Self Organized Feature Maps for Monitoring and Knowledge Aquisition of a Chemical Process.

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An application of Self-Organizing Feature Maps to the problem of process control for a chemical process is described. Very few of the nature and structure of the process can be learned from the trained Feature Map itself. A set of methods called U-Matrix methods have been developed to enhance the representation of data on Feature Maps. This methods allows to discover structure in the process data and allows to judge the quality of the learned maps. It can be used to extract knowledge for expert systems from the Feature Maps. The extracted rules were able to control the chemical process as well as a human designed expert system. The methods presented here are in particular usefull to monitor critical processes and for the design of suitable human interfaces for process monitoring stands.

1. Introduction

Some processes, in particular in the chemical industry are hard to control. One of the reasons for that is that it may be impossible to observe or steer the process directly. This may be due to the general physics of the process or the difficultis of observation without interfering with the process. Other reasons are the nonlinearity and coupeling respectively interference of the control parameters. This means, that if some parameters are changed only slighly, some drastical and unwanted changes in the process may occur. In this paper we describe an application of self-organizing feature maps (SOFM) to the problem of process control for a chemical process [Wayand 92].

2. SOFM for Process Control

The state of a process at a certain time t can be described by a vector of parameters x(t). Components of x(t) are either measurements of some physical parameters or controling information.SOFMs may be trained with these vectors. We know that a SOFM adapts to the training data such that similar vectors are represented in close topological neigborhoods [Kohonen 82]. After enough learning steps the states of the process may be represented on a 2-dimensional SOFM as Figure 1 shows.
The SOFM can directly be used to steer the process. For a given set of measurements from the process the corresponding (most similar) location is found on the map and the settings of the steering parameters are taken from the state-vector. This approach has been followed, for example, by [Tryba/Goser 91].

Figure 1: Representations of process states

If the process' representations on the map are observed in some time intervals, the following Figure arises. It shows the sequence of states at two different time intervals.

Figure 2: Representations of the process' dynamic

The consecutive process states form a line or route on the map. Note in particular, that the process stays in almost the same location on the map for the given interval.
Of the representation of Figure 1 and 2 very few can be learned about the process itself. With a creative eye some regions on the map may be detected, where the process states are more densely distributed than in other regions. These regions may be seen to be separated by gaps where no process state can be found. In this form the interpretation of the map is rather vaque. Looking at the distribution of the parameters on the map, as suggested in [Marks/Goser 88], may help. This approach is however limited to one or only a few parameters. It is clearly prohibitive, if the process can only be described by a large number of parameters i.e. a high dimensionality of the process vector is given.

3. U-matrix methods

Since several years we have been developing methods to detect structures in trained SOFM [Ultsch 91, Ultsch/Panda 91]. These methods we call unified distance matrix (U-matrix-method or UMM). The simplest UMM is to calculate at each map coordinate (X;Y) the sum of the distances of the weight vector at (X;Y) to its neighbouring weight vectors [Ultsch 92a]. The matrix of these distances can be displayed as 3-dimensional landscape on top of the positions of Figure 1 resp. 2.
The landscape may be interpreted as follows: if there are hills or walls, then the neighbouring weights are quite distant. I.e., the process states differ significantly. If a depression or valley can be seen in the U-matrix, then the process states are quite similar. A U-matrix representation of the process control problem can be seen in Figure 3.

Figure 3: U-Matrix for a chemical process
In Figure 3 some definitive states can be distinguished. Some of these states may be recognized by people who are experts in the particular process. In Figure 3, for example, one of the states that could be identified is "loss of pressure" in the process.

4. Applications

SOFM with the UMM may be used in process documentation. Think of an online representation of the actual state of the process as a marker in the U-matrix of Figure 3. Process supervision is then the observation of the movements of a point in the landscape given by the U-matrix. This can be a significant improvement over the observation of a possible large number of gauges. If critical process states are identifieable in the U-matrix, the observer may quickly identify crucial points. The process runs normal as long as the process representation x(t) on the U-matrix stays in safe regions. If x(t) proceeds towards crucial areas, appropriate actions may be taken. This may be a contribution to make process observation more human-like and more safe.
Another application is to extract the structural information from SOFM that can be detected by UMM. This may be done by a rule extraction algorithm [Ultsch 91, Ultsch 92]. In this application the walls or hills in the U-matrix are thought to seperate different classes or clusters on the SOFM. From the weights of the SOFM that are classified with this method a

special designed machine learning algorithm, called sig* derives abstract descriptions of the classes. These descriptions may be used on one hand to discuss the structure of the SOFM with an domain expert. This results also in a methods to judge the quality of the trained map. On the other hand the extracted descriptions may also be used in some expert system.
We have tried this approach successfully for several different applications [Ultsch/Halmans 91, Ultsch/Panda 91, Ultsch et al 91]. For the process control application presented here, the extracted rules were successfully to steer the chemical process [Wayand 92]. The extracted rules showed the same performance as human generated rules that have been build for an expert system for process control. The major cost factor of this expert system was the knowledge aquisition, i.e. the questioning of the experts and the correct design of the rules. This took almost two man-years. With the rules extracted from SOFM/UMM this process can be accelerated significantly.

5. Conclusion

SOFM enhanced with U-matrix methods may be used successfully in process control applications. The artificial landscapes that arise from the U-matrix methodes can be used to judge the quality of the trained map. More important, however, they reveal the intrinsic structure of the data. This means that humans can detect structures in a high-dimensional data space. For process monitoring stands this may result in a better and more safe human-interface. U-matrix methodes may also be used to extract symbolic knowledge from SOFM. With this costly knowledge aquisition steps in the realisation of expert systems may be efficiently accelerated.
Aknowledgements
The realisation of the programs and the field testing was done by M. Wayand. We thank in particular T. Soltysiak for the supply of data. H.-P. Siemon cosupervised the practical work and did some Macintosh adaptation of the graphics. This work has been supported in part by the Bennigsen-Foerde research price of Nordrhein-Westfalia and the BMFT research grant WINA.

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