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The state of traumatic coma patient can be visualized by means of a SOM[1]

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Abstract. This paper aims at efficient visualization and intelligent alarming while monitoring the state of traumatic coma patients. We apply and extend a visualization method that is well known in knowledge discovery to monitoring the state of traumatic coma patients. We argue for state observation using a set of geometric shapes such as cubes or polygons in a single display rather than observing a set of time series graphs. The necessary transformations can be carried out by means of a SOM. Beyond mappings, it allows intelligent alarming and state prognosis. Advantages of this approach are discussed along with some limitations.

keywords: scientific visualization, SOM, efficient monitoring, intelligent alarming, state prognosis

1 Introduction

The measurements available for the evaluation of the status of patients suffering from traumatic head coma has grown permanently both in number and individual resolution in recent years. A computer-aided processing of such high-dimensional, sequential data with the aim of their compact (and intuitively interpretable) display therefore represents a formidable challenge. It would enable medical personnel to observe the development of the patient's status on a qualitatively higher level. Further, it would enhance an estimate of the future status and ease or make possible an identification of erroneous emergencies in an abnormal present or predicted development of the status. Not of least importance, such status analysis entails the possibility to achieve a new quality of the therapy itself.

The feasibility of a visualization of high-dimensional data ultimately rests with the employment of special projection methods which map high-dimensional feature vectors to a lower-dimensional representation while preserving topological properties such as similarity or dissimilarity latent in the data. Among others, especially SOMs (self organizing feature maps) as introduced by KOHONEN have shown their ability to find such topology preserving, low-dimensional mappings ([5]). Beyond that, SOMs offer additional capabilities which can be exploited for fault detection ([12]) and analysis of dynamic patterns. Thus SOMs are applicable for process monitoring as pointed out in a number of papers ([11]) and we argue that their use can be extended to support the monitoring of ICU patients.

In chapter 2, we discuss the deployment of SOM for process visualization in the medical domain in detail. Beyond that we show how some limitations of that approach can be solved in using FRITZKES GNG (growing neural gas) or BRUSKES DCS (dynamic cell structures). Chapter 3 deals with intuitive imaging of high-dimensional sequential data and the utilization of additional knowledge, for example, to rank individual features. In chapter 4, we depict the significance of such visualization tool for the concept of a computer-aided medical assistant (CAMA).

2 State visualization of ICU patients using SOM

The basic idea of status visualization consists of a projection technique, which generates an isometric mapping of the input signal space. High-dimensional feature vectors are projected onto a two- maximally three-dimensional representation plane. This is carried out under preservation of topological properties like similarity and dissimilarity, such that distances between the data in the input space equal those on the projection surface. Among the best known approaches to these topology preserving, dimension reducing mappings list different forms of 'Multi-dimensional scaling'(MDS), linear methods of principal component analysis, yet also procedures derived from KOHONEN's work on self organizing maps (SOM) [5]. It has gained widespread use especially due to its robustness and easy application.

Its applicability to a low-dimensional projection of high-dimensional data is based on the arrangement of a number of artificial neurons in a two-dimensional, elastic grid structure. The weight vectors of the neurons (their reference or codebook vectors) possess the same dimensionality as the n-dimensional input vectors. During training of the net with data gained from the patient, they are distributed in the input space so as to approximate the distribution of training data in an ordered fashion. The grid structure of the net defines a local neighborhood relation between closely located neurons. This relation results in an update of the weight vector not only for the so-called 'best matching neuron' (whose reference vector most closely matches the present data vector), but also for its nearest 'neighbors'. As a consequence,

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neighboring best matching neurons will approximate similar input vectors, thus achieving the desired topology preservation.

2.1 Intelligent Alarming using SOMs

The monitoring of patients in an ICU (Intensive Care Unit) usually produces a lot more data from stable, than from critical conditions of the patient's status or data indicating a malfunction or disturbance of the recording devices. A SOM trained with these data will subsequently not represent the input space homogeneously. Frequently occurring, 'noncritical' states are projected much more exactly (with a much smaller quantization error) than infrequently occurring, potentially critical conditions.

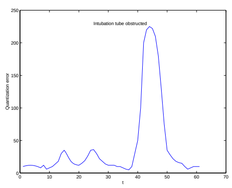

Figure 1. Utilization of the quantization error of a SOM to detect potentially critical conditions (acc. to [12]): An infrequently occurring feature vector is approximated with a high quantization error. The exploitation of this effect can be extended to other clustering approaches.

[12] suggests to utilize this effect to detect potential emergencies (fig.1). A condition classified as potentially critical due to its high quantization error can be identified using additional SOM-structures specially trained with usually artificial data.
This concept can be applied especially to ICU-monitoring by detecting and identifying measurement configurations which substantially deviate from their reference, such that possible causes and consequences of an alarm are already available when the alarm is invoked.

2.2 Approximation of dynamical patterns using SOMs

An important part during the monitoring of patients in an ICU consists of observing the development of a patient's status. The acquisition of its dynamical aspects seems to be of great importance. Although SOM in its formulation by Kohonen was not equipped to handle data featuring a temporal relation, there exist a number of approaches to process dynamical patterns using SOM. Of those, especially the approaches with additional lateral connections between the neurons on the SOM are applicable to ICU-monitoring. The procedure by Kopecz introduced in [7] seems to reach farther than others and thus, will be sketched briefly here. To be able to represent temporal sequences of data as trajectories at all, the lateral connections must be directed, as explained by Kopecz. He suggests the formation of additional lateral connections between temporally successive best matching neurons, and then, adapt those depending on the progress of activity. An increasing activation yields an increase of the lateral connection (excitation), while a decreasing activation results in a decrease of the corresponding connection.
A SOM modified in this manner can be used for prediction tasks, but also for an evaluation of the state dynamic's development, where the grid distance between a desired trajectory and a later, actual sequence of states (best matching neurons) can be quantified ([11]). Therefore, the deployment of a visualization tool amounts to an integral component of a computer-aided medical assistant (CAMA).

2.3 On the limitations of SOMs

A grave and for SOM-based visualization essential problem is termed 'topological defect': although reference vectors of neighboring neurons are similar, i.e. are located in close neighborhood to each other in the input space, the opposite is not necessarily true, i.e. neighboring points in the input space will not necessarily be projected onto neighboring best matching neurons. This causes disruptive and hard to interpret jumps, especially during the visualization of successive feature vectors(see chapter 3). The reason for this effect roots in the grid-like structure of the neurons, which enabled the formation of a topology preserving projection in the first place. [2] points out that in a grid with $N = s * s$-neurons, only $\sum_{i=2}^{s} i$ different distances can be mapped, although N could theoretically encode $\frac{N(N-1)}{2}$ distances. For this reason, the topology preserving capabilities of SOM must fall behind those of other projection methods, i.e. Sammons mapping, a MDS-approach.
With Fritzkes Growing-Neural-Gas-Algorithm (GNG, [3]) and Bruskes Dynamic-Cell-Structures-Algorithm (DCS, [1]) two procedures were introduced that approximate a set of high-dimensional feature vectors according to its intrinsic dimension, and thus, without topological defects. The combination of these algorithms with a projection method such as the Sammons Mapping raises well-founded great expectations for a much more exact topology preserving projection. Compared to Kohonens SOM, this approach possesses further advantages, namely an intuitive way to display disjunct data accumulations.

3 On the intuitivity of high-dimensional data visualization

Information about the patient's status in ICU-monitoring, e.g. the course of the heart rate, are usually visualized using time series graphs akin to those known from signal processing. It is left to the physician to find the important ones among the multitude of those graphs and merge them into a comprehensive notion about the patient's status.
After the discussion on ways to project high-dimensional dynamic patterns onto a planar surface, we now turn to visualization techniques that allow a compact and intuitively understandable display of complex dynamic data.

When using SOM-based approaches to visualize high-dimensional data, the values of an individual feature are normally expressed on the SOM by a height map, a gray or color coded map ([9], [6]). Since many features can only be understood in the context of other parameters, these solutions seem not very well suited to an efficient patient monitoring, for the simultaneous visualization of several features would require the display of a number of such feature maps ([6]). As our investigations and an analysis of commercially available tools ([8]) show, it is much more effective and especially more compact to map the values of multiple features onto the characteristics of geometric objects. For example, the size and

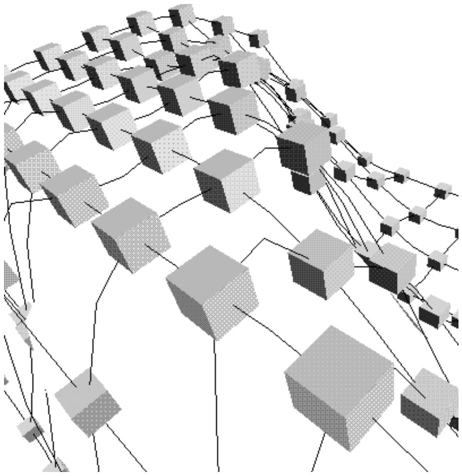

Figure 2. Visualization of a projection of high-dimensional patient data found by SOM using cubes arranged in a grid. The coloration of each side of the cube corresponds to the value of a different feature in the reference vector of the considered neuron.

coloration of the 6 sides of a cube can be changed, such that using a cube, the values of 7 features can be shown within the same figure(fig.2). Even better suited seems a variant based on the usage of polygons. Here, the distance from a vertex to the center of the polygon corresponds to the value of a feature, such that different feature configurations (patient conditions) yield differing shapes. An interesting variant of this depiction results when instead of the values themselves, the respective difference to their reference values is shown. This emphasizes potentially dangerous situations especially well(fig.3).

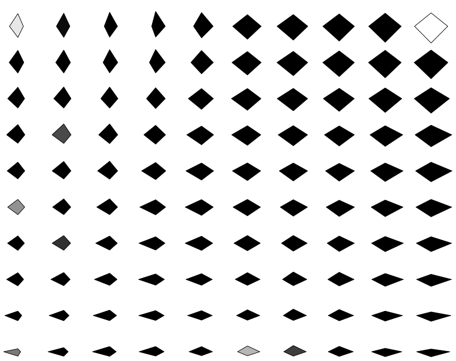

Figure 3. Employment of polygons for the visualization of a projection of high-dimensional patient data found by SOM. The difference of the vertices to the center of the polygon represents the deviation of the corresponding feature from a pre-defined reference value. Bigger polygons signalize potentially critical states and can be easily detected.

3.1 Yet another approach to dynamic visualization

The visualization techniques provided by [6] and [11] draw lines between adjacent best matching neurons in order to visualize dynamical patterns, i.e. trajectories. However, with the help of this projection it is impossible to follow the development of dynamic patterns for some extended period of time, as the lines forming the trajectories cover the entire screen. Therefore we chose a different approach to give an impression about the temporal sequence of feature vectors, and thus the development of the patient's status: each feature vector is represented on the projection plane by its best matching neuron. According to its activation, it is illuminated for a short time and then, slowly dims (fig.4).

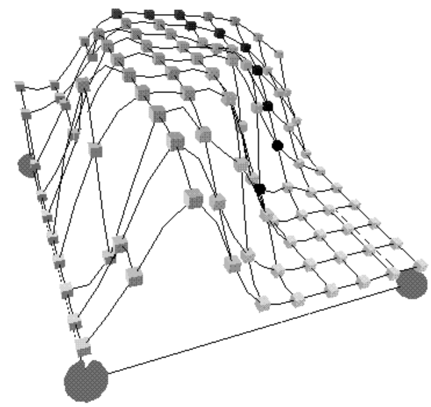

Figure 4. Visualization of a projection of high-dimensional dynamic patterns found by SOM. During a sequential presentation of feature vectors the appropriate best matching neurons light up for a short time and then, slowly dim. The resulting 'trace of light' gives the impression of a trajectory (visible as a trace of dark objects in the gray level display).

Without a doubt this way of visualization is limited to a display of temporal relations in the signal's history. A further extension to include an impression of the predicted signal development (the immediately expected patient's status) is extremely interesting, because only with a prediction can the physician test alternative treatments without direct intervention involving the patient (see also chapter 4). The active interest of the scientific community in time series prediction proves the equipment of a program with prognostic capacities to be highly nontrivial. Nonetheless, from a purely graphical point of view the SOM-structures featuring additional lateral connections mentioned in chapter 2.2 present an obvious approach, in that starting from the appropriate best matching neuron the induced activation propagates via the directed lateral connections to all reachable SOM-neurons, as highlighted by their coloration.

3.2 Utilization of additional domain knowledge for visualization

The evaluation (markup, labelling) of individual regions of the plane used for representation is of great importance for the interpretation of topology preserving projections of a high-dimensional feature space. Traditionally, this is executed manually by an analysis of how selected parts of the input space are represented in the presentation plane und vice versa, which region of influence certain parts of the presentation plane have in the input space. As a result, the individual reference vectors of the SOM can be labelled ([6]).

A (partially) automated evaluation of the mapping found can be formed in a condensation process. It starts out by presenting a few synthetic, evaluated training data (the condensation seeds) to the SOM. After that, the SOM is trained with actual (evaluated) patient data, and the resulting evaluation map is manually corrected, if necessary. In a third phase, the SOM operates on actual, non-evaluated patient data ([10]).

4 On the use of a visualization tool as a module for a computer aided medical assistant

Currently, we attempt the design of a computer aided medical assistant (CAMA). The development of a visualization tool featuring the functionality described above is of central importance. On one hand, the visualization of the patient's status serves as an interface between physician and computer. Thus, it will be possible to

- visualize the theoretical effects of interventions as planned by the physician or suggested by CAMA,
- by marking certain regions, fix milestones in the therapy or required trajectories and so,
- have a positive effect on the quality management of the therapy.

On the other hand do projection methods as described in chapter 2 possess capacities to support other components of CAMA. It seems possible to utilize the prognostic abilities of SOMs with additional lateral connections not only for visualization, but also for intervention planning within CAMA. It could predict the theoretical effects of the interventions suggested by itself and from a discrepancy between predicted and actually realized development of the state, conclude the effectiveness of the interventions. Along with the utilization of additional domain knowledge as introduced in chapter 3.2 this idea can be extended to generate so-called reward maps, which can serve as a source of reward or punishment for other modules of CAMA.

5 Conclusions and Outlook

The paper is based on a visualization tool which is still in a conceptual stage of development. There exist only a few design studies regarding the projection of high-dimensional data. Approaches for fault detection and identification based on the above mentioned quantization-error examining method are actually in discussion. The same holds for the storing of sequential information using lateral connections between SOM neurons. First studies in using KOHONENS SOM as topology preserving projection method have shown some limitations. Using FRITZKES GNG or BRUSKES DCS combined with SAMMONS Mapping we hope to overcome these limitations and to take advantage of a lifelong adaptable extension of the GNG algorithm ([4]). Thus a great amount of work needs to be undertaken until the proposed approach can actually prove its full potential.

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