System design for classification process

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Absract

Changes of a production process and consecutive alterations of products can be analysed by different methods. A particular error usually influences the product very specifically. So, if is it possible to classify the unsuitable product in a specific class of deformation, we could predict changes in the production process. Inspection of the production process is performed by a measuring system with a number of probes placed on the product. On the base of these measured values we could make additional classification of the product that is not required for the production control. The additional classification classifies the product in the appropriate class of deformations and diagnoses the defects in the production process.

The purpose of the paper is to introduce a qualitative system model for classification. The presented concept is very general and could be used in different application domains not only for classification. We developed this concept to classify a product in a proper class of deformation and to identify and eliminate sources for the alteration in a production process.

1 Introduction

Starting point of every process control is an analysis of measured values of products. If the values have not expected magnitudes, it is necessary to find out a reason for this discrepancy. Supposing that data acquisition system (measurement system) works correctly the reason for a defect is an alteration of the production system. To prevent the defects in other products we must identify and eliminate sources for the alteration.

In our contribution we present the classification model based on a mathematical model of the product, which is very suitable for use in expert systems for automatic analysis of production processes. The first generation expert systems were using ***shallow knowledge*** based on heuristic information to solve a problem. This approach has many disadvantages, which can be avoided by using ***deep knowledge*** [7]. Recently the use of modelling (particularly qualitative modelling) in relation to deep knowledge in expert systems is increasingly important.

Our concept of the classification model is defined as a structure of connection between the variables, which are given with the formulas in the mathematical model. The classification model figures out the connections between the variables while a simulation process point out effects and sources of particular variations. The results of classification are classified products in the suitable classes.

2 Problem formulation

Raw data given by acquisition process are generally not sufficient for analyzing the production process. We usually also need the values that define the relation between the data from the same sources and characterise the product more precisely. So we can define different hierarchy of data according to how close to the source they are. At the lowest level are immediate data from the source and on the next levels are computed values from lower level data that illustrate some complex characteristic of the product. All data from the same level express several product characteristics, which are the subjects of the further investigation.

Dependancy beetwen variables in different levels are formally defined as the functions and can be described in elementary mathematics by sets of formulas which is called a **product model**. All values that illustrate data at different level of the product model are represented as different data sets (P, Y, X, W, Z). Product model with its data sets is presented in the Figure 1.

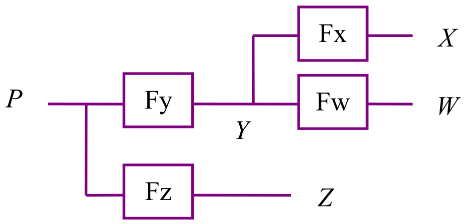

Figure1: Product model

Aim of the inspection or research process is to detect discrepancies between expected and acquired data. Usually the data are checked in a view of dimensional attribute of the product and the computed characteristic according to variations between these values in the sets. For the further investigation any value x in a single set X ($x \in X$) can be represented as a sum $x=x_0+\Delta x$ where x_0 is a nominal (or expected) magnitude and Δx is a variation from the nominal value ($\Delta x=x-x_0$). Because the nominal value of every variable is known it is usually more suitable to represent the data as the sets of variations instead of the actual values. Every set that represents data at different level of the product model is a sum of two sets; one contains the expected values and the other variations from expected values.

Now, we can define the inspection as a process of checking whether the variations are smaller than the allowable. For illustration we will illustrate the inspection of values in the set X. It is a sum of two sets $X=X_0+\Delta X$, where X_0 is a set of expected values and ΔX a set of variations. Allowable variations for data set X are given in a set X_T. So the formula

$$|X_T| \geq |\Delta X|$$

represent the inspection formally. If the formula is satisfied the variations of data represented by X set are under specification limits.

In the case the formula is unsatisfied, at least one variation is larger than allowed and the product is unsuitable. To find out reasons for this discrepancy we must analyze all lower level data (up to the source) that influence the X set. The analysis to be done for this purpose classifies the product in a proper class of deformation according to discrepancy. Classes are defined in a manner that gives us the answer about production process alterations that are responsible for the product defects.

3 Theoretical background

To understand and to prove our approach to model design we developed an adequate formal concept. Because of the lack of space we describe only the indispensable part of the formal concept.

Definition 1. *System set S* includes basic statements that assign values from the *domain DOM* to all variables of a system collected in a *variable set V*

$$S = \{s \mid s := (v = a), v \in V, a \in DOM\}$$

Definition 2. *Universe* ***U*** is a space that includes all different *system sets S*

$$\mathbf{U} = \{S \mid S = \{s \mid s := (v = a), v \in V, a \in DOM\}\}$$

Universe ***U*** is a *closed space* that contains all possible combination of system sets. Therefore the universe always contains a set that represents any real situation in the system. And vice versa the universe includes also sets that illustrate situations that never occurred on the artefact.

Definition 3. *System space* ***S*** includes all sets of universe ***U*** that illustrate possible situation on a system and *conflict system space* $\neg$***S*** includes all sets of universe ***U*** that illustrate impossible states of the system.

System space provides a mechanism to express any situation on a system and represents a very naive system model. For more sophisticated model design we need a more concise and less restrictive definition.

Definition 4. *SD*, the ***system description***, is a set of first-order sentences that

$$SD \cup S$$

is satisfiable for all sets $S \in \boldsymbol{S}$ and unsatisfiable for all sets $S \in \neg \boldsymbol{S}$.

The system description *SD* formalises description of system and makes possible to predict its behaviour. It helps to find out magnitudes of system variables. In this case we need information about the actual system behaviour, which we get them by observation with sensors, laboratory tests, etc. – depends on sphere of activity. For further research a result of observation must be defined more formal.

Definition 5. *OBS*, the *observations* of a system, is a set of first-order sentences that assigns values from the domain *DOM* to all or some variables of a system in a way that represent an actual observed system behavior

$$OBS = \{s \mid s := (v = a), v \in V', V' \subseteq V, a \in DOM\}$$

If the observation includes all system parameters the *OBS* set is an element of a system space ($OBS \in \boldsymbol{S}$) and illustrates a real situation on an artefact. Usually an initial observation does not include all system parameters and we want to conclude the situation on the base of this partial observation.

Theorem 1. For any observation *OBS* and given system description *SD* the term

$$SD \cup OBS \cup S$$

is satisfiable for all $S \in \boldsymbol{S}$ where $OBS \subseteq S$.

Proof. For the given condition $OBS \subseteq S$ the result of union $OBS \cup S$ is the system set *S* itself and the validity of the theorem is assured by the Definition 3. ♦

The theorem proofs that on the base of the observation all possible system sets that describe the system behaviour can be computed. The forecasting is more precise when the less system sets satisfy the term in the theorem.

4 System model

Artefacts are usually studied as computer models. Because of different reasons they are as simple as possible, and simulate only functions that are subject of an investigation. Generally, they simulate system behaviour, which reflects its inputs and outputs. Model parameters are then variables that represent input and output values.

Knowledge-based systems often do not simulate system behaviour but predict the system parameter (values of variables) on the base of limited information about the system. Typical example is to find out which inputs cause the irregularities when some outputs have unexpected values. In such cases only qualitative relations are important, therefore the variables could be represented with qualitative values and naturally the system model must be arranged for computing the qualitative values.

4.1 Qualitative model

Figure 2 shows the symbolic sketch of a *system model* SMOD. From the outside, the model is defined by INPUT and OUTPUT sets which contain values that represent respective inputs and outputs of a system. Behaviour of the artefact given by a system description (see Definition 4) could be defined in the most suitable way for a proper application domain. The only prerequisite to be met by designing a model is that it should make possible to simulate input/output system behaviour.

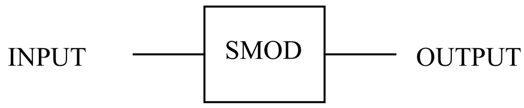

Figure 2: System model

The simulation of system behaviour is not the main goal in knowledge-based systems. As a result of a simulation process on the system model we usually want only a qualitative estimation how a change of a particular system variable influences to the others. To avoid an additional analysis to interpret a numeric result of the simulation process we suggest the use of symbolic values. Naturally, in this case the system model should be rearranged for computing the qualitative values and variables in the model sets are represented by qualitative values.

Variables on a qualitative model that represent the system input and output can occupy only a limited numbers of qualitative states. All these different qualitative states compose a *quantity space QS* (in Definition 1 it is defined as domain *DOM*). The size of the quantity space depends on the information we want to receive from the system. Because of the limited size of the quantity space, an application of the standard arithmetic operations for designing the qualitative model causes specific problems [2, 5].

The result of a simulation process on the qualitative model is qualitative values of variables. These values represent specific states of the system and there is no need for additional analyses to interpret the result. Computing algorithms for the qualitative values are usually simpler as numeric ones, and the qualitative simulation is thus more efficient.

Designing the qualitative model is also a relatively simple task because it can be realized in a nonprocedural way. Qualitative model implemented in a nonprocedural-programming environment (programming language *PROLOG* for instance) has a very important feature: it is *bi-directional*. Bi-directional means that it is not important which values illustrate the inputs and which the outputs of the system. So this approach directly implements the finding of Theorem 1 for a model design.

4.2 Input/output study

A physical system is usually described by a differential equation model of the real word. In this case the qualitative model is essentially a qualitative abstraction of differential equations. The most important property of a variable in a qualitative simulation process is its change: whether it is decreasing, increasing or remains unchanged. Because of this, the variables have two parts. The first shows the expected value and the second shows if the variable is smaller, equal or greater from the expected value. For this purpose the quantity space with three different symbols “m”, “z” and “p” (QS={m, z, p}) to illustrate the magnitudes of the input-output variables is needed.

Therefore the whole set of all real numbers R is represented with only three symbols from quantity space QS. Where each symbol represents the defined interval of the real numbers R:

$p \equiv a \Rightarrow a>0;\ a \in R,$

$z \equiv a \Rightarrow a=0;\ a \in R,$

$m \equiv a \Rightarrow a<0;\ a \in R,$

The quantity space QS for qualitative variables is equivalent to the set of real numbers R that represents a domain of variables for numeric model ($QS \equiv R$). Variables in our case are not a time function. In some way they have a constant value that could increase, decrease or stay unchanged:

$X_R = x_0 + dx\ \ ;\ x_0 \in R,\ dx \in R$

$X_Q = \langle x, x' \rangle\ \ ;\ x \in QS,\ x' \in QS$

Constant value x_0 in the numeric variable X_R represents expected value and derivative dx represents a magnitude of the change. The same is true for the qualitative variable X_Q presented as a pair $\langle x, x' \rangle$ where x is the constant and x' the derivative part. It must be equivalent to the belonging numeric variable

$X_Q \equiv X_R \Rightarrow x \equiv x_0 \wedge x' \equiv dx$

Definition of the arithmetic operations on the qualitative variables must be also equivalent to the numerical ones. For a qualitative modelling we must define also qualitative arithmetic operations. The following two formulas lead to the addition and the multiplication of quality variables

$$V_Q = X_Q + Y_Q = \langle x, x' \rangle + \langle y, y' \rangle = \\ = \langle x + y, x' + y' \rangle$$

$$W_Q = X_Q * Y_Q = \langle x, x' \rangle * \langle y, y' \rangle = \\ = \langle x * y, x' * y + x * y' + x' * y' \rangle$$

Both expressions ensure equivalency with the arithmetic operations on numerical variables. They are basis for a quality model design where both operations are defined as predicates

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add(Input1,Input2,Output)
mult(Input1,Input2,Output)
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for which qualitative values are defined in Table 1. Table 1 represents results of the addition and the multiplication for all possible combination of the symbolic values from the quantity space QS.

	I2				**I2**		
I1	p	z	m	**I1**	p	z	m
p	p	p	any	p	p	z	m
z	p	z	m	z	z	z	z
m	any	m	m	m	m	z	p
	a) addition				b) multiplication		

Table 1: Arithmetic operations

5 Example of a connecting rod

Practical approach to design the classification model will be given by an example of a connecting rod. Arranging of the probes and consequently measuring positions of particular values on the connecting rod is presented in Figure 3. Formulas to compute the values needed for the inspection and the classification (see Table 2) present the mathematical model of the connecting rod.

All values are computed on the base of primitive values in set $P=\{t_1,t_2,\ldots,t_{16}\}$ measured by the probes. Diameters on different positions and lengths (upper and lower) between the centres of the both holes compose the set of basic values $Y=\{d_1,d_2,\ldots,d_8,dc_1,dc_2\}$. The set of characteristic values $W=\{ds_1,ds_2,dc\}$ contains the mean values of the diameter of both holes and the mean value of the lengths between the centres. Set of control values $X=\{o_1,o_2,o_3,o_4,k_1,k_2,k_3,k_4\}$ is very important in the inspection. It contains different ovalness (upper and lower) and conoids of the both holes.

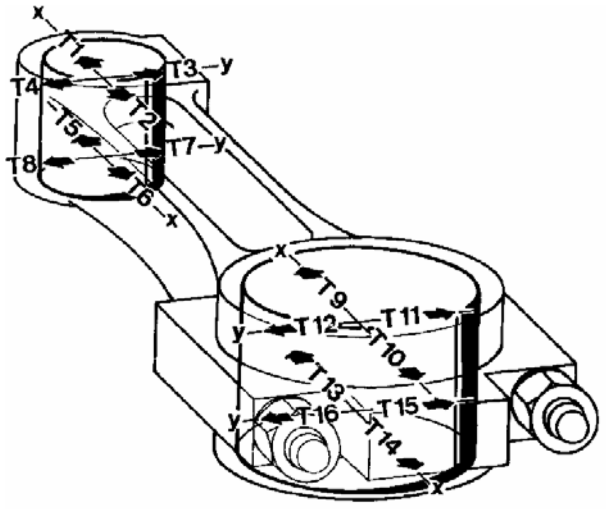

Figure 3: Connecting rod

All others values in Table 2 are members of the set of auxiliary values $Z=\{c_1,\ldots,c_8,lc_1,\ldots lc_4,pc_1,pc_2\}$. We need them only as an additional aid for the classification. The values c_1 to c_8 are the central points of all diameters.

Magnitudes of the values lc_1 to lc_4 present leaning of the axes for both holes in different directions. Remaining two values pc_1 and pc_2 are conoids between the central axes of the holes.

$d_1 = t_1 - t_2$	$d_5 = t_9 - t_{10}$	$dc_1 = c_1 - c_5$
$d_2 = t_3 - t_4$	$d_6 = t_{11} - t_{12}$	$dc_3 = c_3 - c_7$
$d_3 = t_5 - t_6$	$d_7 = t_{13} - t_{14}$	$pc_1 = lc_1 - lc_3$
$d_4 = t_7 - t_8$	$d_8 = t_{15} - t_{16}$	$pc_2 = lc_2 - lc_4$
$o_1 = d_1 - d_2$	$o_3 = d_5 - d_6$	$lc_1 = c_1 - c_3$
$o_2 = d_3 - d_4$	$o_4 = d_7 - d_8$	$lc_2 = c_2 - c_4$
$k_1 = d_1 - d_3$	$k_3 = d_5 - d_7$	$lc_3 = c_5 - c_7$
$k_2 = d_2 - d_4$	$k_4 = d_6 - d_8$	$lc_4 = c_6 - c_8$
$c_1 = (t_1 + t_2)/2$	$c_5 = (t_9 + t_{10})/2$	
$c_2 = (t_3 + t_4)/2$	$c_6 = (t_{11} + t_{12})/2$	
$c_3 = (t_5 + t_6)/2$	$c_7 = (t_{13} + t_{14})/2$	
$c_4 = (t_7 + t_8)/2$	$c_8 = (t_{15} + t_{16})/2$	
$ds_1=(d_1+d_2+d_3+d_4)/4$		
$ds_2=(d_5+d_6+d_7+d_8)/4$		
$dc=(dc_1+dc_2)/2$		

Table 2: Formulas of the Connecting rod model

Classification model of the connecting rod (Figure 4) illustrates the mathematical model presented in Table 2. It shows only the structure of the values in the formulas and reflects very clearly connections and consequently dependencies and hierarchy between defined values. Measured values at the probes P are at the lowest and the computed values pc_1 and pc_2 are at the highest hierarchy level.

Computer model then reflects the mathematical model using the qualitative arithmetic operations. The first step to analyze the artefact is an observation or measurement. Measured values irrespective of which variables in hierarchy levels they represent are the inputs for simulation process. The result of the simulation process is the qualitative sets of all possible competitive consistent solutions for all missing values according to the observation.

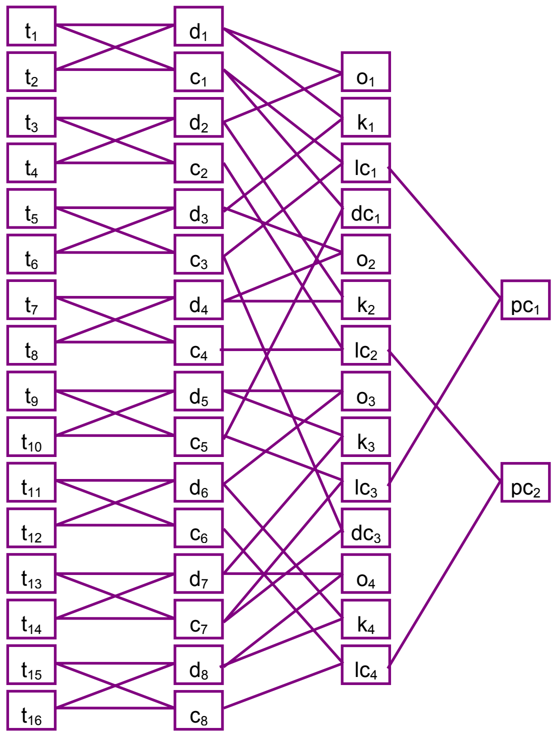

Figure 4: Classification model

6 Conclusion

The paper describes a concept where the expert reasoning is implemented by the model-based approach. The qualitative system model in our approach needs not to be specially adapted for use in a specific application domain.

The main feature of the proposed concept of the qualitative model is irrelevance which values illustrate the inputs and which the outputs of the system. Known values received by observation are simply fixed and missing values are computed in a simulation process irrespective if they illustrate inputs, outputs of the system. The simulation process could be successful even with incomplete data, but the result in this case is several competing solutions.

The presented concept is applicable in very different application domains. Any physical system could be described by differential equations that are model of the real word. This mechanism is governed by the physical laws and its qualitative model is essentially a qualitative abstraction of differential equations.

Designing a qualitative model on the basis of the formulas of a product model is very simple. The model takes over a structure of the formulas and the qualitative dependencies between the variables. Presented concept is very convenient for solving classification problems in expert systems.

It is also necessary to point out that the result of the classification generally is not unique in all cases. The result of the classification could be several competing solutions or may be none. This depends on how perfect is the classification model and on the quality of measured data. The efficiency depends on the definitions of the classification classes.

Finally, we want to point out that simulation results in described concept depend on a system model. The better is the system model the more exact is the result. Complexity of the model influences on computational effort and efficiency therefore is reasonable to use the simplest model as possible to satisfy the lowest requirements that still lead to a satisfactory result. Thus, the suitable design methodology that makes possible different simplifications of the system model with the predictive influence on results is very important and will be a subject of our future research work.

7 References

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