Self-Organizing Maps in Adaptive Health Monitoring

Satu Tamminen, Susanna Pirttikangas, Juha Röning
Machine Vision and Media Processing Group, Infotech Oulu
University of Oulu, Computer Engineering Laboratory, FIN-90014 OULU

Abstract

A method for health monitoring is considered. Measured physical signals have been dynamically classified to low-, middle- or high-levels and self-organizing map (SOM) has been utilized to combine the information.

The data were collected during the spring 1996 and consist of over eight weeks of physical measurements and diaries recorded in a home environment by four test subjects.

The research shows that this method can be used to monitor the system of human being. The system finds some daily structures as well as differences between weekdays and weekend. The physical activities have much stronger effect on the signals than mental stress states, which show no clear clustering on maps.

Keywords: process control, dynamic control limits, self-organizing maps

1 Introduction

The purpose of this research was to develop a simple and descriptive device for people interested in their own well-being. It helps to recognize the changes in physical parameters occurring during normal life. There is no ambition to substitute the doctor in diagnosing, but to help people to maintain good health.

The process modelling was initiated by defining the normal and abnormal states of the system. The measured signals of the system can be analyzed with dynamic control limits in order to monitor their variability. In this application, dynamic control limits were used to produce an adaptive classification of each signal to different levels. This helped to identify fast changes in signals and also to monitor their relations to each other. The calculation of dynamic control limits can be done on-line. For data reduction, old data are deleted when new data are entered in the system. A history of four days is used in this class-identification.

The monitoring of a process usually requires an analytical system model. In industrial applications this is often difficult to accomplish, and for a human being it is impossible, because the environment cannot be controlled and the person’s routines frequently change in every-day life. Neural networks provide a nonlinear solution where no analytical process model is needed. The self-organizing map is an unsupervised method, needs no target values and provides a visualization tool for temporal process control. The areas of the map can be identified based on the content of each area.

For eight selected variables, adaptive class-identification were performed and (0,1) indicators for low-, middle- and high-level observations were obtained. The most descriptive indicators were chosen among a total of 28, and they were entered into the self-organizing map with the original signals.

The research shows that this method can be used to monitor the system of a human being. Since, however, everyday activities are not repetitive, it is too ambiguous to try to predict the future states. The natural daily variation of physical signals explains why the morning and evening measurements have been clustered separately on maps. There is also some differences between weekday and weekend measurements except for mornings. Physical activities seem to have some impact on the results. This is understandable, because some of the chosen variables reflect immediately the effects of physical stress. No general implication for mental stress was found, however. This was due to the fact that all the test subjects lived quite a steady life during the measurement period.
2 Data Description

The data for this research were obtained during the spring of 1996. Fourteen healthy middle-aged male volunteers collected their physiological data daily for eight to ten weeks. Four of them were selected for the research. Their R-R interval and activity were measured continuously with an R-R interval recorder and an activity monitor during the daytime. A R-R series consists of the time spans measured between two R peaks in an ECG signal. Diastolic and systolic blood pressure along with body temperature were recorded three times a day by the subjects. The first measurements were made in the morning after waking up. The second measurements were made between 2:00 and 8:00 PM and the third in the evening before going to bed. The quality of sleep was evaluated at night. During the measurement period, all the subjects were living normal life. The variation in measurement times was due to unsupervised self-measurements.

Furthermore, the subjects filled in a diary, indicating their daily emotional states, such as fatigue, happiness, pain etc. The amounts of coffee, tea, cigarettes and alcohol consumed were also reported. The notes on the emotions during the daytime were made at 2:00-8:00 PM and those on the rest of the day before going to bed. The physical exercise and meal times were also recorded.

The measurement time of over eight weeks produced a very large data set. To make the signals compatible, the continuously measured variables were discretized by taking averages for one-hour spans simultaneous to the discretely measured variables. Thus, three values for each day resulted in data vectors of 170 observations or longer.

The data were analyzed with different statistical methods. This analysis and discussions with experts led to the selection of eight variables with high quality, stability and descriptivity. The others were discarded because of the long missing periods (several days or even weeks) and noisy or clearly erroneous measurements. The variables were diastolic and systolic blood pressure, the mean and the standard deviation of R-R intervals, activity, body temperature, weight. The quality of sleep was available for two test subjects.

3 Methods

The idea of using confidence limits of the expected mean in process control is not new. Control charts are an essential part of statistical process control, as they distinguish the normal variability of the process from abnormal, presuming the distribution of the signal to be normal [1]. Control charts have a middle line and two straight control lines defined on the basis of the confidence limits computed from at least four samples of the process, or else the result is not reliable. The process is under control if all measurements remain between the control lines.

The control limits can be formed in an adaptive way, that is, they can evolve with the signal if a proper time window and sliding technique is used [2]. This dynamic approach can also be used in the classification of the time-varying signal into three different categories: low-, middle- and high-levels. The control limits are then tighter, and the purpose is not to recognize abnormal or out of range situations, but to explore the behaviour of the signal in a fuzzified manner (e.g. if one signal is in a low level, how does it effect the other signals?).

In those cases, where the system contains a lot of irregular signals (high variation in signal levels), an appropriate T-value for the classification must remain low (e.g. $T = 3$), so that about 25 percent of the observations will maintain in the lower and upper level each and 50 percent in the middle level. The sliding history also influences the narrowness of the limits, and this is an important factor with a suitable weighting procedure to consider when forming the class-identification.

With this approach, three $(0, 1)$ indicators are established; one for the low-, middle- and high-level of the signals each. If the observation is in the lower-, middle- or upper-level, formed by the dynamic control limits, then the corresponding $(0, 1)$ indicator connotes this information.

The self-organizing map (SOM) provides a data-driven approach to process monitoring and modeling. The method has the advantage that little or no a priori information is needed about the system domain and it is not necessary to define the process model analytically [3].

The monitored process should be static or else the map is not able to visualize the data correctly. A problem will arise especially if the future measurements have some kind of trend or gradual development.

As with other neural networks, the SOM will also yield poor results if erroneous data are used. Therefore, the input data must be pre-processed carefully. The data variables must be quantitative, e.g. symbolic data.
should be transformed into a suitable form. If the scales of the input variables are very different, the variables should be normalized, which gives all the variables an equal influence in the training phase of the SOM. The SOM is able to handle missing values, but if a large number of components is missing, it will affect the reliability of the map.

The quality of mapping can be measured using the average quantization error, which is the average distance between the input vectors and the corresponding BMUs. The accuracy of the results can be visualized with independent quantization errors for each observation. For better understanding of the results, the map can be characterized by labeling the data units. If no labels are available, inspection of the weight vectors and the clusters of the map may help in characterization [5].

For more information about self-organizing maps, the comprehensive book of Kohonen is recommended [4].

4 Application Results

4.1 Health Indicators

There are many events that influence the behavior of the selected signals of the test subjects. The class-identification with dynamic control limits is simple, and they give us guidelines for research on the system. In this alarm system, the critical points of the data are not as important as the drastic change. As mentioned above, eight variables were chosen for the study of the dynamic behavior of human physical structure. After filtering the artifacts, the idea of dynamic control limits in class-identification was applied to the data. The limits were calculated using the Matlab version 5.3, and a Sun Ultra 10 workstation.

The variables modeled were diastolic (DBP) and systolic (SBP) blood pressure, the mean and the standard deviation of R-R intervals (RR and RRSTD respectively), activity (ACT), weight (WEIGHT), body temperature (TEMP) and quality of sleep (Q5%). They were assumed to describe the person’s physical condition in the best possible way. Both SBP and DBP were chosen, because they are affected by different physical states [6].

An appropriate $T$-value and sliding history [2] were chosen to be three and 12 respectively. This means that four days of measurements were taken into account in building the present value of the dynamic control limit and all the previous values were ignored.

The weighting procedure for DBP was defined to follow the person’s diurnal blood pressure rhythm [7]. The weights were chosen to strengthen the previous value and the measurement made at the same time on the previous day. The value between these two was also weighted. A similar weighting procedure was used for the other variables, too.

Because of the long measurement period, the subjects were not able to carry out the measurements continuously. The data therefore contain a great deal of missing values. This is also due to problems with the measurement devices. The missing values were replaced by the average of the earlier values of the signals within the sliding history.

4.2 Health Monitoring

Self-organizing maps have been used to monitor many different industrial processes [3]. As far as the human being is concerned some substantial differences can be found compared to industrial processes, however. First of all, the conditions in normal life are not homogeneous and not always predictable. The physical system of a human being is not stable, and many normal every day activities may affect the measured signals considerably. SOM visualizes this complex system into a simple and descriptive picture. A Sun Ultra 10 workstation and SOM TOOLBOX [8] with Matlab 5.3.1 was used for the training and visualization of the self-organizing map.

For the four subjects, the data were divided into a training period and a test period. The test period covered the last four weeks from the data set, and it was used to confirm that the contents of the areas remain similar when new data is fed into the map.

The size of the map was 30x21 units and linear initialization was used. After the training, the map was compared with the diary and other records in order to find a correlation between the results and daily activities or subjective feelings.
Figure 1: Self-organizing map with quantization errors.

Figure 2: Component planes of SOM.

Figure 1 contains many different light areas separated from each other with darker borders. The content of the areas can be seen in Figure 2, where the component planes of each variable are shown. The quantization errors for measurements in the test period are visualized with circles. The bigger the circle, the poorer is the mapping result. Poor results are mostly due to the high variability between the other measurements in that area.

A small R-R average and low heart rate variability overlapped in several areas, which can be noticed especially in the component planes of original signals. Usually the same tendency was there also for high values. One test subject with high physical activity had some exceptions with high heart rate variability, because the exercise was done during the measurement time, which confused the signal.

There were also quite clear difference between morning and evening measurements. The position of daytime measurements depended mostly on the measurement time and its variation from day to day. Sometimes they were more similar to morning measurements, but usually they were clustered near evening measurements.

The weekends did not separate from the others. However, there were some areas, which contained only daytime and evening measurements from weekdays. Morning measurements showed no such separation.

Body temperature may have biased the results, because it can be easily measured wrongly, and actual temperatures can therefore be higher than in the data. This would explain some of the odd results.

The SOM TOOLBOX provided a tool for tracking the system’s state in time with the trajectory. If signals do not change their level too often, the tool is very useful, but for human beings it only jumps around
5 Discussion

The narrowness of the dynamic control limits can be controlled with the T-value and sliding history. Appropriate values for these parameters lead to class-identification where about 25% of the observations maintain in the upper- and lower-level each and 50% in the middle-level.

The dynamic limits are fairly adaptive, and they therefore provide no alarms for trends. In this way, important aspects of the person’s general health may go unnoticed. For the subjects at hand, this is not a problem, because the measuring periods were quite stable, which was investigated carefully.

The method has only been applied to four subjects so far, and the results cannot be generalized to larger populations. But the idea can be utilized straightforwardly for new subjects. If a totally different application is concerned, some effort is required for variable selection and parameter adjustment.

Based on the findings on these four subjects, it is clear that no map can adequately apply to all the subjects, because the reactions caused by different stress states occur individually.

There are clear differences between morning and evening measurements. Afternoon and evening measurements tend to appear in the same areas, however. It is a well known fact that many of these signals have a daytime variability, i.e. the values are lower in the mornings, and this explains also the results in maps.

One subject had a low percentage of quiet sleep during the test period. The cause for this was not found, but it affected the daytime coffee consumption. The others did not have similar incidents, but the whole measurement periods were more or less stable.

The effect of physical exercise was present for some test subjects. The impact of physical activities to the physical signals can be noticed immediately and therefore they project also to the map. The subjective diary records (e.g. busyness, mental strive and happiness) had no clear structure in the maps, and therefore it remained unsolved how they affect the physical signals.

An analysis of the quantization error in the map for different measurements showed that the biggest errors were in the alarm areas. This was due to the fact that the measurements with alarms were not so homogeneous as the normal measurements, and small alarm areas showed quite large variability. The same tendency was also found during the test periods. When visualizing the response surfaces of the map, notable quantization errors also occurred whenever the winning neuron of the map was not clear.

The high number of missing values was a problem for most of the subjects, and extrapolation of the signals was performed. This procedure does not give right values for the data and may bias the results, but at this point of research it helped to develop the tools for analysing the results.

References


