Information Fusion Application On Security Printing
With Parametrical Fuzzy Classification

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Abstract - Bank note inspection is a complex task. As more and more print techniques and new security features are established, total quality security and bank note printing must be assured. Therefore, this factor necessitates change of a sensorial concept in general. We propose an optical-acoustical inspection method based upon the concepts of information fusion and fuzzy interpretation of data measures. Furthermore, we present a simplified scheme for information fusion for pattern recognition and data classification based on parametrical unimodal potential functions and a Sugeno-type score value analysis.

Keywords: Image processing, information fusion, fuzzy pattern classification, industrial processes.

1 Introduction

The authenticity checking and inspection of bank notes is a high labour intensive process where traditionally every note on every sheet is inspected manually. Machines for the automatic inspection and authentication of bank notes have been on the market for the past 10 to 12 years, but recent developments in technology have enabled a new generation of detectors and machines to be developed [1]. However, as more and more print techniques and new security features are established, total quality security, authenticity and bank note printing must be assured. Therefore, this factor necessitates amplification of a sensorial concept in general. Such systems can be used to enhance the stability of inspection and authentication results for user convenience while improving false classification rates.

A generic multi-sensor system consists of four important units: a) the sensor unit, which captures raw data from different measurement modules (sensors); b) the feature extraction unit, which extracts an appropriate feature set as a representation for the machine to be checked; c) the classification unit which compares the actual data with their corresponding machine data stored in a database; d) the decision unit, which uses the classification results to determine whether the obtained results represent a good printed or valid banknote.

Many detection systems are based on one main sensory apparatus. They rely on the evidence of a single source of information (e.g. photo-diode scanners in vending machines, BW cameras in inspection systems, etc.). These systems, called unimodal systems, have to contend with a variety of general difficulties and have usually high false error rates in classification. Systems, which are known as multimodal systems, are expected to be more reliable due to the presence of multiple, mainly signal-decorrelated, sensors. They address the problems of non-universality and in combination with meaningful interconnection of information (fusion), the problem of interclass variations [2]. At least, they can inform the user about problems with intraclass variations and noise. Detailed information can be found in [3].

During printed products manufacturing, measures are typically taken to ensure a certain level of printing quality. This is particularly true in the field of security printing, where the quality standards which must be reached by the end-products, i.e. banknotes, security documents and the like, are very high. Quality inspection of printed products is conventionally limited to the optical inspection of the printed product. Such optical inspection can be performed as an off-line process, i.e. after the printed product has been processed in the printing press, or, more frequently, as an in-line process, i.e. on the printing press, where the printing operation is carried out.

The classical threshold inspection methods exhibit a certain number of disadvantages as described in detail hereafter. These inspection methods may be adapted for inspection of security documents, but under certain conditions threshold-based inspection methods are not directly suited for the inspection of security documents, as security documents use specific printing processes (such as intaglio printing: in contrast to offset printing, all
techniques where lines or areas are scratched or etched into a plate), which are not commonly used in commercial printing. The conventional threshold-based inspection methods must be adapted accordingly to the specific printed features of security documents.

The mentioned methods however, have the disadvantage that high, but nevertheless tolerable fluctuations during the production process can lead to detection of pseudo-errors in regions of the inspected images, where an abrupt change of contrast is present. In order to prevent such pseudo-errors from occurring, the specific regions which are characterized by abrupt changes of contrast are typically rendered insensitive to error detection (i.e. by attributing high tolerances to these regions), so that the inspection process can be stabilized. Error detection in these regions is thus made almost impossible.

The above optical inspection methods are by definition limited to inspection of the printed products optical quality, such as; whether too much or too little ink has been applied onto the printed material, whether the density of the applied ink is acceptable, whether the spatial distribution of the applied ink is correct, etc. While these systems are adapted to detect such printing errors in a relatively efficient manner, the known inspection systems are however unable to perform an early detection of progressively-building printing errors. Such printing errors do not occur in an abrupt manner, but rather in a progressive and cumulative manner. These printing errors typically occur because of a gradual degradation or deviation of the printing press behaviour. As optical inspection systems inherently exhibit inspection tolerances, printing errors will only be detected after a certain period of time, when the errors exceed the tolerance of the optical inspection system.

Experienced printing press operators may be capable of identifying degradation or deviation in the printing press behaviour, which could lead to the occurrence of printing errors, for instance, characteristic noise produced by the printing press. This ability is however highly dependent on the actual experience, know-how and attentiveness of the technical personnel operating the printing press. Furthermore, the ability to detect such changes in the printing press behaviour is intrinsically dependent on personnel fluctuations, such as staff reorganisation, departure or retirement of key personnel, etc. Moreover, as this technical expertise is human-based, there is a high risk that this knowledge is lost over time, the only available remedy is to organize secure storage of the relevant technical knowledge in one form or another and appropriate training of the technical personnel.

2 Approach

2.1 Visible Light-based Optical Inspection

Usually only the existence or appearance of colours and their textures are checked by an optical inspection system. Obviously there is a need for an improved inspection system which is not merely restricted to the optical inspection of the printed end-product, but which can take other factors into account than optical quality criteria. A general aim is to improve the known inspection techniques and propose an inspection methodology that can ensure a comprehensive quality control of the printed substrates processed by printing presses, especially printing presses that are designed to process substrates used in the course of the production of banknotes, security documents and the like.

Additionally, a second aim is to propose a method, which is suited to be implemented as an expert system designed to facilitate operation of the printing press. In this context, it is particularly desired to propose a methodology, which is implemented in an expert system adapted to predict the occurrence of printing errors and/or provide an explanation of the likely cause of printing errors, should these occur. These aims are achieved by the methods and the expert system defined below.

2.2 Detector-based Inspection

In the approach, different methods of print flaw detection are combined, which can be used for printing machines in general. We have not exclusively used optical printing inspection methods, but also acoustical and other measurements like temperature and pressure of printing machines. For the latter Cepstrum methods are implemented. All signals or combinations respectively parts of signals are analyzed in the time related frequency (quefrency) domain with a Fuzzy Pattern Classifier model [4, 5].

The selection and location of the sensors should be made in view of the actual set of behaviour patterns one desires to monitor and of the classes of printing errors one wishes to detect. As a general rule, it is appreciated that sensors might be provided on the printing press in order to sense any combination of the operational parameters.

Depending on the particular configuration of the printing press, it might be useful to monitor different operational parameters. For example, in the case of an intaglio printing press, monitoring key components of the wiping unit has shown to be particularly useful in order to derive a representative model of the behaviour of the printing press, as many printing problems in intaglio printing presses are due to a faulty or abnormal behaviour of the wiping unit.

2.3 Signal Performance

In this section we explain, that elementary estimates are sufficient for a principle analysis of multi-sensor systems in a printing machine. It is a known fact, that in printed product manufacturing the waste rate should not exceed approx. 5 % of the production (world wide waste constant, wwwc) [6].

As an example we describe our statistical approach with the help of the detection of print flaws in a machine. The concept can easily be generalized. There is no information
about pseudo-errors (alpha and beta errors), the question arises how many printed good sheets are in the bad sheet pile and vice versa? It is well known, that production processes can be described with a binominal probability distribution in the case of decorrelated occurrences of true and false decisions in a process. This fact is in general true for high volume production with low waste rates (e.g. banknotes, electronic devices, screws, etc.). It can also be assumed, that the process is

1. stationary – the occurrence is only dependent on the measurement and analysis time,
2. memoryless – the number of events is not dependent on the statistic of the occurrences itself and
3. ordinal – two events with different results can only occur consecutively.

In this case the statistical behaviour can be described with a Poisson stream (Poisson distribution):

\[
W_p(\lambda, M) = \sum_{i=0}^{M} \frac{\lambda^i e^{-\lambda}}{i!},
\]

\[
\lambda = N \cdot p = \text{const.,}
\]

were \(M\) is the number of occurrences. For example, in a pile of 20,000 produced sheets are 1,000 sheets classified as bad (wwwc = 5%) and 19,000 classified as good. The number of good sheets in a bad sheet pile must be checked. It is assumed that the a-priori probability of such a pseudo error is \(p = 0.005\) and the number of sheets in the bad pile is \(N = 1000\). Applying the equation (1) on the parameters, results in the discrete distribution curve in figure 2. Here, \(M = 11\) for \(p = 0.0055\). This means that not more than 11 good sheets will be in the bad pile (cf. figure 1).

The mentioned procedure applies to monomodal systems in general. In the next step it is assumed that different channels of a multimodal system operate on a specific detection or inspection procedure. The signal sources may not be of the same type – they can be different (image sensors, acoustical sensors, etc.). However, a signal decorrelation in a broader sense is necessary. Hence, an optical colour inspection system should not operate in the RGB space, because the channels are not much decorrelated. Though other colour spaces, like Hering’s opponent colour spaces [7] are much more convenient for multimodal systems.

This fact applies as well for mechanical measurement, like cylinder pressure and motor current of a main motor drive. These parameters (pressure, current) are also correlated. Due to this fact all signals which are in use for a multimodal system have to be considered as decorrelated. Therefore, a proper sensor dependency analysis has to be accomplished before designing a multimodal system.

Now we examine the multimodal sensor case, supposing decorrelated signals. Therefore, the probability of a statistical event (signal) can be assumed as independent from all other events.

We consider a system with four decorrelated inspection channels which can be described via their distribution functions \(W(E_k)\) of the events \(E_k, k \in \{1, 2, 3, 4\}\). The complementary probability of the mentioned events is

\[
W(E_k^c) = 1 - W(E_k).
\]

If now \(n = 4\) inspection channels are operating parallel, then the probability that at least one specific channel will detect an error or an authentication marker is raised. Figure 2 shows a combination of four channels with the help of a valuation function.

The valuation operation \(V\) reflects the process description of a logical level. We assume that at least one channel will deliver the correct inspection result (error, no error) with a certain probability. Therefore, the function \(V\) has to be interpreted in a sense of probability interconnection. The table 1 shows the connection in form of a fuzzy-logical disjunction matrix (a: sensor action, r: system reaction).

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As the probability distribution functions of the channels are usually equipped with different \(\lambda_i\), the valuation function has to be defined in the canonical disjunctive form. For example, the connection of two sensor probability functions is as follows:

\[
W = (E_2 \cdot E_1) + (E_2 \cdot E_1^c) + (E_2^c \cdot E_1),
\]

\[
\overline{W} = E_2 \cdot E_1.
\]

The resulting distribution function which is coupled via the valuation function is therefore:
It can be shown that the general case results in:

$$W(E_1 + \ldots + E_n) = 1 - \prod_{k=1}^{n} (1 - W(E_k)).$$

(5)

In particular, for the Poisson distribution it follows from the above

$$W_p(E_1 + \ldots + E_n) = 1 - \prod_{k=1}^{n} \left( 1 - \sum_{i=0}^{M} \frac{\lambda_k^i}{i!} e^{-\lambda_k} \right),$$

$$\lambda_k = N \cdot p_k.$$  

(6)

We will now refer to the first example in this section. As an assumption we consider a four channel system ($n = 4$) with $M = 100$, $N = 19,000$, $p = 0.005$ and $\lambda_k = 95$.

The probability that there are not more than 100 bad sheets in the good pile of 19,000 sheets is approx. 72% in a monomodal system. Whereas the probability for a four channel multimodal system results in 99.4%. Figure 3 shows the probability distribution for a monomodal and a four channel multimodal system as a difference plot. However, it must be accentuated that the above mentioned holds in cases where the detection result is a contribution of more than one channel. In some cases only one signal source is able to detect a specific signal class. Then a multimodal system converts into a monomodal system.

2.4 Fuzzy Pattern Classification

The in-line analysis of the printing press behaviour is based on fuzzy pattern classification techniques. Broadly speaking, fuzzy pattern classification is a known technique that concerns the description or classification of measurements and data fusion [8, 9 and 10]. The idea behind fuzzy pattern classification is to define the common features or properties among a set of patterns (in this case the various behaviours a printing press can exhibit) and classify them into different predetermined classes according to a determined classification model.

In this paper we propose as a basic fuzzy classifier the well known Tagaki-Sugeno-Kang-model (TSK-model) [11] which is usually applied to controls. However, the model is adapted and modified to sensor and data fusion. The TSK-model comprises of “if-then-else” rules and a defined output function. Therefore, the TSK-model is also called functional inference machine. The first and second part of a TSK-model is exactly the same as the well known Mamdani-model [12]: (a) definition of membership functions and (b) connection of the membership functions in form of rules like ”IF < premise > THEN < conclusion >”. The main difference between the Mamdani-model and the TSK-model is the functional connection of the rule outputs, which is not defined as a defuzzyfication (Centre of Gravity, etc.). The rule design is as follows ($m$ is a feature):

Rule:

$$\text{IF} \ (m_1 \ \text{is} \ \mu_1) \ \text{AND} \ (m_2 \ \text{is} \ \mu_2) \ \text{AND} \ \ldots \ \text{AND} \ (m_N \ \text{is} \ \mu_N) \ \text{THEN} \ y_R = f(m_1, m_2, \ldots).$$

(7)

For each rule the equation (7) is applied. Usually the conclusion is modelled as a linear function of the input variables, like $y_R = p_{R,0} + p_{R,1} \cdot m_1 + p_{R,2} \cdot m_2 + \ldots$. In our approach only the constant value $y_R = p_{R,0}$ of each
A rule is used for the model. In this case the model is called static. The conclusion is known as a singleton, which is nothing else as a discrete weighted Dirac impulse \( y_R = \mu_R \cdot \delta_{\text{allocation}} \). The weight is the resulting output of the premises. For each rule the output has to be allocated to a specific singleton. In the applied model two types of singletons were used: one singleton represents the overall “good” value, the other represents the overall “bad” value for the model (cf. figure 4).

The AND function is interpreted as a fuzzy-AND function which is in our case the average of all membership functions values for the particular \( m_i \) in one rule.

\[
\mu_R = \frac{1}{N} \sum_{i=0}^{N-1} \mu_i(m_i).
\]

(8)

The aggregated output (score value) for all rules is determined by:

\[
y = \frac{\sum \mu_{R_i, \text{good}} \cdot \delta_{R_i, \text{good}} + \sum \mu_{R_i, \text{bad}} \cdot \delta_{R_i, \text{bad}}}{\sum \mu_{R_i}}.
\]

(9)

The model is based on membership functions \( \mu(m; p) \). They are modeled as unimodal potential functions (cf. Figure 6) [4]. The behaviour of the feature \( m \) is described with the appropriate parameter vector \( p \). The advantage of those functions is their adaptation on different inputs by a learning process or by an expert’s tuning with linguistic modifiers.

Therefore, we call our approach modified singleton classifier (MSC). A feature vector \( m \) is generated by a preprocessing unit, which in our case computes different signal processing algorithms derived thereof being interpreted as a feature vector \( m \).

For each feature a membership function is determined. The membership function can be described with 8 parameters which are defined below. The parameters are determined in a learning phase, or by an expert (mixed strategies are also possible), finally resulting in a time-invariant or time-variant classifier [4, 5].

In the working phase a level of affinity is calculated for every incoming set of data and used for the classification. The prototype of a one-dimensional potential function \( \mu(m; p) \) can be expressed as follows [5] (cf. Figure 5):

\[
\mu(m; p) = A \cdot 2^{-d(m; p)},
\]

(10)

with the difference measure

\[
d(m; p) = \begin{cases} 
\frac{1}{B_r} - 1 \cdot \frac{|m - m_0|}{C_r} & \forall m < m_0 \\
\frac{1}{B_f} - 1 \cdot \frac{|m - m_0|}{C_f} & \forall m \geq m_0
\end{cases}.
\]

(11)

This difference can be interpreted as a generalized Minkowski distance. The potential function is comprehensively determined by the parameter vector \( p = [m_0, B_r, B_f, C_r, C_f, D_r, D_f] \). Referring to Figure 5, the elementary parameters belonging to the vector \( p \) are defined as follows.

The parameter \( m_0 \) corresponds to the average value of a one-dimensional signal or feature. The value \( A \) denotes the maximum value of the function. In the cases described in this paper, \( A = 1 \). The elements \( m_0 \) and \( A \) are interrelated by the formula \( A = \mu(m_0; p) \).

The parameters \( B_r \) and \( B_f \) determine in turn the value of the membership function on the boundaries \( m_0 - C_r \) and \( m_0 + C_f \). The membership values for the rising and falling edges are given by the expressions \( \mu(m_0 - C_r; p) = B_r \) and \( \mu(m_0 + C_f; p) = B_f \). The parameters \( C_r \) and \( C_f \) define the maximum distance from the average value. This value is calculated from the maximum and minimum of the signal amplitude of each feature. The parameters \( D_r \) and \( D_f \) are determined from each feature’s amplitude distribution. They model the decrease in membership with the increase of the distance from the center of gravity. A detailed description of the parameters and their calculations can be found in [4, 5].
First, the average amplitude value of data of “good data” is calculated. This value is identified as \( m \) in accordance with the above principle, i.e. this value is the typical (average) representative of the class. The parameter \( C_r \) is calculated with the following equation:

\[
C_r = m - m_{\min},
\]

whereby \( m_{\min} \), denotes the objects lying furthest from \( m \) on the left side of the class. Therefore the following is valid for \( C_f \):

\[
C_f = m_{\max} - m,
\]

whereby \( m_{\max} \), denotes the objects lying furthest from \( m \) on the right side of the class. The parameters \( D_r \) and \( D_f \), which convey the information on the object distribution in the corresponding class and which determines the form of the membership function on the right and left sides are calculated as follows:

1. The geometrical sequence \( q \) is calculated (equation 14).

\[
q_1 = \frac{m_{n_3} - m_{n_0}}{m_{n_2} - m_{n_1}}, \ldots, q_{l-2} = \frac{m_{q_2} - m_{q_1}}{m_{q_{j+1}} - m_{q_{j-2}}},
\]

2. The average ratio of progression in the geometric progression \( \overline{q} \) is calculated as the measure of distribution (equation 15).

\[
\overline{q} = \frac{1}{I_k} \sum_{j=1}^{I_k-2} q_j.
\]

3. The following equation [4] is set as the functional relation between \( \overline{q} \) and the parameters \( D_r, D_f \):

\[
D = \int_{18 \cdot \exp(-3(\overline{q}-1)) + 2}^{20} \quad \text{for } \overline{q} \leq 1 \quad \text{and} \quad \overline{q} > 1.
\]

\( D_r = D_f = D \) was set under practical considerations. With these calculations a membership function can be designed. The complementary functions are designed accordingly.

### 2.5 Cepstral analysis

It has been mentioned that it might be desirable to pre-process some of the signals outputted by the sensors which are used to monitor the behaviour of the machine. This is particularly true in connection with the sensing of noises and/or vibrations produced by the printing press, which signals a great number of frequency components. The classical approach to processing such signals is to perform a spectral transformation of the signals. The usual spectral transformation is the well-known Fourier transform (and derivatives thereof) which converts the signals from the time-domain into the frequency-domain.

The processing of the signals is made simpler by working in the thus obtained spectrum as periodic signal components are readily identifiable in the frequency-domain as peaks in the spectrum. The drawbacks of the Fourier transform however reside in its inability to efficiently identify and isolate phase movements, shifts, drifts, echoes, noise, etc., in the signals.

A more adequate “spectral” analysis is the so-called “cepstrum” analysis. “Cepstrum” is an anagram of “spectrum” and is the accepted terminology for the inverse Fourier transform of the logarithm of the spectrum of a signal. Cepstrum analysis is in particular used for analysing “sounds” instead of analysing frequencies [13, 14 and 15].

### 3 Results

The approach was tested in particular with an intaglio printing machine in a production process. The opto-acoustical behaviour was tested. As an interesting fact print flaws were detected in an early state by using acoustical and optical measurements. It has to be noted that one of the most common types of print flaws caused by the wiping were detected in a very early stage.

#### 3.1 Image parameters

The images taken (797 sheets) during test were first binarized i.e. the images from optimal production were used as learning images in order to learn the maximum variation of the pixel differences of the images, namely a maximum dark image and a maximum light (approx. 100 sheets). The images from test Variation of the wiping cylinder pressure were then compared with the learned variation of the learned images. The pixel grey values outside the tolerance interval, which was formed by the light and dark images, were set to 255; the others were set to 0.

The image was split into five columns and the average grey value of each column was calculated. These five grey values are entered in the classifier as five parameters. As the average grey value for good images is 0 per column, the classifier cannot be trained with the data set available in accordance with the principles described above. At this point, expert knowledge is applied in which the parameters of the membership function are set manually in such a way as to ensure a reliable good-bad classification.

For test, the parameters of the membership functions for the five columns were set as follows: \( A = 1, m_0 = 0, C_r = C_f = 0.25 \) and \( D_r = D_f = 8 \). Where the maximum membership value of the function is \( A \), \( m_0 \) is the average grey value of the binarized learnt images from test (cf. figure 6). \( C_r \) and \( C_f \) set the class boundaries (as there are no negative grey values, only parameter \( C_r \) must theoretically be initialised, but for technical reasons of programming both parameters were initialised here) and \( D_r \) and \( D_f \) govern the drop of the slopes.
It has to be pointed out, that the expert’s tuning method gives good results under practical considerations. We refer to [1 and 4].

3.2 Cepstrum parameters

In addition to the image signal the acoustic signals measured are implemented in the classifier as a parameter. First of all, the cepstrum of the acoustic channels is calculated as described above. To do so, the acoustic signals are split into ten second sections and the real cepstrum is calculated over the above mentioned time. Detail can be found in [15].

Four acoustical channels measurements were taken at four different points on the machine. Two channels contain the acoustic recordings from side 1 of the machine (the motor side) and the other two channels the acoustic sounds from side 2 (the operator side). In our simplified approach the channels were fused by data averaging per side (avCep_side1, avCep_side2) [3]. This fact is in contrast to first results which were obtained with classification of six cepstral signals [15]. The cepstrum data which relates to the “sound” of one cylinder revolution and one printing plate was inputted to the classifier.

3.3 Fuzzy rules

Once the membership functions have been established, the rules have to be defined; the following rules are used:

R1: IF (Col1 is Col1good) AND (Col2 is Col2good) AND (Col3 is Col3good) AND (Col4 is Col4good) AND (Col5 is Col5good) AND (avCep_side1 is ceps1_good) AND (avCep_side2 is ceps2_good) THEN \( y_{R1} = \mu_{R1} \cdot \delta_{R1,\text{good}} \).

R2: IF (Col1 is Col1max) THEN \( y_{R2} = \mu_{R2} \cdot \delta_{R2,\text{bad}} \).

R3: IF (Col2 is Col2max) THEN \( y_{R3} = \mu_{R3} \cdot \delta_{R3,\text{bad}} \).

R4: IF (Col3 is Col3max) THEN \( y_{R4} = \mu_{R4} \cdot \delta_{R4,\text{bad}} \).

R5: IF (Col4 is Col4max) THEN \( y_{R5} = \mu_{R5} \cdot \delta_{R5,\text{bad}} \).

R6: IF (Col5 is Col5max) THEN \( y_{R6} = \mu_{R6} \cdot \delta_{R6,\text{bad}} \).

R7: IF (avCep_side1 is ceps1_bad) THEN \( y_{R7} = \mu_{R7} \cdot \delta_{R7,\text{bad}} \).

R8: IF (avCep_side2 is ceps2_bad) THEN \( y_{R8} = \mu_{R8} \cdot \delta_{R8,\text{bad}} \).

The rule R1 describes the interconnection of all used parameters and their membership functions. The rules R2 to R6 define the deviation of the average grey value per column. The rules R7 and R8 describe the sound deviations of the acoustical channels.

In figure 7 the fusion result of the opto- and acoustical sensor combination can be viewed. A commercially available optical colour inspection system for bank notes (Nota Save III) was used for benchmarking (small line in figure 7). While the optical inspection system reacts with an error output from sheet number 530 onwards, the acoustical channel gives an indication in an early stage, approximately some ten sheets before the optical inspection system reacts. As described above the combination of both signal channels gives a clear indication of faulty machine behaviour. The correlation between manually inspected sheets and the fusion model gives excellent results, whereas the optical inspection system gives a clear print error indication only after consecutively presented bad sheets.

4 Conclusions

A simplified scheme for information fusion for printed securities was presented in this paper. Our opto-acoustical approach was tested in particular with an intaglio printing
machine in a production process. It has to be noted that one of the most common types of print flaws caused by the wiping were detected in an early stage. We cite examples like not enough pressure between wiping cylinder and plate, damaged wiping cylinder surface, and others.

A modified classifier concept was described, which is based on Sugeno’s approach in combination with unimodal potential functions, which can be generated by a learning process or by an expert. Based on expert knowledge, the rules were defined, which supply a sympathy value between one and zero at the output of the classifier on the basis of the relation of machine parameters.

The system concept “observes” the various machine parameters and decides using a classifier model with manually tuned or learned parameters whether the datas are as expected or not.

References