

# Chapter 2

## On Visual Analytics in Plant Monitoring

Tim Tack, Alexander Maier and Oliver Niggemann

**Abstract** This chapter introduces methods from the field of visual analytics and machine learning which are able to handle high feature dimensions, timed systems and hybrid systems, i.e. systems comprising both discrete and continuous signals. Further, a three steps tool chain is introduced which guides the operator from the visualization of the normal behavior to the anomaly detection and also to the localization of faulty modules in production plants.

**Keywords** Anomaly detection · Production plant · Automation system · Visualization technique · Visual analytics

### 2.1 Introduction

Modern production plants grow more and more complex. A reason for this is the growing number of sensors and actuators used. Programmable Logic Controllers (PLCs) process the signals and operate the plant. Supervisory Control and Data Acquisition (SCADA) systems analyze the data provided by the PLC, to manage the process automatically. The operators activities on this level change to a passive role; from actual plant operation to plant monitoring and analysis. Due to the increasing number of signals, analyzing modern processes and detecting anomalies becomes a difficult task.

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To tackle this problem, visual analytic approaches from different scientific areas are adapted to the field of automation. As result, a novel visual anomaly detection approach is presented. It guides the operator in a top-down manner, starting from a general overview to a detailed description of identified anomalies. In this approach, visualizations of a learned reference process behavior and the currently observed one are placed side-by-side. 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. In the approach, three main ideas are combined: (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 chapter is organized as follows: In Sect. 2.2 an overview of the state of the art is given and the research gap is pointed out. Section 2.3 defines some requirements for the visualization of technical processes and introduces a new method for the visualization of high-dimensional discrete data. Based on the defined requirements, in Sect. 2.4 the visualization techniques are evaluated. For this, real data from the Lemgo Smart Factory [1] is used. To exploit the advantages found, Sect. 2.5 introduces a new plant visualization. It combines different techniques in one new approach. With it's help, a neat and informative view on the process is provided. Thus, it supports the anomaly detection performance of the operator. The results are discussed in the conclusion.

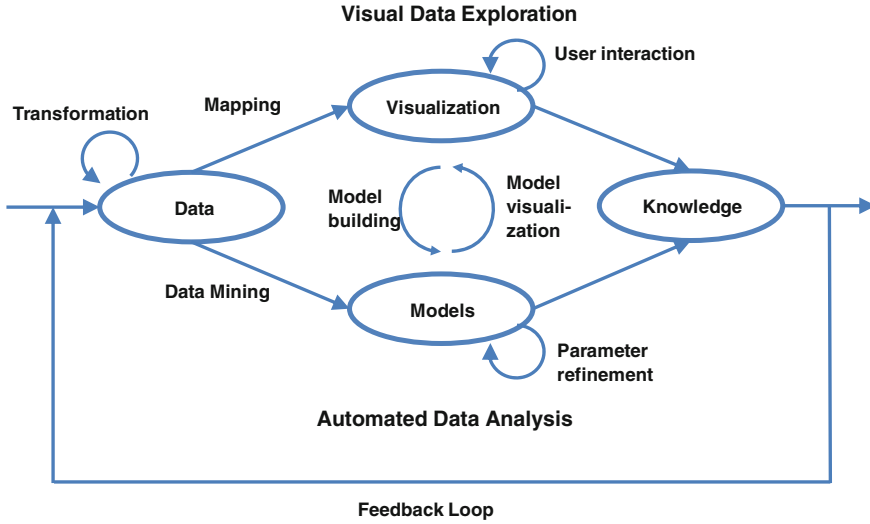
## 2.2 State of the Art

This section gives an overview about the state of the art and related work. In Sect. 2.2.1 some basics ideas of the visual analytics process are presented.

In Sects. 2.2.2 and 2.2.3 techniques, that can be used to visualize discrete, continuous or hybrid data (a combination of both) are described. These should support an operator with two features. At first, the high-dimensional data should be visualized in a neat way, that allows humans to deal with the overwhelming information input provided through the SCADA system. The second feature is, to enable an operator to perceive process anomalies visually.

### 2.2.1 Visual Analytics

In short term, visual analytics can be described as *the science of analytical reasoning facilitated by interactive visual interfaces* [2]. According to Keim [3], the visual data exploration process is organized as follows (see also Fig. 2.1):



**Fig. 2.1** Principle of visual analytics according to [3]

First, the data have to be acquired from the observed system. In many cases the data needs 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 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.

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 [4].

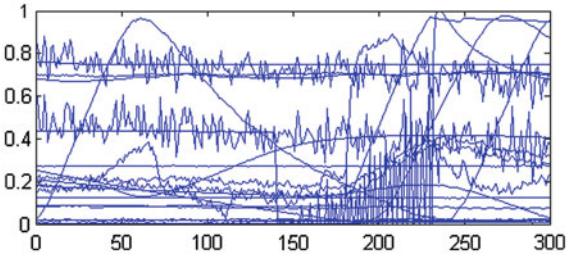
Approaches in visual analytics are considered in different research areas. For example it is used in the financial sector to visualize and analyze the fall and rise of stocks and to detect frauds, e.g. in [5]. The study of environment and climate change also often uses visualization approaches. The temperature 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 would be the prevention of terrorist attacks [6].

There are only few examples where visual analytics has been applied to the manufacturing industry. Example Frey uses self-organizing maps to generate a two dimensional map to visualize the observed process [7]. However, there exist many approaches to create a system's model using observations. Example in [8] a method to learn a behavior model by means of hybrid timed automata is presented. In many

**Fig. 2.2** An example dataset (Figure published in [9])

time	f <sub>1</sub>	f <sub>2</sub>	f <sub>3</sub>	f <sub>4</sub>	f <sub>5</sub>	f <sub>6</sub>	f <sub>7</sub>	f <sub>8</sub>	f <sub>9</sub>	f <sub>10</sub>	f <sub>11</sub>
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

**Fig. 2.3** Visualization with data curves (Figure published in [9])



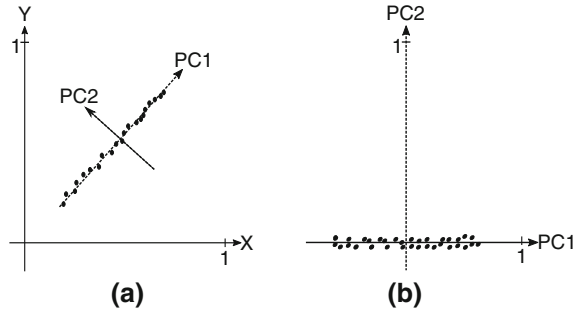
cases, especially with high amounts of data, these models are created to be used by computers and are therefore not easily accessible for humans. In this context, no appropriate method exists to visualize the plant’s state to the operator. For this, special visualization methods have to be developed.

### 2.2.2 Visualization of Multidimensional Data

Figure 2.2 shows an excerpt taken from a process dataset. The dataset comprises a timestamp and the corresponding process variables  $f_1 \dots f_{11}$ . 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 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 method helps to get an overview of continuous signal trends e.g. temperature over time. Further, crossing thresholds can be seen very well. However, this method is only usable for a small number of signals using the same scaling. The visualization of many signals in one diagram leads to an information overflow, such that the single curves cannot be detected separately. Figure 2.3 shows the visualization of 30 signals with 300 data points each. Even for this small dataset the single curves cannot be separated well and it is very difficult to find an anomaly in this figure. This

**Fig. 2.4** Example dataset with (a) original features and (b) principal components (Figure published in [9])



disadvantage is even worse for binary data, because the constant parts of the signals overlap and only the signal changes can be seen.

In [10] the method of parallel coordinates is introduced. This technique overcomes the problem of overlapping signal curves and allows the visualization of multiple dimensions (as coordinates) in parallel. With this, the dependencies between signals become visible. As disadvantage, it has to be mentioned, that the quality of the visualization is highly dependent on the arrangement of the features. Another method which overcomes overlapping curves in high dimensions, is the plot matrix [11]. In this, several scatter plots are depicted in a matrix such that the dependency of each pair of signals is displayed in one figure. However, very high dimensions cannot be displayed clearly as well. Example an input dimension of 20 leads to a matrix with 400 plots. An overview and comparison of the described visualization methods can also be found in [12].

### 2.2.3 Principal Component Analysis

As outlined in Sect. 2.2.2, it is difficult to visualize high-dimensional data. Therefore, dimensionality reduction methods have to be applied. The Principal Component Analysis (PCA) was introduced by Pearson and Hotelling and is described in the following based on [13].

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 [13]. In this contribution, a two dimensional approach is used for visualizing (choosing two principal components), because it is more difficult to extract information from a figure with three dimensions. It is impossible to create a visualization for more than three dimensions.

Figure 2.4a shows an example dataset visualized based on its two features X and Y. In Fig. 2.4b 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. 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 features to two 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. Besides the potential of dimensionality reduction it has to be considered, that the process is not visualized explicitly with respect to its time line. Further, the principal component analysis of high dimensional datasets can lead to interferences. Data and even anomalies, that can be distinguished in the original feature space, may be not distinguishable in the principal component space.

## 2.3 Visual Data Exploration

In this section some major requirements for the visualization of technical processes are given. In Sect. 2.3.2 a new visualization approach, the Discrete State Encoding (DSE), is introduced. It is especially developed for the visualization of high-dimensional discrete data.

### 2.3.1 *Requirements for the Automation Domain*

Every domain uses different methods to visualize the data. While climate studies use heat maps indicating the temperature, the financial industry uses curves to show trends of stocks. Visualizing automation related data, certain requirements have to be considered:

**High Dimensionality.** Data of production plants are typically high-dimensional. This is caused by a large amount of sensors and actuators which are used to realize production 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 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 sets different requirements on the visualization.

**Importance of Data.** Due to the high amount of data, visualizing all values would lead to an information overflow. Occurring anomalies may remain undetected. Therefore, only the most important data have to be visualized. This results in the need of methods, that 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 these time information. The operator should be able to assess the plant state wrt. a certain point in time.

**Cyclic Processes.** In typical mass production plants, process phases reoccur during the production of the same product. Therefore, the operator should be able to recognize recurring process phases as such, by examining the process visualization. As a consequence plant states, that are unusual (maybe anomalies) should be visualized in a more exposed way, to support the operator's analysis.

### 2.3.2 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. The DSE represents the plant behavior by one feature only. This new feature is then visualized over time, to provide the operator with a neat view on the plant state.

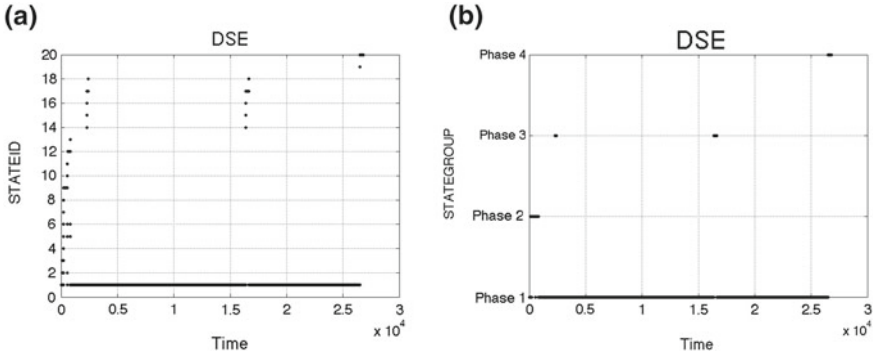
A Datasets is represented as a table with  $N$  features  $f_i$  in the columns and the measured process data, the observations, per row (see also Fig. 2.2). The DSE encodes each row of the dataset and creates a representative number, the *stateID*.

The DSE considers only discrete features, continuous features are ignored. Slightly changing continuous values would result in a new state for each observation even though the actual information has not changed significantly. The *stateID* computation is based on the following equation.

$$stateID = \sum_{i=0}^{N-1} f_{N-1-i} \cdot 2^i \quad (2.1)$$

In the next step the *stateID* values are renumbered. A serial number is assigned to each unique plant state. The *stateID* 1 is assigned to the first occurring plant state. To each newly occurring state, the next unused number is assigned, e.g. 2. To recurring states, always the same number is assigned.

Renumbering *stateIDs* is necessary to avoid bias in the visualization. Example 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 misleading perception should be avoided, following the notion of the *Lie Factor* in figures, introduced



**Fig. 2.5** **a** Discrete state encoding of an example dataset (Figure published in [9]) and **b** enhanced discrete state encoding of the same dataset

in [14]. 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 2.5a shows a visualized discrete state encoding. The process contained more than 30 binary features and has a length of about 27,000 time units, i.e. observations.

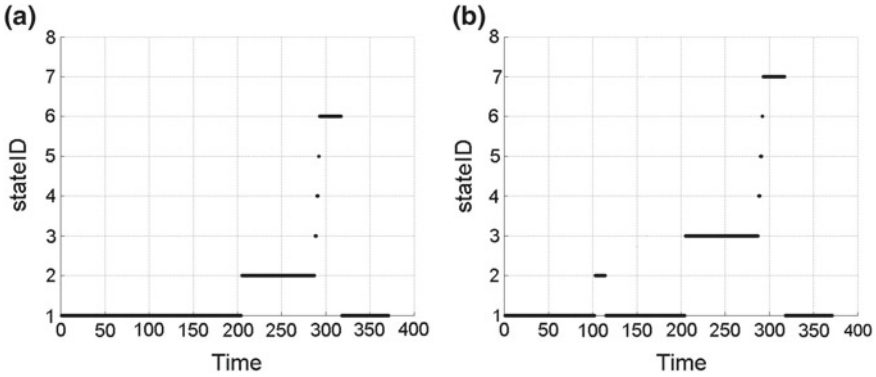
## 2.4 Evaluation of Visualization Methods

In this section the visualization techniques described in Sects. 2.2 and 2.3 are evaluated. As basis, the requirements from Sect. 2.3.1 are used. While visualizing technical processes, the most important requirement is the proper visualization of the high dimensions. Since most visualization techniques (mentioned in Sect. 2.2.2) 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 (Sect. 2.4.1) and the principal component analysis (Sect. 2.4.2).

For the evaluation, a dataset from the Lemgo Smart Factory is used. The first objective is to provide an abstract process overview. The second is to detect anomalies. This is done by comparing the visualization of a reference process with the observed process, which may contain anomalies.

The observed process produces popcorn out of the resource corn. In total 19 continuous and discrete features need to be analyzed online. The production process is separated into two modules. Module one creates the product. The corn 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.





**Fig. 2.6** Discrete state encoded process: **a** reference and **b** observed with failure (Figure published in [9])

### 2.4.1 Discrete State Encoding of a Production Process

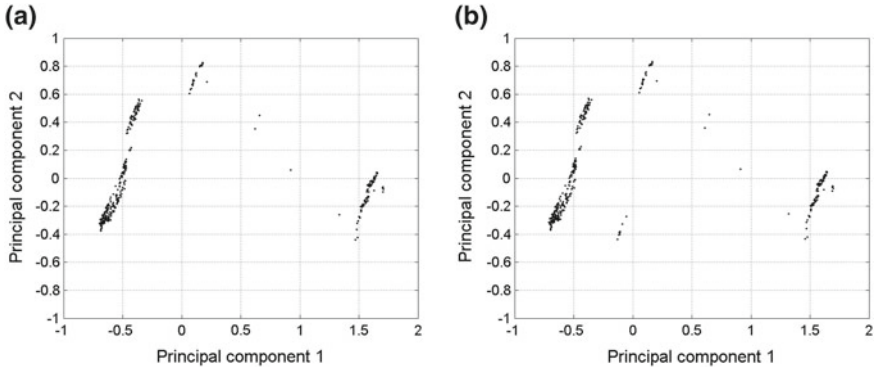
Figure 2.6a shows the discrete encoded *stateIDs* for one process, visualized over its time line. Out of the former 19 features, one new feature, the *stateID*, is created. As mentioned before, continuous values are not taken into account to compute the *stateIDs*.

As depicted in Fig. 2.6a, the visualization provides an abstract process overview. The operator is able to analyze the process wrt. its time line. 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. Plant experts confirm, that the process phases 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 Fig. 2.6a the operator is able to keep track of the process in a very convenient way. The operator is able to see the process wrt. its actual time line. Furthermore, repeating process phases are represented correctly.

In the next step, the anomaly detection performance of the DSE is tested. For that purpose, an anomaly is induced into the same dataset that has been used before. A discrete sensor (e.g. a cup filling level sensor) changes its value in an unusual moment. Figure 2.6b shows the *stateID* representation of that dataset. As depicted, the anomaly can be recognized by comparing Fig. 2.6a and b. 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.

Concluding, the discrete state encoding provides a neat view on the process. Further, discrete anomalies can be detected by comparing the visualizations. Even repeating process phases can be perceived easily while monitoring the *stateIDs*.



**Fig. 2.7** PCA based visualization of a process: **a** reference and **b** observed with failure (Figure published in [9])

Nevertheless the operator needs some expert knowledge about the process to benefit of all information provided. A disadvantage of this visualization technique is the missing ability of visualizing continuous data.

### 2.4.2 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 Fig. 2.7a the process is visualized with the help of two new features, the first and second principal components. The reduction to two new features, in the given case, preserves about 80% 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 Sect. 2.4.1, 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.

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 2.7b shows the visualization of the anomaly-induced process. Comparing Fig. 2.7a, b, 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.

**Table 2.1** Comparison of DSE, PCA and the new hybrid approach

	DSE	PCA	Hybrid approach
High dimensionality	+	o	+
Time	+	–	+
Continuous data	–	+	+
Discrete data	+	–	+
Hybrid data	–	+	+
Loss of information	+	–	+
Cyclic processes	+	+	+

In summary, the visualization based on the principal components is able to show anomalies in continuous, discrete or hybrid datasets. However, in the worst case an anomaly is not depicted by this visualization method. The reason for this can either be the lack of influence the original feature had on the principal component, the loss of information during feature reduction, or due to the interferences that are mentioned in Sect. 2.2.3. To maintain the anomaly detection performance of this visualization method in large scale datasets, expert knowledge is used to preselect significant process parts, which are used as input for the principal component analysis.

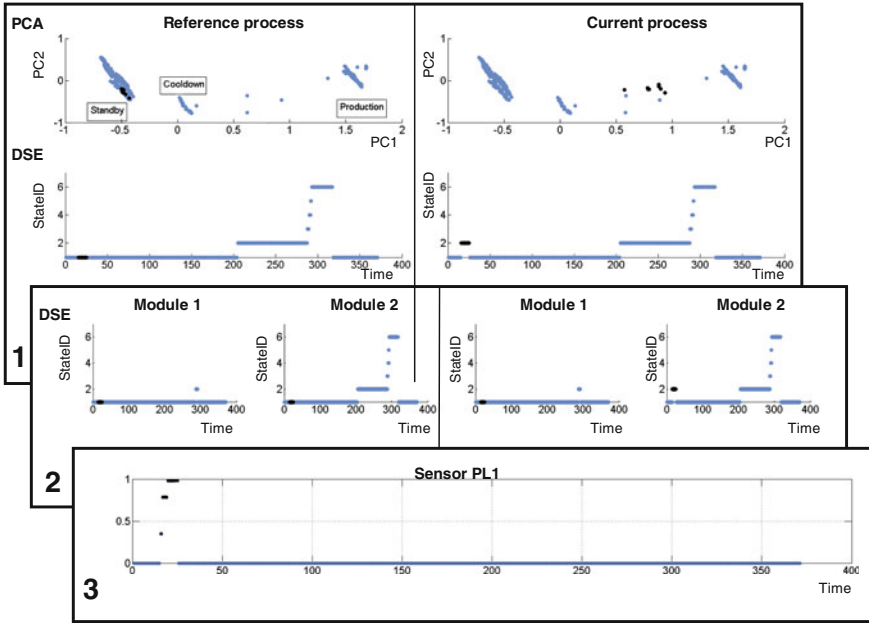
## 2.5 Anomaly Detection in Production Plants

The main goal of the proposed visualization approaches is to detect anomalies in the production process. In Sect. 2.5.1 a new hybrid anomaly detection approach based on visual analytics is presented. In Sect. 2.5.2 it is evaluated and some experimental results are given.

### 2.5.1 Hybrid Visualization and Anomaly Detection Approach

As mentioned in Sect. 2.4, both visualization techniques are able to provide 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 a more abstract process overview and allows the viewer to detect anomalies in continuous and hybrid data. Yet, the process time line is not visualized.

Table 2.1 shows the advantages and disadvantages for both methods. It can be seen that a combination of both methods, the hybrid approach, improves the visual anomaly detection performance.



**Fig. 2.8** Hybrid visualization and anomaly detection approach (Figure published in [9])

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 Fig. 2.8:

**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 observed behavior in a convenient 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 Fig. 2.8, 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 s.

**Step (2)** *Determination of anomalous module:*

In this step, the process is separated based on its modules, to gain a more detailed 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):**

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. This allows the operator to determine which continuous sensor value differs 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* [15], 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 occurred.

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.

### 2.5.2 Discussion

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 represents 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 may be unconsidered by using only the first two principal components or by the described interferences. In most cases tested, the anomalous behavior could be detected and the corresponding module and signal could be determined correctly.

Latest results in the analysis of more complex plants, larger than the Lemgo Smart Factory, showed, that the DSE based visualization can be improved further: The enhanced DSE visualization shown in Fig. 2.5b provides a more abstract view on the process with the help of *stateGroups*. One *stateGroup* represents all *stateIds* in a certain main process phase such as 'idle', 'production' or 'failure'. Expert knowledge about the process is used, to determine the *stateGroups* and to assign particular *stateIds* to its group.

A minor disadvantage of the proposed approach is that expert knowledge is still 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, by assessing the visualization.

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

## 2.6 Conclusions

In this chapter a novel visual analytics approach for 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 is 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 allows operators to detect anomalies visually. Different abstraction levels support a detailed process analysis, by zooming into module or even signal level. Thus, the operator is guided step by step to the signal, that caused the anomaly.

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

**Acknowledgments** This work is an extension of the chapter titled *Visual Anomaly Detection in Production Plants* by Alexander Maier, Tim Tack and Oliver Niggemann, published in *9th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2012)*, Rome, Italy.

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Informatics in Control, Automation and Robotics

9th International Conference, ICINCO 2012 Rome, Italy,

July 28-31, 2012 Revised Selected Papers

Ferrier, J.-L.; Bernard, A.; Gusikhin, O.; Madani, K. (Eds.)

2014, XVII, 316 p. 163 illus., Hardcover

ISBN: 978-3-319-03499-7