and identification system

In this section, an example of the fault detection and identification in an anaesthesia system is described. The anaesthesia system comprises the anaesthesia machine, the patient, and the anaesthesia personnel. The purpose of monitoring is to minimise the risks of anaestheisia by detecting and identifying the faults before they cause injury to the patient [22], [23].

The detection and identification of faults can be done in two stages. First, the fault is detected based on the increase in the quantization error. This is done using the so called fault-detection map. Only after the detection of the fault, its reason will be identified. The fault detection and identification system is depicted in detail in Figure 5.

In dynamical systems where the operation point is not stable or where it is not possible to exactly define "normal" situations, two levels of maps can be used in analysing faults or alarms, as shown in the lower part of Figure 5. On the first

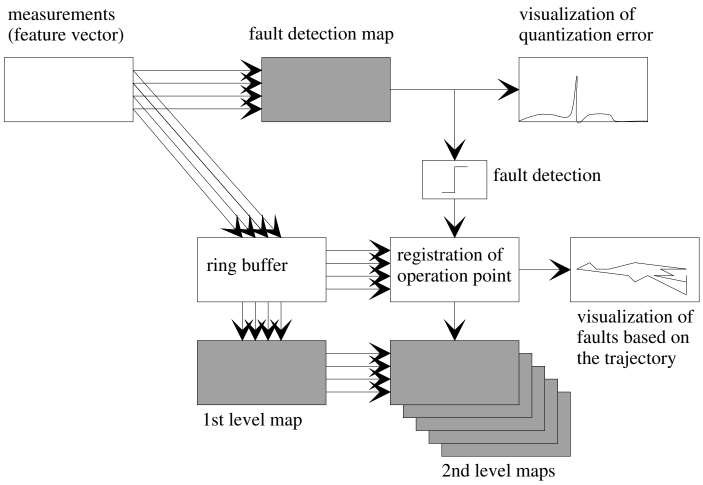


Figure 5. Fault detection (upper part) and identification (lower part) system.

level, the self-organizing map is used to identify the operating point based on the measurements. On the second level, a more detailed map (or a set of maps) can be used to locate faults based on the deviations in the parameters compared to the operating point.

The purpose of the first level map is to increase accuracy by dividing the operation space into different parts. The amount of deviation caused by a faulty situation may strongly depend on the operation point of the system. Thus, each map on the second level corresponds to a relatively small part of the operation space of the first level map. By storing a sequence of feature vectors, the behaviour of the process before and during the occurrence of the fault can be analysed in more detail.

The monitoring system was implemented by collecting training data in a real operating room environment. Different fault conditions included leaks and obstructions in the tubes in different parts of the anaestehesia system. In the experiments, the recognition accuracy of the second level map was 87 % on the average, if the operation point of the test set was relatively close to the operating points of the training set. When the location of the operation point deviated considerable from those of the training set, the recognition accuracy decreased to 70 % on the average.

The performance of the fault detection and identification was tested using samples from true situations as well. In this example, the position of the patient was changed and the intubation tube was accidentally obstructed for a short period of time. Figure 6 (a) shows the quantization error of the fault detection map. In Figure 6 (b) it can be seen that the trajectory of the operation point moves from the area corresponding to normal situation (N) to obstruction area (O5).

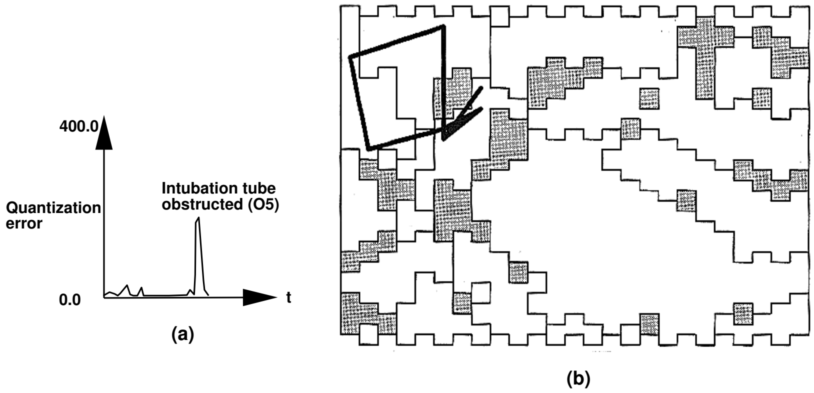


Figure 6. Quantization error of the fault detection map (a) and the trajectory of the operation point during the faulty situation (b).

4. Visualization of speech signals

The following example demonstrates the application of the self-organizing map algorithm in analysis of time series data. We have used the speech signal as the input data, but similar dynamic phenomena can be detected in many processes and the analysis methods are rather generic. Studing the similarities and differences between speech samples is analogous to corresponding studies for operating states of any dynamic process.

In speech analysis the self-organizing map algorithm has been used to create a mapping from the speech signal space to a two dimensional plane. Similar speech sounds are mapped to nearby locations on the map (plane). The mapping thus preserves the similarity of the acoustic signals (to a certain degree). The mapping also takes into account the probability density function of the input samples so that the distribution of inputs to the map units approximates the density function directly.

Perceptually meaningful features of speech derive from complex features in the speech spectra. Such features are represented by self-organizing map as locations on a two dimensional map. Visualization of voice quality with SOM is therefore easily comprehendable when compared with, for example, spectrograms. Because the probability density function of the input samples is also taken into account, those sounds that are more common are represented with more details than less frequently occurring sounds. Thus more emphasis is put on the deviations of more common sounds. It is possible to directly observe the similarities of the sounds by observing the distance between the respective representations on the map.

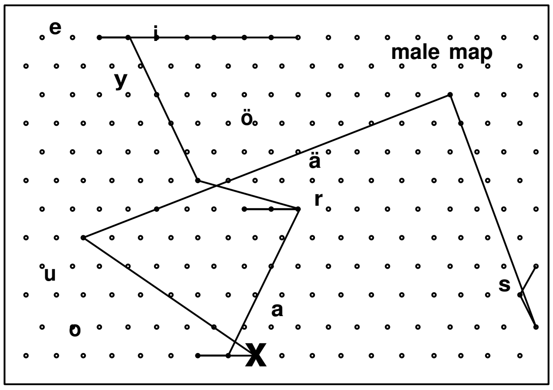


Figure 7. A self-organized map computed with Finnish speech samples from 15 men. The map areas for the vowels, /s/ and /r/ are shown on the map. The trajectory produced by an utterance of /sa:ri/ is indicated by the line beginning from /s/ area and ending in /i/ area.

The self-organizing map method is especially useful for the visualisation of the changing of speech spectra in time. The representations of consecutive short-time spectra form a trajectory on the map and changes in time can be observed from the representations. The abrupt changes in the speech signal observed in some dysphonic patients are depicted by the trajectory curve. Some examples of speech trajectories on Self-organized maps are shown in Figures 7 and 8.

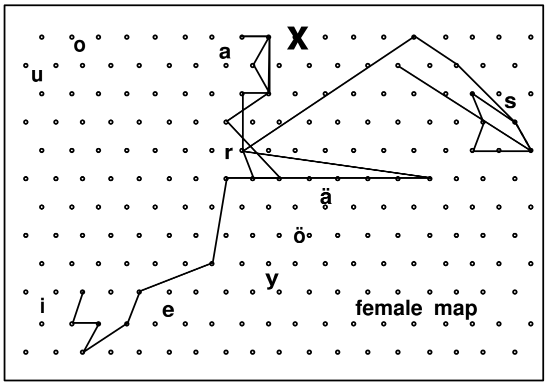


Figure 8. A self-organized map computed with Finnish speech samples of 18 women.

The maps in Figures 7 and 8 were used to analyze the voice during long

/a:/ vowels. We measured the smoothness and regularity of the speech sound by computing diagnostic figures from the trajectory. For the evaluation of the stability of the samples, the following parameters were calculated.

1. The total length of the trajectory during an interval of 150 ms,
2. the mean length of shifts, and
3. the number of cases where consecutive samples have the same representations on the map.

The length of trajectory indicates large scale changes in consecutive samples, and the number of consecutive samples having the same representations gives an indication of a small scale stability.

The permanent changes in the speech spectra (as opposed to cycle-to-cycle variations) can also be observed from the trajectory. In these cases, the trajectory is smooth without any abrupt 'jumps' in it but it is located on a 'wrong' area on the map. When normal speakers utter a known phoneme, we expect the samples to be projected into a specific area. Normal interspeaker differences are seen as small differences in locations within this area. By determining a sample trajectory in reference to this 'normal area', we can thus diagnose the 'normality' of the speech sound.

4.1. Experiments

The above ideas on speech signal visualisation have been tried in several experiments.

In [11] an approach to develop an automatic device for voice quality analysis was described. In this paper, the self-organizing map was used to visualise the speech signal and the speech signal variations in time, and from the mapping created by the SOM process it was further possible to construct some quantitative measures of the voice quality. In the studies the voice quality of vowels was analyzed.

In [15] another application of the self-organizing map algorithm for speech signal analysis is described. In this paper the self-organized map was used to distinguish between the /s/ samples perceptually classified as acceptable/unacceptable, as judged by 21 speech pathologists. It was shown that the map was a suitable tool for the extraction and measurement of acoustic features corresponding to the audible deviations of /s/.

From acoustic voice analysis using spectrograms it can be observed that the vowel following a word-initial /s/ clearly affects the spectra towards the end of the /s/ sound. Thus the following vowel type could be recognised based on the changes in spectra due to the preparatory movements of lips and tongue for the following vowel.

In [12] and [13] the phenomenon was further studied to find out if the self-organizing map algorithm could extract useful, perceptually meaningful features in the /s/ sound. The objective was to see if the representations of the /s/ samples before different vowels could consistently be recognised from the trajectories produced by projecting the consecutive speech samples into a map plane.

5. Other Applications

In [18] the applicability of the SOM algorithm to process state monitoring and control was explained. The SOM method was explained in sufficient detail and the benefits of the algorithm as applied to monitoring applications were pointed out. The example application was a distillation process. In [17] another study of using neural networks in fault diagnosis of a chemical process was explained.

In [1] a preliminary study of the potential of the SOM algorithm for process monitoring was described. self-organizing map was used to detect abnormal states in a real-time process by examining the quantisation error between the best matching unit on the map and the input vector. The detection was based on the fact that the map units were distributed in the space occupied by those input samples that were encountered during the training. Rising quantisation error obviously indicated some process state that had seldom occurred during the training period. A similar principle of error detection was used also in [7] where some error states were classified by observing the projection of samples to 'forbidden' areas in to map, determined using a known set of error samples. A similar system was described in [4], where the training algorithms were improved.

In [2] a similar system as above was used to detect errors in a nuclear power plant, where it is important to notice previously unknown situations. The quantisation error given by the SOM algorithm is used to give some indication of the novelty of the input sample.

In [3] two neural network models (self-organizing map and a kind of autoassociative back-propagation model) were applied to a monitoring application of an engine condition. The results were promising. The authors found the SOM to be especially useful in the visualisation of data properties and highlighting the deviant data values. In [21] a U-matrix method for the visualisation of the process properties through the map was explained (the U-matrix method was introduced in [19] and [20]).

In [14] the self-organizing map was used to analyze some financial data from a group of Spanish banks. It was shown how different regions on the map represented solvent and bankrupt banks, respectively. It was also possible to follow the time evolution of the banks from the trajectory created by mapping the data of successive years.

The self-organizing map has been used to monitor electric power systems for different kinds of failure detection. In [5] several studies were reviewed. As an example one can take the paper [16], where self-organizing map was used for power system static security assessment. It was shown that the map can be used in monitoring of power systems.

In [24] the self-organizing map was used to visualise measurement signals collected from test car during test runs. The system consisted of two layers of SOMs where the first layer handled static measurements and the second layer collected data from longer durations of time. The visualisation of the measurements was done by colour coding the map units; similar driving states have therefore similar colour codes. The driving states during the test run was then illustrated as a colour coded trajectory on a map of test lane.

In [10] an error back-propagation model was used to estimate the final quality of paper from process measurements. A separate self-organizing map was used to monitor the movement of the operating point of the process and to give a hint of the estimation error of the primary network.

6. Discussion

The self-organizing map has been applied to various applications in monitoring complex processes. The nonlinear mapping from a high dimensional input space to a usually two dimensional grid efficiently characterises complex systems. Due to the topology preserving property of the SOM algorithm it has shown to be an extremely powerful visualisation tool.

Using SOM the dependencies of the system parameters and variables can be investigated in a straightforward manner. The method is applicable to the analysis of any system where true measurements of process parameters or simulated data are available. For instance, in the analysis of complex chemical processes various dependencies can easily be examined. The high dimensionality of the feature vector is not a significant drawback with today's computers.

In addition to monitoring and visualisation, the SOM algorithm can be used in simulating and estimating the behaviour of the process. Various parameters can be optimised by following the process behaviour on the map. Even the control of complex systems may be possible by using feedback from the monitoring system.

References

[1] J. T. Alander, M. Frisk, L. Holmström, A. Hämäläinen, and J. Tuominen, Process error detection using self-organizing feature maps, In T. Kohonen, K. Mäkisara, O. Simula, and J. Kangas, editors, *Artificial Neural Networks*, pages II–1229–1232, North-Holland, 1991.

[2] Y. Bartal, J. Lin, and R. E. Uhrig, Nuclear power plant transient diagnostics using LVQ or some networks don't know that they don't know, In *Proc. ICNN'94, Int. Conf. on Neural Networks*, pages 3744–3749, IEEE, Piscataway, USA, 1994.

[3] S. Cumming, Neural networks for monitoring of engine condition data, *Neural Computing & Applications*, 1(1):96–102, 1993.

[4] F. Firenze, L. Ricciardiello, and S. Pagliano, Self-organizing networks: A challenging approach to fault diagnosis of industrial processes, In M. Marinaro and P. G. Morasso, editors, *Proc. ICANN'94, Int. Conf. on Artificial Neural Networks*, pages II–1239–1242, Springer-Verlag, 1994.

[5] R. Fischl, Application of neural networks to power system security: Technology and trends, In *Proc. ICNN'94, Int. Conf. on Neural Networks*, pages 3719–3723, IEEE, Piscataway, USA, 1994.

[6] J. Kangas, *On the analysis of pattern sequences by self-organizing maps*, PhD thesis, Helsinki University of Technology, Espoo, Finland, 1994.

[7] M. Kasslin, J. Kangas, and O. Simula, Process state monitoring using self-organizing maps, In I. Aleksander and J. Taylor, editors, *Artificial Neural Networks, 2*, pages II–1531–1534. North-Holland, 1992.

[8] T. Kohonen, Self-organizing formation of topologically correct feature maps, *Biological Cybernetics*, 43(1):59–69, 1982.

[9] T. Kohonen, The self-organizing map, *Proc. of IEEE*, 78:1464–1480, 1990.

[10] J. Lampinen and O. Taipale, Optimization and simulation of quality properties in paper machine with neural networks, In *Proc. ICNN'94, Int. Conf. on Neural Networks*, pages 3812–3815, IEEE, Piscataway, USA, 1994.

[11] L. Leinonen, J. Kangas, K. Torkkola, and A. Juvas, Dysphonia detected by pattern recognition of spectral composition, *Journal of Speech and Hearing Research*, 35:287–295, 1992.

[12] L. Leinonen, T. Hiltunen, K. Torkkola, and J. Kangas, Self-organized acoustic feature map in detection of fricative-vowel coarticulation, *Journal of the Acoustic Society of America*, 93(6):3468–3474, 1993.

[13] L. Leinonen, R. Mujunen, J. Kangas, and K. Torkkola, Acoustic pattern recognition of fricative-vowel coarticulation by the self-organizing map, *Folia Phoniatrica*, 45:173–181, 1993.

[14] B. Martín-del-Brío and C. Serrano-Cinca, Self-organizing neural networks for the analysis and representation of data: Some financial cases, *Neural Computing and Applications*, 1(3):193–206, 1993.

[15] R. Mujunen, L. Leinonen, J. Kangas, and K. Torkkola, Acoustic pattern recognition of /s/ misarticulation by the self-organizing map, *Folia Phoniatrica*, 45:135–144, 1993.

[16] D. Niebur and A. J. Germond, Unsupervised neural net classification of power system static security states, *Int. Journal of Electrical Power and Energy Systems*, 14(2-3):233–242, 1992.

[17] T. Sorsa and H. N. Koivo, Application of artificial neural networks in process fault diagnosis, *Automatica*, 29(4):843–849, 1993.

[18] V. Tryba and K. Goser, Self-Organizing Feature Maps for process control in chemistry, In T. Kohonen, K. Mäkisara, O. Simula, and J. Kangas, editors, *Artificial Neural Networks*, pages I–847–852, North-Holland, 1991.

[19] A. Ultsch and H. P. Siemon, Exploratory data analysis: Using Kohonen networks on transputers, Technical Report 329, Univ. of Dortmund, Dortmund, Germany, 1989.

[20] A. Ultsch and H. P. Siemon, Kohonen's self-organizing feature maps for exploratory data analysis, In *Proc. INNC'90, Int. Neural Network Conf.*, pages 305–308, Kluwer Academic Publishers, 1990.

[21] A. Ultsch, Self-organized feature maps for monitoring and knowledge acquisition of a chemical process, In S. Gielen and B. Kappen, editors, *Proc. ICANN'93, Int. Conf. on Artificial Neural Networks*, pages 864–867, Springer-Verlag, 1993.

[22] M. Vapola, O. Simula, T. Kohonen, and P. Meriläinen, Monitoring of an anaesthesia system using self-organizing maps, In C. Carlsson, T. Järvi, and T. Reponen, editors, *Proc. of the Conf. on Artificial Intelligence Research in Finland*, number 12 in Conf. Proc. of Finnish Artificial Intelligence Society, pages 55–58, Finnish Artificial Intelligence Society, 1994.

[23] M. Vapola, O. Simula, T. Kohonen, and P. Meriläinen, Representation and identification of fault conditions of an anaesthesia system by means of the Self-Organizing Map, In M. Marinaro and P. G. Morasso, editors, *Proc. ICANN'94, Int. Conf. on Artificial Neural Networks*, pages I–350–353, Springer-Verlag, 1994.

[24] P. Weierich and M. von Rosenberg, Unsupervised detection of driving states with hierarchical Self-Organizing Maps, In M. Marinaro and P. G. Morasso, editors, *Proc. ICANN'94, Int. Conf. on Artificial Neural Networks*, pages I–246–249, Springer-Verlag, 1994.