Visual Anomaly Detection in Production Plants

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Abstract: This paper presents a novel method for visual anomaly detection in production plants. Since the complexity of the plants and the number of signals that have to be monitored by the operator grows, there is a need of tools to overcome the information overflow. The human is highly able to recognize irregularities in figures. More than 80% of the perceived information is captured visually. The approach proposed in this paper exploits this fact and subjects data to make the operator able to find anomalies in the displayed figures. In three steps the operator is lead from the visualization of the normal behavior over the anomaly detection and the localization of the faulty module to the anomalous signal.

1 INTRODUCTION

Modern production plants nowadays grow more and more complex. Thus, the number of sensors and actuators grows also. Programmable Logic Controllers (PLCs) are used to manage the signals and to operate the plant. Supervisory Control and Data Acquisition (SCADA) systems get the data from the PLC to manage the process automatically. Due to the increasing number of signals the analyzing task gets more difficult. More and more the activity of the operator changes to a passive role; from operating to analyzing the production plants. Figure 1 illustrates a typical production plant monitored with the help of a SCADA system.

Figure 1: A typical complex interface of a SCADA system.

Different visualization techniques can help the operator to analyze the plant behavior. The goal is a graphical representation of the data which provides the operator with an overview of the current plant state. Additionally, the operator should be supported in detecting unusual behavior, i.e. anomalies. Examples for anomalies are unusual power consumptions or wears of conveyor belts. This paper adapts visual analytic approaches from different scientific areas to the field of automation.

In this paper, a novel visual anomaly detection approach is presented which guides the operator in a top-down manner starting from a general overview to a detailed description of identified anomalies. A main new idea here is to place a visualization of the learned normal behavior side-by-side to a visualization of the current behavior. This side-by-side visualization starts with an abstract graph computed by means of data dimensionality reduction techniques which give a coarse, time-independent system overview. The user is then guided to a more detailed visualization of the system's timing behavior. So three main ideas are combined here: *(i)* the usage of machine learning techniques to give the operator initially an abstract view onto these complex data, *(ii)* the usage of machine learning techniques to visualize the normal behavior (in comparison to the current behavior) and *(iii)* a guided interface which leads the user step-by-step to more detailed views onto anomalous data items.

The paper is organized as follows: In section 2

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an overview to the state of the art is given and the research gap which should be closed is pointed out. Section 3 defines some requirements for the visualization of technical processes and introduces a new method for the visualization of high-dimensional discrete data. In section 4, based on the defined requirements the visualization techniques are evaluated. For this, real data from a production plant are used. Advantages and disadvantages regarding process overview and anomaly detection are evaluated. To exploit the advantages found in the analyzed techniques, section 5 introduces a new approach. It combines the techniques in one new visualization approach to provide a more informative overview and to increase the anomaly detection performance. The results are discussed in the conclusion.

2 STATE OF THE ART

This section gives an overview to the state of the art and related work. First, in subsection 2.1 some basics of visual analytics process are presented.

The subsections 2.2 and 2.3 give an overview of some techniques which can be used to visualize discrete, continuous or hybrid data which are a combination of both. The visualization techniques should support the operator in two ways. At first, the high-dimensional data should be visualized in a neat way that allows humans to deal with the overwhelming information input. The second is to make process anomalies visible in the visualization.

2.1 Visual Analytics

According to (Keim et al., 2010) the visual analytics process is organized as follows (see also figure 2):

First, the data have to be acquired from the observed system. In many cases the data have to be preprocessed (e.g. normalization or feature generation). From this, a (mathematical) model is created using data mining approaches. The model can be extended by parameter refinement. In parallel the data are visualized for the further usage. This visualization is enhanced by user interactions. Very important in this context is the tight coupling of automated and visual analysis through interaction. Both steps lead to the requested knowledge, i.e. the needed information about the systems behavior. Based on this knowledge the operator is able to detect anomalies.

There exist many approaches to create a system's model using observations. E.g. in (Niggemann et al., 2012) a method to learn a behavior model by means

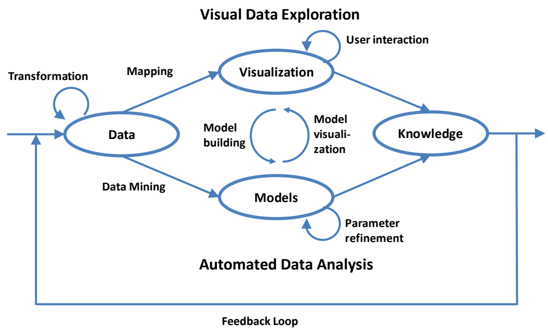

Figure 2: Principle of visual analytics according to (Keim et al., 2010).

of timed automata is presented. In many cases, especially in the case of high amounts of data, these models are created to be used by computers and are therefore not easily accessible for humans. For this, special visualization methods have to be developed.

Visual analytic approaches have been applied for many years. One early example is the Londoner physician Dr. John Snow in the year 1854. To find the reason for a cholera pandemic he used a visualization method. He marked each place of occurrence in a map and was therefore able to find the reason, which was a contaminated water fountain (Tufte, 1997).

Approaches in visual analytics are applied to different research areas. For example it is used in the financial sector to visualize and analyze the fall and rise of stocks and to detect frauds, e.g. in (Huang et al., 2009). The study of environment and climate change also often uses visualization approaches. The temperature and other relevant parameters are recorded over a long period of time. These data are visualized to recognize dependencies and to show up the changes over time. Another area of application is the prevention of terrorist attacks (Thomas and Cook, 2006).

However, there are only few examples where visual analytics have been applied to the manufacturing industry. Frey uses self-organizing maps to generate a two dimensional map which visualizes the observed process (Frey, 2008).

2.2 Visualization of Multidimensional Data

Figure 3 shows an excerpt taken from a process data set. The dataset comprises a timestamp and the corresponding process variables $f_1 \ldots f_{11}$. The example is rather small. Yet following the process or detecting an anomaly by viewing this figure is not easy. It can be seen that monitoring and anomaly detection in high dimensional process datasets is a tough task for computers and humans. Operators need to react on

time	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
25	0	0	1	1	1	0	1	0,60	993,3	235	1,5
60	0	0	1	0	0	0	1	0,50	983,4	235	1,8
124	0	1	1	1	1	0	0	0,38	983,7	236	2,2
149	0	1	1	0	1	1	0	0,44	982,4	233	2,5
248	0	0	1	1	0	1	1	0,46	980,1	234	2,9
324	1	0	1	1	0	1	1	0,52	978,5	231	3,2
419	1	1	1	1	0	0	0	0,48	980,5	231	3,6
455	1	1	1	0	1	0	0	0,44	990,2	232	3,9
513	1	0	1	1	1	0	0	0,42	993,4	232	4,3

Figure 3: An example dataset.

changes of large amount of different variables in different value ranges quite fast.

A trivial method to visualize data is to use signal curves in dependency of time. This simple yet especially for continuous data effective method helps to get an overview of the trends of a signal e.g. temperature over time. Further, the crossing of thresholds can be seen very well. However, this method is only usable for a small number of signals. The visualization of many signals in one diagram leads to an information overflow, such that the single curves cannot be detected separately. Figure 4 shows the visualization of 30 signals with 300 data points for each. Even for this small number the single curves cannot be separated well and it is very difficult to find an anomaly in this figure. This disadvantage is even worse for discrete data, because here the constant parts of the signals overlap and only the signal changes can be seen.

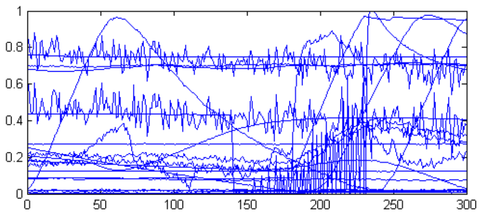

Figure 4: Visualization with data curves.

In (Alfred, 1985) the method of parallel coordinates is introduced. This technique allows the visualization of multiple dimensions (as coordinates) in parallel. This makes the dependencies between signals visible. As disadvantage, it has to be mentioned that the quality of the datapoints within the visualization is highly dependent on the order.

To get along with overlapping signals in high dimensions several figures can be depicted in a plot matrix (Cleveland, 1993). Here, the dependency of each pair of signals is displayed in one figure. All these figures are then arranged in a matrix. However, very high dimensions cannot be displayed clearly as well. E.g. an input dimension of 20 leads to a matrix with 400 single plots.

A detailed description of these methods can be found in (Keim, 2002).

The Multidimensional Scaling (MDS, e.g. in (Bronstein et al., 2006)) is a set of techniques from the mathematical statistics. The goal is the arrangement of objects and their relation to each other. The farther the objects are from each other, the more dissimilar they are and the closer they are, the more similar they are. There are thus collected information about pairs of objects to identify them to metric information about objects.

2.3 Principal Component Analysis

As outlined in the previous section, it is difficult to visualize high-dimensional data. Therefore, dimensionality reduction methods have to be used. The Principal Component Analysis (PCA) was introduced by Pearson and Hotelling and is here described based on (Jolliffe, 2002).

The PCA finds new uncorrelated features, the principal components. The dimensionality of the dataset is then reduced by using just two principal components to describe the dataset. This is possible, because most of the variance of the original dataset, i.e. the information, is represented by the first few principal components. (Jolliffe, 2002). In this contribution a two dimensional approach is used for the visualization (choosing two principal components), because it is difficult to extract information from a figure with three dimensions and for more than three dimensions it is impossible to create a visualization.

Figure 5 shows an example dataset visualized based on its two features X and Y.

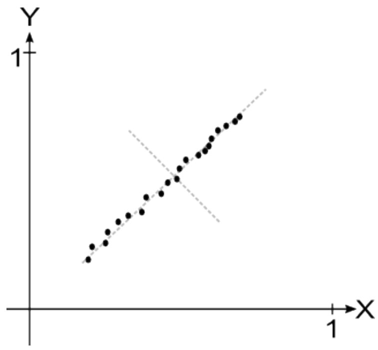

Figure 5: Example dataset with original features.

In figure 6 the same dataset is depicted based on its first two principal components. We can see that the most variance is represented by the first principal component (PC1). The variance represented by the second principal component (PC2) is rather small. In the notion of feature reduction only PC1 would be used for data representation of the example dataset.

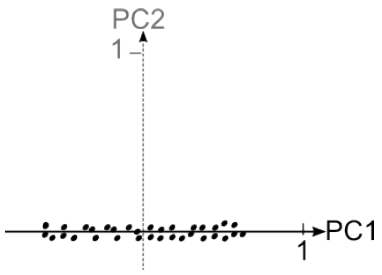

Figure 6: Example dataset with principal components.

The most information of the original dataset is preserved.
Although the most variance is kept it must be taken into account how many information is lost due to the reduction. For example reducing a dataset from 20 signals to 2 principal components (reduction of 90%) while keeping 80% of the information (loss of 20%) is a quite effective way of dimensionality reduction. Nevertheless the informational loss is highly dependent on the dataset and maybe worse than in the given example. Therefore this should be considered. Besides the potential of dimensionality reduction it has to be considered that the process is not visualized explicitly with respect to its time line.

3 VISUAL DATA EXPLORATION

This section gives some requirements for the visualization of technical processes. These requirements will be used for the evaluation in the next section. Based on the requirements section 3.2 introduces a new approach, the Discrete State Encoding (DSE), which is especially developed for the visualization of high-dimensional discrete input data.

3.1 Requirements for the Automation Domain

Every domain uses different methods to visualize the data. While the climate study uses maps which are colored to show the temperature, the financial industry uses curves to show the trends of stocks. To place a visualization method in the area of automation, technical requirements have to be considered:

High Dimensionality. Data of production plants is typically high-dimensional. This is caused by a large amount of sensors and actuators which are used to realize processes. Most of them are controlled by PLCs and need to be monitored by operation personnel in SCADA systems.

Different Data Types. The variety of sensors and actuators that are used to realize a process may result in different types of data. For instance a temperature sensor provides a continuous value, the temperature. Whereas a switch that activates a conveyor belt provides a discrete value, the state of the conveyor belt. Each data type puts different requirements on the visualization.

Importance of Data. Due to the high amount of data visualizing all values would lead to an information overload. Occurring anomalies may remain undetected. Therefore, only the most important data have to be visualized. This results in the need of methods which distinguish between important and less important data.

Time Dependency. Processes in the automation domain are dependent on the factor time. The system's states are usually observed in relation to the process time. Therefore, the visualization approach should consider and preserve time information. This enriches the process analysis and enables the operator to access the plant state in a natural way.

Cyclic Processes. In typical production plants products are produced in large amounts. This leads to reoccurring process phases. Therefore, system states that recur should be depicted in the visualization, so that the operator is able to recognize them as such. As a consequence new occurring states (maybe anomalies) can be visualized in a more exposed way. This is an ease for the operator.

3.2 Discrete State Encoding

Since no appropriate method for the visualization of discrete data exists, this section introduces the Discrete State Encoding (DSE). It can be utilized for the visualization of datasets which consist of discrete features only. Like the PCA this technique also compresses high dimensional information. Here, the plant behavior is represented by one feature only. This feature is then utilized in process visualizations to give operators a neat view on the process progress.

Datasets are represented as tables with N features f_i in the columns and the measured process data, i.e. the observations per row (see also figure 3). Each row from the dataset is encoded to a representative number, the *stateID*. It needs to be mentioned that the encoding uses only discrete values while continuous features are ignored. Slightly changing continuous values would result in a new state for each observation although the information has not changed significantly. The *stateID* computation is based on the following equation.

$$stateID = \sum_{i=0}^{N-1} f_{N-1-i} \cdot 2^i \quad (1)$$

In the following step the *stateID* values are renumbered. The first occurring *stateID* is renumbered to 1. To each newly occurring state a new number is assigned, whereas already known *stateIDs* always get the same number.

Renumbering *stateIDs* is necessary to avoid bias in the visualization. E.g. a bit change in a highly weighted feature would affect the visualization with a higher impact than a bit change in a rather low weighted feature. This misguiding perception should be avoided, following the notion of the *Lie Factor* introduced in (Tufte, 2001) in a figure. In the dataset the state change itself is the important information, not the artificial weight that is introduced for computation purpose. The renumbering preserves the state change information, but removes the bias resulting from the weights. Figure 7 shows a visualized discrete state encoding. It can be seen that two cycles are detected which describe the same process or at least two similar ones.

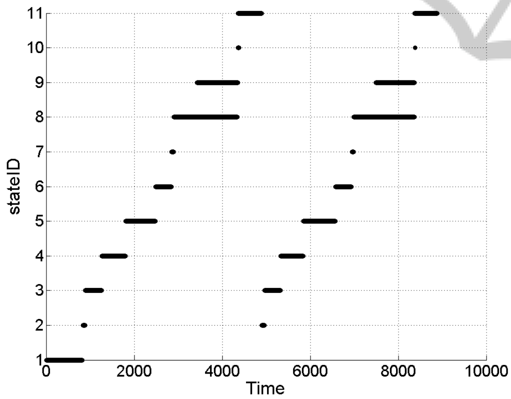

Figure 7: Discrete state encoding of an example dataset.

4 EVALUATION OF VISUALIZATION METHODS

In this section the visualization techniques described in sections 2 and 3 are evaluated. As basis, the requirements from section 3.1 are used. In the context of visualization of technical processes, the most important requirement is the visualization of high dimensions. Since most visualization techniques (mentioned in subsection 2.2) are not able to handle high dimensions properly or to reduce to the main information, only two methods are considered for detailed evaluation: The discrete state encoding (subsection 4.1) and the principal component analysis (subsection 4.2).

For the evaluation, a dataset of a part of a Model Factory (shown in figure 8) is used. The first objective is to provide an abstract process overview. The second is to detect anomalies. This is done by comparing the visualizations of a reference process with the observed process, which comprises anomalies.

The observed process produces popcorn out of the resource maize. In total 19 continuous and discrete features need to be analyzed online while the process is active. The production process is separated into two modules. Module one creates the product. The maize is heated until it pops. Via exhaustion the popcorn is transferred to a weight cell. In module two the popcorn is filled into cups or a larger pot, depending on what is available at time. The whole process works sequentially. First the popcorn is produced, next it is filled into the cups.

Figure 8: A model factory as exemplary plant.

4.1 Discrete State Encoding of a Production Process

Figure 9 shows the discrete encoded *stateIDs* for one process visualized over its time line. Out of the former 19 features, one new feature, the *stateID*, is created. As mentioned before, continuous values are not taken into account in the discrete state encoding.

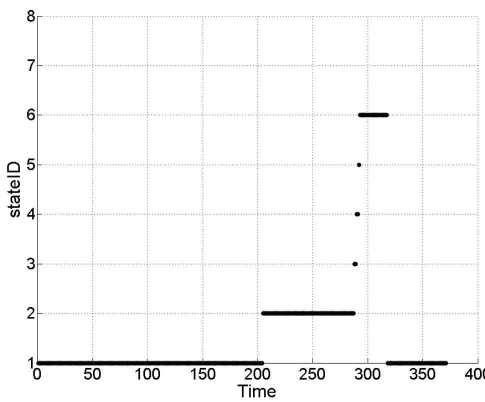

Figure 9: Discrete state encoded process.

As depicted in figure 9, the operator is provided with an abstract process overview by following the process visualization. Without any expert knowledge, it can be seen that the process has three main operation phases, and some short transfer phases between time units 285 - 295. Expert knowledge allows us to say, that the process states have been identified correctly. The *stateID* 1 represents the standby state of the process. In *stateID* 2 the production phase is displayed. Once enough popcorn is produced, it is filled into a cup. *StateIDs* 3-5 represent the cup filling. In *stateID* 6 the heating is turned off while the ventilation is still active to cool down the production module. Afterwards the process returns to standby (*stateID* 1).

Utilizing the visualization from figure 9 the operator is able to keep track of the process in a very convenient way. The operator is able to see the process over its actual time line. Furthermore, repeating process phases are represented correctly.

In the next step, the technique is tested regarding anomaly detection in the process. For that purpose, an anomaly is induced into the same dataset that was used before. A discrete sensor (e.g. a cup filling level sensor) changes its value in an unusual moment. Figure 10 shows the *stateID* representation of that dataset. As shown, the anomaly can be recognized by comparing figures 9 and 10. The operator is also able to determine the point in time where the anomaly occurred. However, the operator is not able to interpret the shown anomaly in a semantic way.

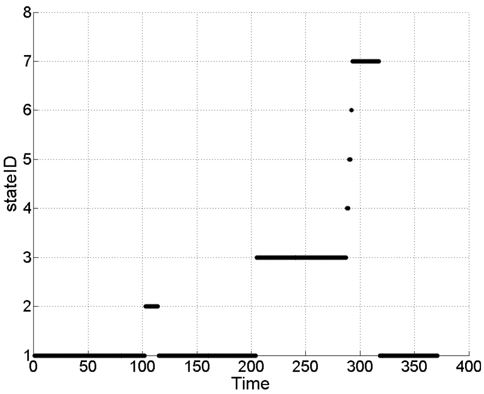

Figure 10: Discrete state encoded process containing an anomaly.

Concluding, the discrete state encoding provides the operator with a neat view on the process. Besides, discrete anomalies can be detected by comparing the visualizations. Even repeating process phases can be perceived easily while monitoring the *stateIDs*. Nevertheless the operator needs some expert knowledge about the process, to benefit of all information presented by the visualization. A disadvantage of this visualization technique is the missing ability of visualizing continuous data.

4.2 Visualization of the Principal Components

In contrast to the discrete state encoding the principal component analysis considers both continuous and discrete features for computation. In this subsection the principal component analysis is utilized to reduce the 19 features of the dataset to two representative features which are used in the visualization. The timestamp is used as an additional feature for the principal component computation. In figure 11 the process is visualized with the help of two new features, the two principal components. The reduction to two new features preserves about 83% of the variance former represented by 20 features; the informational loss is about 20%.

At first, the operator is able to see a neat process visualization. The process is grouped into three clusters. Considering the knowledge gained in section 4.1, it can be said that this is the number of the main process phases. However, the operator is not able to semantically interpret the three clusters. It is not possible to determine whether the process phases are clustered correctly, nor to see the process phases with respect to the process time line.

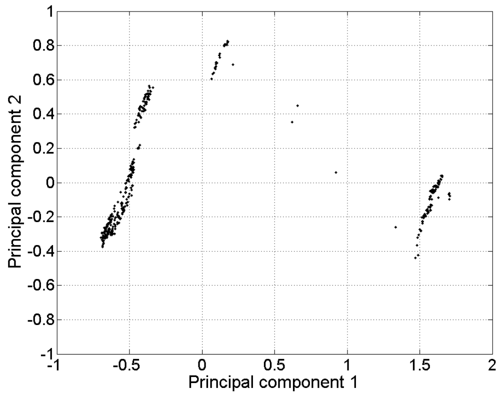

Figure 11: Principal component based process visualization.

To evaluate the performance in anomaly detection, an anomaly has been induced into a continuous signal. The power consumption rises without any bit change, i.e. without actively switching on a consumer. Figure 12 shows the visualization of the anomaly-induced process. Comparing figures 11 and 12, an anomaly is perceptible. The operator is able to recognize a fourth cluster in the visualization. In addition anomalies in discrete and hybrid features were tested. Both were visualized by this technique.

In summary, the visualization based on the principal components is able to show anomalies in continuous, discrete or hybrid datasets. Yet it must be admitted that not all anomalies are depicted by the principal component based visualization. Depending on the influence the original feature had on the principal component, the anomaly can be visualized in a less exposed way than shown in figure 12. In the worst case, anomalies in features that have no significant influence on the used principal components will not be visualized as failures.

The PCA works well for continuous and hybrid data. Here, the data points form a cluster in which a certain spread is given such that a tolerance in the test data set is allowed. In the case of only discrete data the clusters consist of overlapping data points. Due to the informational loss caused by choosing the principal components, not all signal changes would result in a new cluster and therefore not all anomalies could be displayed.

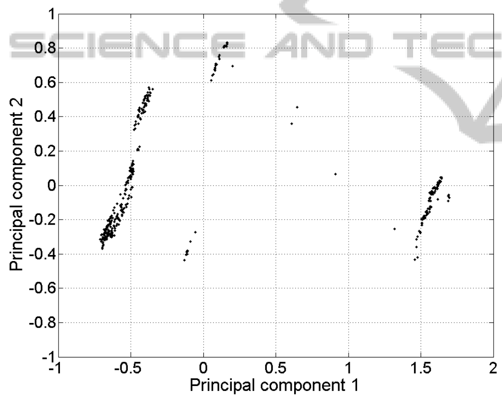

Figure 12: Principal component based process visualization containing an anomaly.

5 ANOMALY DETECTION IN PRODUCTION PLANTS

The main goal of the proposed visualization approaches is to detect anomalies in the production process. In subsection 5.1 a new anomaly detection approach based on visual analytics is presented. In subsection 5.2 it is evaluated and some experimental results are given.

5.1 Hybrid Visualization and Anomaly Detection Approach

As mentioned in section 4, both visualization techniques are able to provide the operator with a neat process overview, but still have issues in visualizing different types or special anomalies. The discrete state encoding focuses on anomalies in discrete signals and gives a process overview with respect to the time line. The principal component analysis based visualization provides the operator with a more abstract process overview and allows the viewer to detect anomalies in continuous and hybrid data. Hower, the process of dimensionality reduction considers the time information, but the operator is not able to see the process with respect to its timeline.

Table 1: Comparison of DSE and PCA.

	DSE	PCA
high dimensionality	+	+
time	+	-
continuous data	-	+
discrete data	+	-
hybrid data	-	+
loss of information	+	-
cyclic processes	+	+

Table 1 shows the advantages and disadvantages for both methods. It can be seen that a combination of both methods would enrich the possibilities of visual anomaly detection.

To combine the advantages of both methods, the hybrid visualization and anomaly detection approach is introduced. The method is organized in three steps. These three steps are illustrated in figure 13:

Step (1) *Observation of the process and detection of anomalies by comparing the reference process with the currently running process:*
The visualization of the principal components is used to get an abstract view on the process based on its continuous and discrete values. The discrete state encoding is used to extend the process visualization with a reference to the point in process time. Now the operator is able to compare the reference with the ovserved behavior in a convinient way.

Anomalies in discrete signals can be seen in the discrete state encoding, anomalies in continuous signals are displayed in the principal component visualization. To demonstrate the anomaly detection, in figure 13, an anomalous process is observed. The anomaly can be seen in both representations. In the PCA based visualization the anomalous data items form a new cluster. The discrete state encoding additionally gives the timing information: the anomaly occurred around the time stamp 20 seconds.

Step (2) *Determination of anomalous module:*
Additionally the process is separated based on its modules, to get a more detailed view insight. Discrete state encoding is utilized again to visualize each module separately. In this example, it can be seen that the anomaly occurred in the second module.

Step (3) *Determination of anomalous signal(s):*

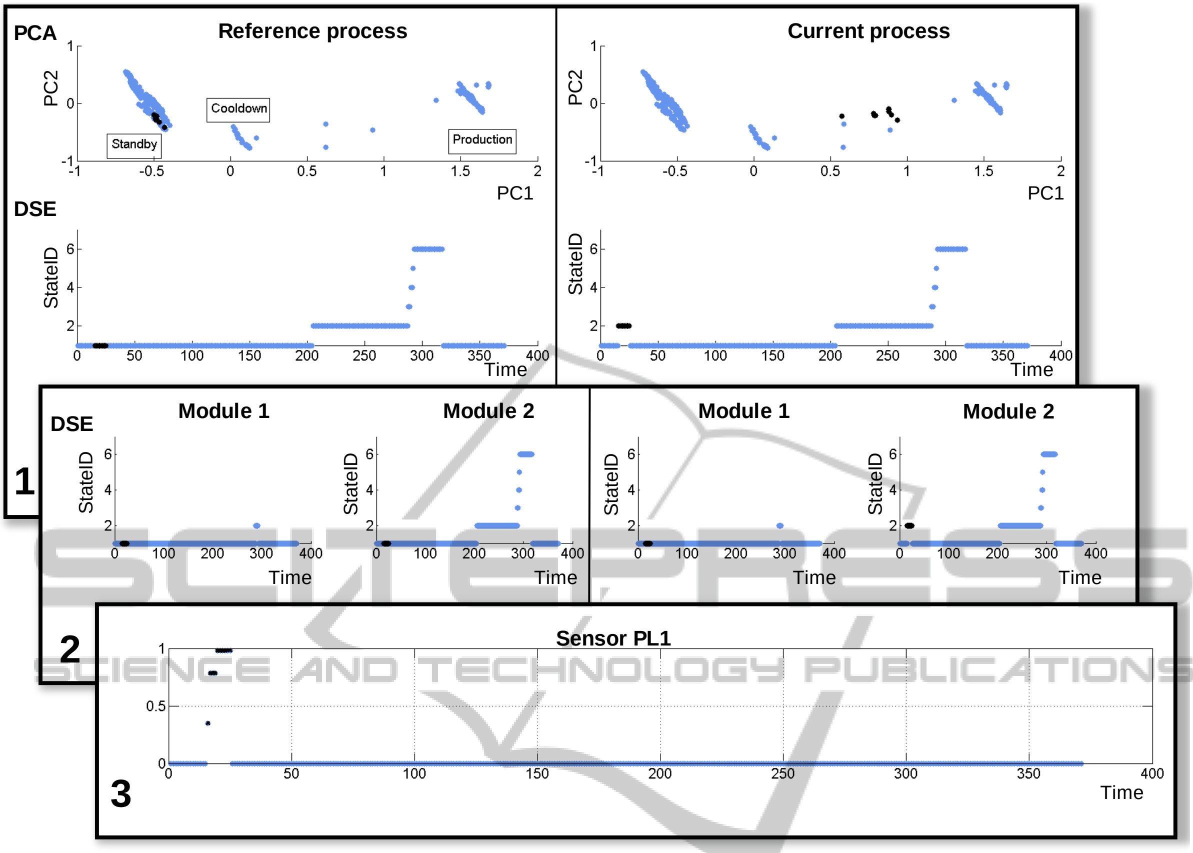

Figure 13: Hybrid visualization and anomaly detection approach.

The last element of the hybrid visualization approach refers to the continuous process values. The difference between values in a reference process and such in an anomaly induced process is calculated and shown. It allows the viewer to see which continuous sensor value differs by which amount to the process time line. Following the example in the top down manner, it can be said that the anomaly is based on an unusual energy consumption; in the signal P_{L1}.

All mentioned visualization methods are internally linked with the help of the timestamp. Based on Shneidermann's information seeking mantra *Overview first, zoom and filter, then details-on-demand* (Shneiderman, 1996), the operator gets a process overview and is able to interactively explore the process. Interesting data points can be marked in one figure and corresponding data points will be highlighted in each other figures. The operator is able to see the process behavior in different levels of abstraction with respect to the time line.

In the given case, the visualization enables the operator to determine the point in time the anomaly occurred precisely. Additionally, the user is able to localize the module in which the anomaly occured with the help of the module separated visualization.

The combination of linkage and different visualization techniques allows the operator to find anomalies and learn about the dataset. Because of this, the PCA based visualization could be enriched with labels to provide semantic information.

5.2 Discussion

As can be seen in table 2 the advantages of the proposed methods could be combined. The hybrid visualization approach allows an enhanced visualization since the abstract view of the principal components is combined with the temporal process visualization of the system's states. Additionally, the hybrid approach is able to handle all relevant data types for technical processes. It was confirmed by experts that the data abstraction using the PCA reduces the information to the most important needed to mirror the normal behavior of the system. Despite these results, it is possible that not all anomalies will be displayed by the PCA based visualization. Especially in the case of high dimensional input data, important information

Table 2: Evaluation of the hybrid visualization and anomaly detection approach.

	hybrid approach
high dimensionality	+
time	+
continuous data	+
discrete data	+
hybrid data	+
loss of information	+
cyclic processes	+

may be unconsidered by choosing the first two principal components only.

The approach was also evaluated in order to detect anomalies. In most cases the anomalous behavior could be detected and the anomalous module and signal could be determined correctly.

A minor disadvantage of the proposed approach is that still some expert knowledge is needed to analyze the plant's behavior in detail. Nonetheless it is possible to detect anomalies and the anomalous production module(s) and signal(s) without any expert knowledge.

Another disadvantage is that the proposed approach works well for the cyclic process, but not for extended production plants which deal with different variants of products. This will be improved in future work.

6 CONCLUSIONS

In this paper a visual analytics approach to the visualization of technical processes is presented. The discrete state encoding gives a neat overview of the observed process and shows the main process states over the time line. The principal component analysis gives a more abstract overview of the process and additionally includes continuous data. Both methods were connected to combine their advantages.

Further it was shown how the visualization and anomaly detection approach can be used to analyze a technical process. In three steps the operator is guided through the observation of the current behavior and the corresponding reference behavior. This side-by-side visualization enables to detect an occurring anomaly. In the further steps (by zooming into the process) the operator is guided to the anomalous module and finally to the anomalous signal.

In further work some other visualization approaches will be explored. These shall show the most relevant data in a more intuitive way to give the possibility to analyze the process behavior without (or at least with less) expert knowledge. To face the disadvantage of the DSE, continuous values can be discretized using an n-bit-discretization. This will also be considered in future work.

Furthermore, the visualized reference process will consider more than only one reference process. This will provide a more generalized view on the plant's behavior.

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