Interactive, Adaptive Time Series Analysis for Online Diagnosis of Technical Processes

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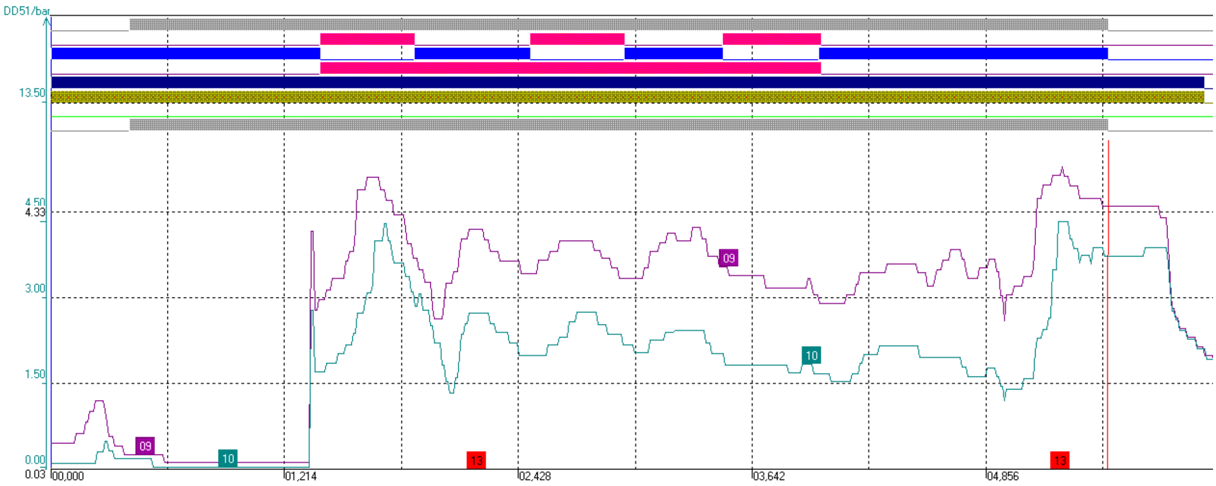
Abstract
In manufacturing processes with very high workpiece costs production errors shall be detected online to avoid a series of defective workpieces. This article describes a qualitative evaluation method for time series that is applied to the diagnosis of spraying procedure parts of car bodies. The parameter determination for the procedure is gained through learning data which simplifies the industrial use enormously. An already employed prototype in the production confirms the expected functionality of the procedure.

Keywords: online-process diagnosis, manufacturing process, qualitative time series analysis, finite state machine, trend-analysis

1 Introduction

In car painting processes with very high workpiece costs production errors that lead to defective workpieces are to be avoided at any rate. Moreover, the further processing of the workpiece in the assembly line shall be stopped immediately if a process anomaly occurs in order to minimize the reparation costs (which are very high in case of car paintings since the applied lacquer has to be removed first before the car can be painted again). The importance of employing online-diagnosis systems for that type of problem is obvious. They shall decide online over the quality of the spraying on the basis of the machine's control- and sensor signals. For the diagnosis of the painting processes over the time measured data have to be evaluated. The following picture 1-1 shows the measurement data of a flush program. Painting robots in modern painting plants are able to spray with several different colours. This requires a control program to change the colours in the system. This program washes the respective previous colour out of the pipes of the robot. The correctness of the running flush programs is very important for the result of the painting process, since "colour procrastinations" are possible if residues of the previous colour remain in the pipe.



Picture 1-1 To be evaluated time series of a flush program

At the top the picture shows the binary valve controls for the thinning and the compressed air. But these signals show online if the control drives the valves to open or to close. If the valve opens or closes in fact can not be decided by the binary signals. Because of the leakage of sufficient sensor information the complex physical models of the flush process can not be applied. That means that a

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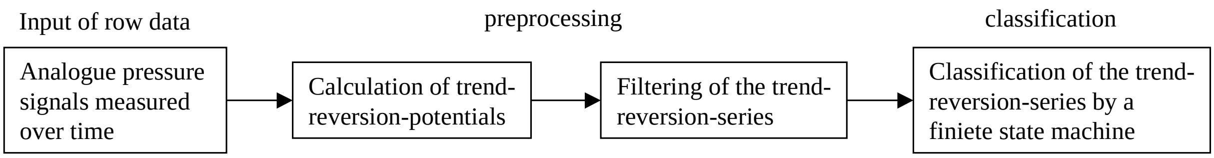
residual based diagnosis (s. [Füssel98]) does not succeed. The absolute values of the pressure signals also vary because of the different viscosities of the different lacquers. That's why marginal based methods (s. [Büttner96] [Spiewak91]) are not promising success. For that reason a human expert visually, qualitatively analyses the analogue pressure sensor data to state if the flush program is faultless or not (see the time series in Picture 1-1 at the bottom). Due to the large number of cars painted every day the expert can only diagnose some flush processes. Our task is to set up a system that evaluates the analogue sensor information for every flush program, so that the high quality of painted cars can be guaranteed.
One common approach for these systems is to use specific process characteristics, which are given by the process experts, for describing the time series. Using these characteristics a classifier for the process diagnosis can be created. The establishment of these classifiers can be made data based or rule based [Puppe96]. Examples are: the tile diagnosis based on a Fourrier analysis combined with a artificial neuronal network [Zim95], the classification of frequency threshholds realised by fuzzy-inference [Bitterlich96] and a system for the automatic diagnosis of oil pipelines realised by parallel working RPROP-networks using special data characteristics [Suna96].
The problem of the diagnosis based on characteristics is their determination. It mostly can be solved only by applying specific know-how. Furthermore these characteristics have mostly a process context. This means that they are only significant in special process states. Sometimes they even can influence the classification result negatively if they are applied to some other process states. To take the process context into consideration the *statechartmodel* was introduced [Harel87]. This hybrid model of calculations is currently implemented in many different peculiarities [Simulink98]. In [Feucht98] a basis approach was suggested how the state machine can be generated automatically out of the control data. Then suitable diagnosis methods are assigned to these generated states. This approach is based on *extended machine* [Quade94] and is suitable for both, the diagnosis of the control programs and the process segmentation. Due to the creation of a new state when the signal changes the machine only memorizes the training-data if applied to analogue sensor data. So no generalisation can be achieved. Ideas of discretisizing the analogue values have also been overruled, because of the large amount of training data that is necessary to teach the machine. The following calculation confirms this consideration. Given a discretisation so that there are 100 signal changes per time row and per change there are at least two value-intervals affected the amount of necessary training examples exploids to 2^{100}. For that reason this article describes how to use a suitable preprocessing method for time series, so that a finite state machine can be used as a classifier for time series. For adapting the classifier to the flexible control task it is essential that the classifier is taught incrementally. This adaptability is a requirement for the use of methods in industrial diagnosis, because the constraints of the physical process may change very often and lead to a invalid classifier. Another postulation is that the time needed for the classification of a time row has to be less than the production cycle, so that the sensor data can be evaluated online.

2 Classification of analogue time series

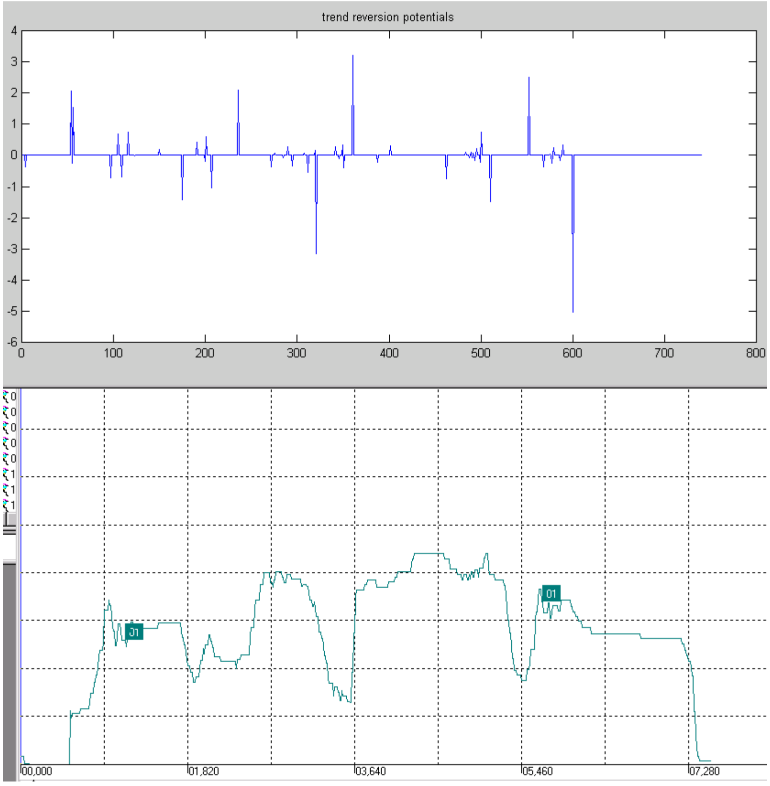
The evaluation of the analogue pressure signals is done by a function-net that applies a classifier to preprocessed data. The preprocessing is done by trend series analysis (s. paragraph 2.1). The classification is solved by a finite state machine (s. paragraph 2.2)..



Picture 2-1 Function-Net for the classification of the analogue time series

2.1 Calculating and filtering trend-reversion-potentials

By the examination of stock prices it is the hope of venturers to detect trends and particularly trend reversion points in time and to use them gainful. Therefore Wegscheider suggested a method [Schlittgen94], that describes characteristics which connect to local trends of a not necessarily equidistant time row T.



Picture 2-2 Illustration of the trend-reversion-potentials (top) for an analogue time series (bottom).

A measure $p(t)$ is assigned to every time point t, the so called *trend-reversion-potential*, whereby large potentials fit to reversion points of large trends. Trend reversion points are those time points which are at the end of one trend direction and at the beginning of the reverse direction (s. picture 2.1). The iterative algorithm for calculating the reversion-point-potentials is described in [Schlittgen94]. In the described form the algorithm unfortunately has the unpleasant property that small changes of the time row can cause big changes in the trend row. For a classification task this is not acceptable, so we changed the algorithm. For understanding the algorithm we state the following definition of [Schlittgen94].

Definition 2.1 Left, right and inner points

Given a not linear subset $T \subseteq \{1,2,...,N\}$ of time points. The smallest time $t_{\min}$ is called **left marginal** and the largest time $t_{\max}$ is called **right marginal** of T. All other points are called **inner points** of T. We write $T^{<}$ for $T \setminus \{t_{\max}\}$. For $t \in T$ with $t > t_{\min}$ the left neighbour of t is named with t_L, formally written $t_L = \max\{t' : t' \in T, t' < t\}$, and respectively t_R denotes the right neighbour of t for $t < t_{\max}$.

The algorithm for the calculation of the trend-reversion-potentials is now given.

Algorithm 2.1 Calculation of the trend-reversion-potentials

Given $(x_t)_{t\in T}$ with $T_0 \subseteq \{1,2,\ldots,N\}$ a time series with at least two values.

Step 1: For all $t < t_{\max}$ with $x_{tR} - x_t = 0$ set $p(t) = 0$ and regard t as cleaned.

Let T_1 be the set of not cleaned time points.

Step 2: If T_1 is singleton set $p(t) = 0$ and stop the iteration. Otherwise set $p(t) = 0$ for all inner points t of T_1, where $x_{tL} < x_t < x_{tR}$ or $x_{tL} > x_t > x_{tR}$ holds and regard t as cleaned.

Let T_2 be the set of not cleaned time points.

Step 3: Let t' be the smallest time point where the distance of all neighboured values in T_2 is minimal:

$$t' = \min\left\{t : t \in T_2^<, \left|x_{tR} - x_t\right| = \min\left\{\left|x_{sR} - x_s\right| : s \in T_2^<\right\}\right\}$$

i) If t' and t'_R are both inner points of T_2 the potential of t' is defined as $p(t') = x_{t'_R} - x_{t'}$ and t' is regarded as cleaned. If $x_{t'_L} < x_{t'_R} \le x_{t'_{RR}}$ or $x_{t'_L} > x_{t'_R} \ge x_{t'_{RR}}$ holds for t'_R set $p(t'_R) = 0$ and regard t'_R as cleaned.

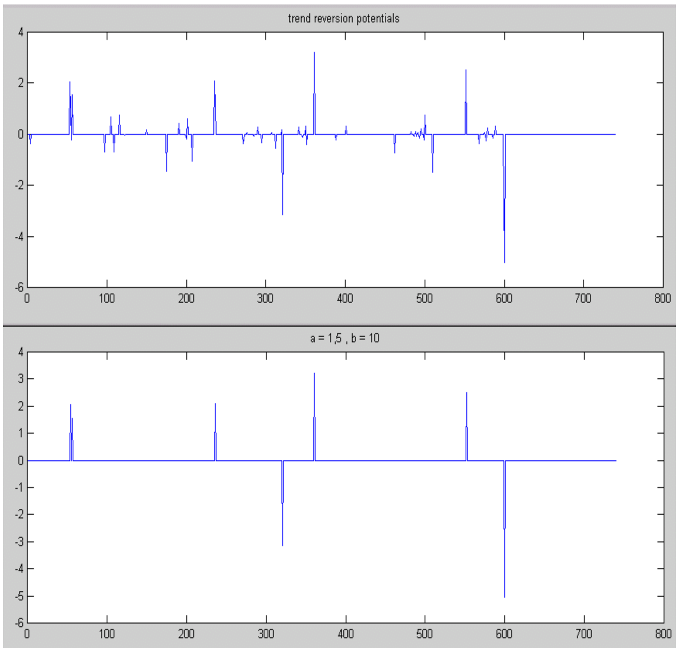
ii) If t' and t'_R are both marginal points of T_2 set $p(t') = x_{t'_R} - x_{t'}$ and regard both points as cleaned.

iii) If $t' == t_{\min}$ and $t'_R < t_{\max}$ set $p(t') = x_{t'_R} - x_{t'}$, and regard t' as cleaned.

iv) If $t'_R == t_{\max}$ and $t' > t_{\min}$ set $p(t') = x_{t'_R} - x_{t'}$ and regard t'_R as cleaned.

Let T_3 be the set of not cleaned time points.

Step 4: If T_2 is not empty set $T_2 = T_3$ and return to step 3.



Picture 2-3 Filtered potential row

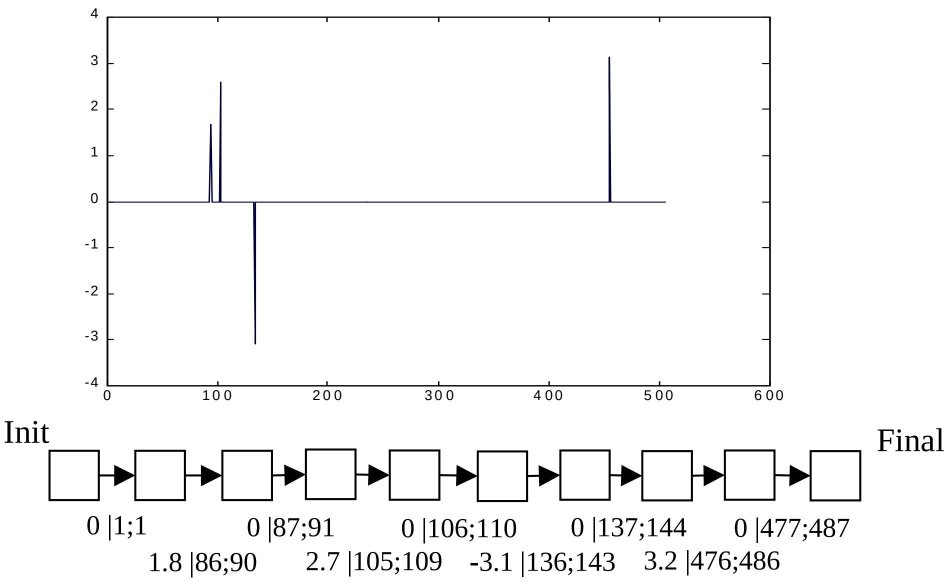
Let $P = (p(t))_{t\in T}$ be the calculated potential series. For further processing the rows $P_{a,b}$ are extracted out of P. The elements of $P_{a,b}$ are defined as

$$p_{a,b}(t) = \begin{cases} p(t) & \text{, if } a \le |p(t)| < b \\ 0 & \text{, otherwise} \end{cases}$$

For the determination of the parameters a and b we need the input of a human process expert. This is a disadvantage, but we still work on an automatic determination out of process data. Picture 2-3 shows a filtered row with the parameters $a = 1{,}5$ and $b = 10$. This filtered row of trend-reversion-potential can now be used as input for a finite state machine, which solves the classifying task.

2.2 *Using a finite state machine for classifying the trend series*

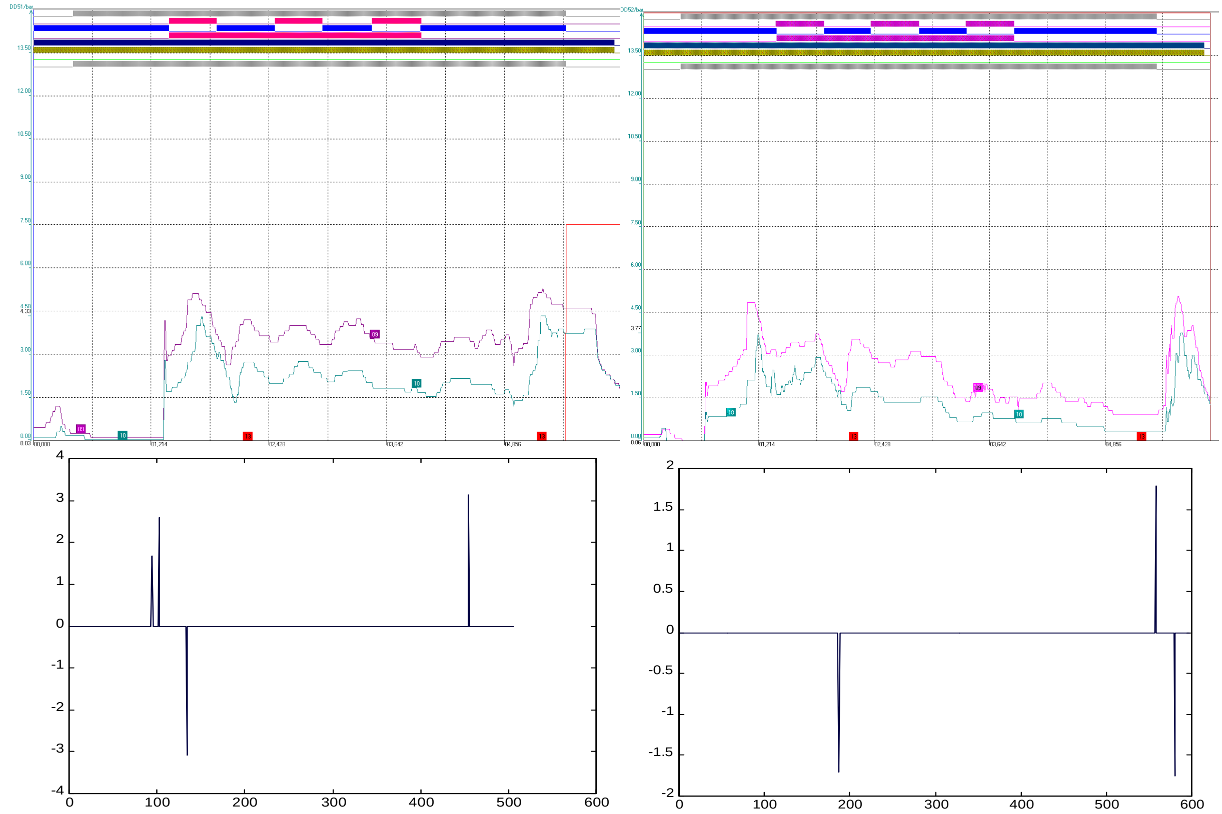
The used finite state is described in [Feucht98] and explicitly models the time. That is important because for the comparison of the trend-reversion-potentials the point of time where a trend-reversion occurs is very important. The finite state machine is generated out of a training set of processes, which are classified as faultless (s. Picture 2-4). Each state transition represents a trend-reversion-potential and the corresponding time interval in which the value occurred. The algorithm for generating a finite state machine is a modified form of the algorithm of [Quade94]. The training of the machine depends on two cases. The first case is that a new transition to a new state has to be generated if a different signal value is given, while the other case is that the time interval is changed adaptively in an existing transition condition. The expansion of the time intervals, restricted by a limit, generalizes the series. Parsing a trend-reversion-row with the finite state machine a tolerance value is used for the comparison of the current value with the value that occurs to the considered state transition. That is necessary because the calculated trends are analogue values and the comparison demands equality.



Picture 2-4 Finite state machine generated out of trend-reversion-potential rows.

3 Results - Diagnosis of “flush programs”

For the automatic diagnosis the function-net was trained with 40 correct flush programs of one painting robot. It is now applied online to every flush program (750 per day) and automatically alarms if a pressure series can not be parsed. The example shown in Picture 3-1 is an automatic alarmed error. The valve for the compressed air doesn’t open in time in the last part of the flush program.



Picture 3-1 The left picture shows a faultless flush program. The right one shows a faulty program. Beneath these pictures the corresponding filtered trend-reversion-potentials are illustrated.

4 Conclusion

In this paper, we have developed an qualitative approach for the online diagnosis of time series of industrial processes. It calculates the significant trends of time series and applies the preprocessed data to a finite state machine that solves the classification task. The advantage of this method is that it can be taught out of data and so no expensive parameterisation is required. We implemented the methods and tested it for the data of “flush-programs” of a car painting process. The developed system is now in use and realises an automatic online diagnosis for any flush-program of one painting robot. The next steps are to expand the system to the whole assembly line so that every robot can be controlled. A further task to be faced by us will be the transference of the method onto other processes, as e.g. the lacquer spraying.

5 Literature

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