# Online-process diagnosis exemplarily shown at a car painting plant

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29. March 2000

**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, diagnosis-architecture, manufacturing process, qualitative time series analysis, finite state machine, dynamic time warping

## 1 Introduction

Because of the high workpiece costs at car painting processes 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. The indirect way of quality measurement is necessary, since the directly measured quality data are only available when the bodywork has left the dryer. In other words, spraying errors basing on a machine defect could at the earliest be detected after 45 minutes. Modern car painting plants have the opportunity to spray several different body types (about 10) with about 20 different colours which aggravates the machine diagnosis in a way as the control- and sensor signals are always to be examined in connection with the actual system configuration. In [Feucht98] a hybrid, hierarchic, modular system architecture is described that realizes a segmentation of the whole problem in problem parts through finite state machines. The segmentation bases on the control signals so that the actual context of the plant can be used for the diagnosis functions of the single segments. The data that have to be evaluated are over the time collected measurement lines by the system's sensory. Dependent on the segment they can have a size from 50 up to 2000 single measurement points. Those data can in principle be evaluated through data- or model based [Puppe96] methods. A study over data based solutions for the automatic diagnosis [Schmid97] of the painting process has shown that the therefore necessary labeled training examples are neither quantitatively nor qualitatively available. The shortage of training examples is based on the continual optimization of painting systems which hinders the collection of sufficient representative data. The missing quality of the labeled data is due to the fact that the quality control of the sprayed bodies consist of a visual, subjective examination of the body's surface.
Mathematical models with the help of which a residual- based diagnosis [Füssel98] could be carried out are only occasionally available and too complex for a online diagnosis of the measured data. The present evaluation of the control- and sensor signals are rather carried out by experienced system experts who judge the time series surveying their qualitative course [Schiller97] („when the supply valve opens, the pressure sensor has to indicate a strong rise“ ). The expert forms his judgment by comparing the data shape with his own physical basis- and experience knowledge. The experience knowledge bases on

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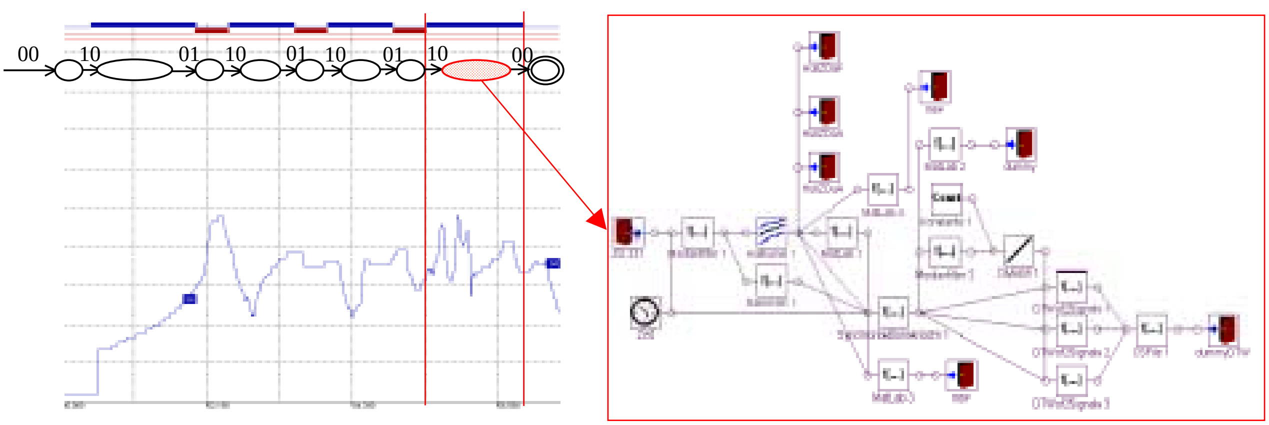
observations of painting processes that didn't give any cause for complaints. This procedure shall be mapped onto a diagnosis method to enable an evaluation by machine. [Büttner96] presented a procedure that allows the expert to describe the form of the time series via predicate logic. The application of the predicate-rules on the data via PROLOG- Interpreters decides whether a relationship of the observed data series can be deduced from a reference series or not. An industrial use of this method in a dynamical process, however, is problematic on account of the procedure's poor adaptation ability and the labor-intensive creation of the knowledge-basis. In the following we introduce at the example of the "flush program" a procedure that distinguishes itself first of all by its simple way of knowledge acquisition and parameterization.

## 2 Diagnosis of "flush programs"

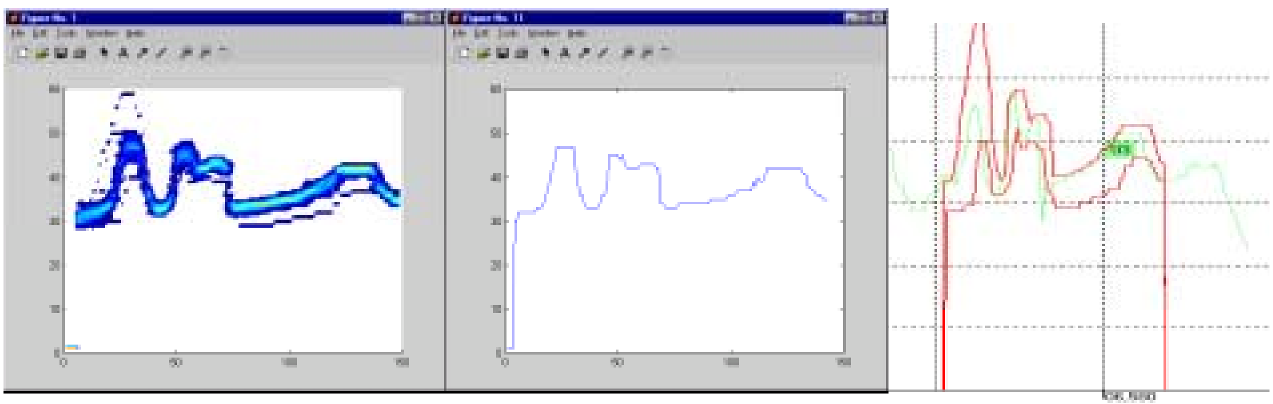
Painting automates in modern painting plants are able to spray with several different colors. This requires a control program to change the colors in the system. This program washes the respective previous color out of the pipes of the automate. The correctness of the running flush programs is very important for the result of the painting process, since "colour procrastinations" are possible if residues of the previous color remain in the pipe. In [Feucht98] the concept of a "diagnosis node" has been introduced that encloses function-nets created by a construction kit. For the diagnosis of a flush program a *diagnosis node* has been parameterized that contains a finite state machine. The latter is generated by binary valve controls for the thinning and the compressed air (see binary series in picture 1, left upper picture). Each state of the machine is a respective diagnosis node assigned. In the following sections we describe a diagnosis method that carries out context dependent, qualitative evaluations of analog measurement series. The signal for the method is the statically taken pressure in the lacquer pipe over the time. The following picture 1 shows the via state machine created structuring of the diagnosis problem.




**Picture 1: assignment of the function-net to the last "compressed air interval"**

### 2.1 Method for the evaluation of measurement lines

Since, as described above, the aim is a qualitative diagnosis of sensor signals and the interest lies in the signal shape in principle, the signals are cleaned from impulse-shaped disturbances. In order not to distort the reference data we use a median filter (see [Goll96]). Another pre- processing step is the standardization of the value range to the interval [0,1]. This step is necessary, since on account of their different viscosity the different colours create different signal levels. With the help of the standardization the method becomes invariant with regard to the used color which minimizes the effort of parameterization enormously. The classification of the time series takes place by comparing them with already given ones. The comparison of the signal templates with the test signal needs an adequate distance metric. A suitable procedure for that type of problem is the Dynamic Time Warping [Sakoe78] as is already used in the language processing. First of all this procedure standardizes the to be compared sequences. This non- linear standardization stretches or compresses the single pattern sections while the necessary warping function is determined by a direct comparison with the reference pattern. One problem in the Dynamic Time Warping is different lengths of the to be compared patterns. In [Myers80] the proposal therefore is a linear standardization to a normative extent before the comparison of the patterns. In our case the finite state machine solves that problem by separating time sequences of almost equal lengths (the control unit defines the time intervals). Another problem of the pattern matching is the definition of the templates. [Ruckhäberle95] uses 9 basic segments and calculates the template by concatenating those segments in an adequate way with the help of the Levenshtein- distance and some selected data series. However, we do not strive for a further segmentation of the time row in favor of a more accurate distance value and haven't therefore decided on this qualitative method. Our templates have the length of the whole data series. For the generating of the template we use the knowledge of a system expert. With the help of a GUI he can visually decide which pressure signal series for the creation of the template shall be used. The graphical, interactive knowledge acquisition is very easy to handle for the user since he does not have to formalize his decisions, but can employ his visual decisiveness. With the chosen number of time series the data distributions are calculated for every point in time. The value range is therefore discretizised and the number of data points determined for the respective discretization intervals. Picture 2 on the left shows the data distribution above the time whereas the coloring corresponds to the number of data points in the respective interval. The template results from the median filtered maximum curve of the histogram (see picture 2 in the middle).



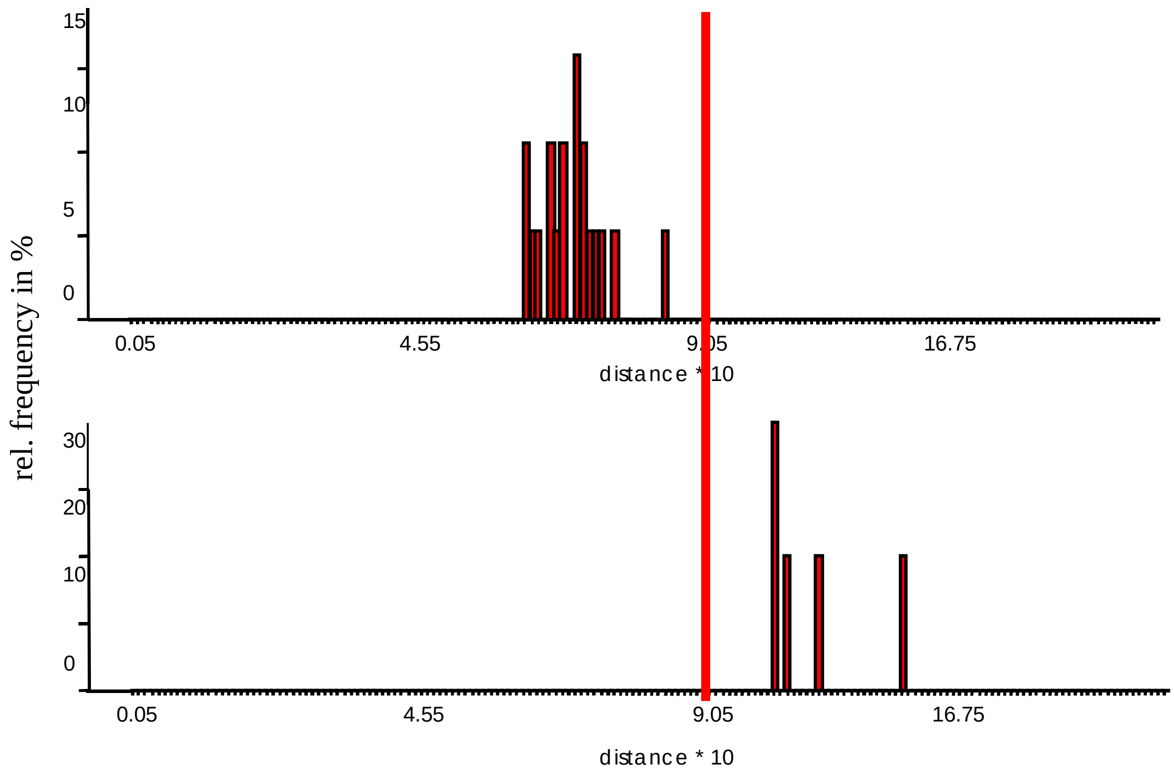
**Picture 2 The generating of template rows**

Picture 2 on the right hand side shows the upper and lower envelope which is taken from the minimum or maximum for every point in time of the regarded data series. A fault diagnosis on the basis of this envelopes [Klein98] is only partly suitable, since a displacement of the time row by some time points would lead to displeasing fault alarms (for example through tolerances in the valve's opening- or closing times).

For the classification of the distance value between the template and the test series a threshold is used and a crossing beyond that value leads automatically to an error message. The determination of that limit is calculated through the distance value distributions of faultless (see picture 3 on the top) and imperfect (see picture 3 at the bottom) flushing programs. The threshold results from an adequate separation of those two histograms (see picture 3). With this kind of flexible calculation of the template together with the corresponding data distributions of the last 200 faultless washing programs we are able to solve the above described problem of the permanently continuing changes of the process conditions. In case the histogram changes that much that it is no longer disjunct to the error histograms the latter have to be generated as well ( see section 3). Only this adaptation makes a long term use of the diagnosis method in the production possible, since a parameterization through the system expert can only be made if the process changes have a great effect on the distance values.

## 3 Experiments and outlook

The evaluation of the diagnosis method took place in the painting assembly line at DaimlerChrysler in Sindelfingen (see [Leisin99]) within the developmental project QUASAR. For the generating of error data that is necessary for the training of the above described diagnosis method separated flush trials have been required, since the quality check of the final product does not deliver the demanded correlation between the emerged error and the responsible machine. That means that out of the production only faultless processes are gained as pre- classified training data for the teaching. In the series of experiments we have deliberately and specifically manipulated components involved in the flushing process. After that the flush programs have been started and the sensor data collected by the diagnosis system PRIMAS developed by the company PRODATAS GmbH in Böblingen. The distribution of the distance values are presented in picture 3.




**picture 3: data distributions of the distance values between the templates and faultless (top) and faulty (bottom) flush programs**

The error message depicted in the histogram of the lower picture can be traced back to a simulated broken off hose of the thinning supply. The line demonstrates that the error can be located by a simple threshold check. The next step will be the online application of the method to the production process. The aim in this connection is to integrate the error detection into the control software to enable the system to react - depending to the respective kind of error- either with an adaptation of the process parameters to the flush program or, in case of a uniquely occurred error, with a repetition of the program. The use in the production would make a continuing documentation of the process variations possible which in turn would help deepen the process understanding of the system experts. This knowledge would be substantial both, for the process optimization and implementing of new lacquer plants, since possible errors in the color changing process are then known and can be avoided from the start. A further task to be faced by us will be the transference of the method onto other processes, as e.g. the lacquer spraying.

# 4 Literature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