Signal Processing in Smart Sensor Systems 1

Milan Mišeje, Ján Šturcel

Abstract
This report is part one of a series of articles that describe the existing classic methods and new perspective methods of sensor signal processing. The first part introduces smart sensor systems, especially sensor arrays. It characterizes in short smart sensor systems, describes their basic properties and presents an overview of them as well. The article also deals with classic methods of sensor signal processing that are appropriate for scene or object status identification. The article is concerned with the correlation method in detail and an example is given for it.

Keywords: sensor array, smart sensor system, sensor signal processing, primary information processing, pattern recognition, correlation method

Introduction

The present state of sensor technology in automation might be characterized as interleaving of classic analogue measuring units and smart measuring units. However, the trend shows that smart measuring units are coming into wide use because of their undoubted advantages from a user point of view (projecting, service, cost reduction of cable distribution, reliability, maintenance) and from a functionality point of view (primary information processing, autonomous operation, diagnostics, auto-calibration and communication with technical environment).

Smart sensor systems [1] are more powerful sensor measuring systems applicable to environmental measurements, automatic control systems, mechatronic devices [2] and many other automation and control techniques. For example, the significant simplification of control algorithms in distributed control systems is achieved by using smart sensor systems built into the control structure, where the smart sensor systems represent the information subsystem. Beacause a smart sensor system already provides "clear" information about a measurand, the control system can use this value without any need for further formatting directly in the algorithm. Thus, the demands on control system computational power are reducing, while the reliability, accuracy and efficiency are increasing.

Since the range of use of smart sensor systems is still expanding, the requirements on the system are changing and enlarging. The purpose of measurement is not only indicating the measurand value, but also in most cases identifying some scene or object status. One of key properties of the sensor system is the real-time response. Sensor signal processing is therefore as important as its own construction. Improving and developing new signal processing methods gives new possibilities for realization of primary information processing tasks implemented in modern smart sensor systems.

The chapters at the begining of the article are dedicated to readers who have never heard about signal processing in a smart sensor system as well as for experts in sensor techniques. In the last chapters, there is presented in more details the correlation method as a representative of the classic methods.

1. Sensor system

First of all, something about a sensor. The term of sensor has been used with ambiguous meaning in several publications. Many people understand sensor as a sensitive element, the other as a certain measuring system (a sensitive element together with a signal processing unit). In this article the term of sensor will represent only a sensitive element.

Information obtained from one sensor is in some cases (usualy for identification) not enough and measurement is ambiguous. There is a need to use more than one sensor for the measurement. Another problem arising with this feature - a lot of information should be processed in real time (the most important of measuring system).

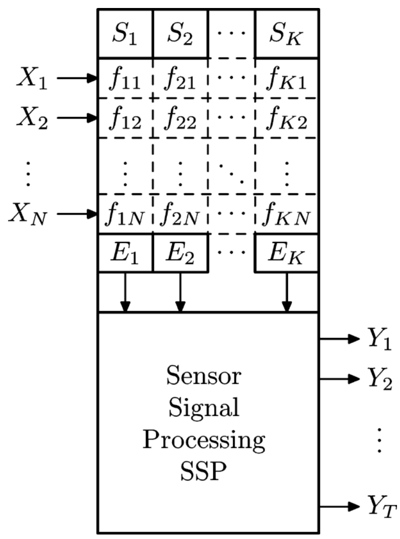

Fig.1 Sensor system

The sensor system (Fig.1) is a measuring system consisting of several sensors, which together make a function unit. The sensors are non-selective (non-zero cross sensitivities) with non-linear transfer characteristics and non-zero dynamics.A sensor system is illustrated in Figure 1.

On the sensors S_i for $i = 1,...,K$ are directly or indirectly acting several physical quantities X_j for $j = 1,...,N$. The number of sensors need not be equal to the number of measured quantities $K \neq N$. The sensors are producing output signals E_i that depend on the measured quantities. The dependences are given by cross sensitivities $(f_{11}$ *to* $f_{KN})$ and it generally holds

$$E_i = F_x\left[f_{i1}(X_1), f_{i2}(X_2), \ldots, f_{iN}(X_N)\right] \tag{1}$$

for $i = 1,...,N$.

The sensor signal processing unit *SSP* provides the output signals Y_k in dependence on the sensor signals E_i

$$Y_k = F_y\left[E_1, E_2, \ldots, E_N\right] \tag{2}$$

for $k = 1,...,T$.

There are essentially two groups of sensor systems: process quantity probes and sensor arrays. In the case of process quantity probes, the cross sensitivities are eliminated. The tendency is to choose sensors sensitive only to one particular measured quantity with proportional transfer characteristics. Thus, the number of sensors is usualy equal to the number of measured physical quantities $(K = N)$ and for sensitivities f_{ij} it ideally holds

$$f_{ij} = \begin{cases} k_{ij} & \text{for i = j,} \\ 0 & \text{else.} \end{cases} \tag{3}$$

One sensor provides information about the main measured (process) quantity (e.g. pressure, temperature, humidity, etc.) and information from others is used for correction of perturbation quantities. Such sensor systems nowadays produced have a relatively high price that is mainly given by the computational power of the control unit and the type of sensors used.

To the second group belong sensor arrays. They are separated upon layout in the environment or sensor type onto homogeneous or heterogeneous. Unlike in process quantity probes, non-zero cross sensitivities are employed. The main consideration is given on effective methods of sensor signal processing.

The principle is based on the fact that a sensor with zero cross sensitivities practicaly does not exist and sensor transfer characteristics are non-linear. Advantage of such a sensor system against the first one is resulting from the usage of common sensors. In addition, the number of sensors can be less than the number of identifiable states. Informations generated by each sensor in the array have the same weight in signal processing.

2. Smart sensor system

A smart sensor system (SSS) is an autonomous digital measuring system equipped with primary information processing, diagnostic and auto-calibration functions and has the ability to communicate with its technical environment. In other words, it is a sensor system integrated with digital blocks that provide digital processing.

The block scheme of a simple smart sensor system is depicted in Figure 2.

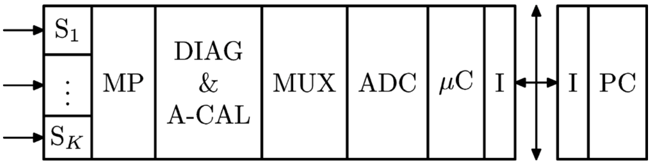

Fig.2 Simple smart sensor system

A sensor S_i represents a filter of type and range of the measured physical quantity, which affects directly or indirectly the sensor. The sensor is continuously tracking the measured quantity and generates information about it. The output signal from the sensor is mostly a low energy analog signal. Modern control systems are almost allways working with information in electronic form. Measuring systems are designed to meet this requirement, hence a measured physical quantity is often already transformed by the sensor into electrical quantity (V, A, R, L, C, etc.).

The sensor S_i provides primary information about the measured quantity and therefore can radically affect the overall quality of measurement. The sensor signals are consequently handled by the measuring transmitter(s) *MT*. The measuring transmitter has to ensure the unified signal in the place of measured data processing. Amplification of sensor's native signal and unification belong to the main tasks of the measuring transmitter. The sensor together with measuring transmitter makes a transducer (i.e. probe, transmitter). The transducer is treated as the basic function block of the sensor measuring system and together with the incoming signal line to the signal-processing unit represents a measuring channel.

Sensor signal processing is realized in digital form, hence the analogue-digital converter *ADC* should be an inseparable part of SSS. The multiplexer *MUX* controlled by the microcomputer *μC* switches the signals from the measuring transmitters to input of *ADC*. In this manner, the microcomputer obtains digital information about chosen measured quantity value. The digital communication between SSS and other technical devices, for example higher-level digital system (e.g. personal computer *PC*), is provided by the communication interface *I*. Special features of SSS are auto-calibration and diagnostics *A-CAL & DIAG* [3] that increasing accuracy and reliability.

3. Primary information processing tasks

The primary information processing (PIP) [4] is a characteristic feature of smart sensor systems. It represents primary conversion of the signal obtained from sensor(s) to ensure clear information about the measured quantity. To the PIP tasks, except for sensor signal amplification and analogue-digital conversion, especially belong:

- measured data reduction,
- filtration,
- transfer characteristics linearization,
- dynamic error correction,
- indirect measurement and calculations.

The intelligent function unit of SSS is usually a custom-made monolithic microcomputer (MMC). MMC often performs only some of PIP tasks listed above. When choosing functions of primary information processing that SSS should perform, many limitations arise. The main limitation is the requirement for real-time operation of SSS. This limitation relates to the computational power of MMC and mathematical operations realized in MMC. Several methods of signal processing in SSS are listed in [5].

3.1 Sensor transfer characteristics

Sensors or transmitters are characterized by meteorological properties that describe their static and dynamic parameters. One of the most important static parameters is the static transfer characteristic (TCH). It expresses the relation (dependence) between the input quantity *x* and output quantity *y* in a steady state by the following equation

$$y = f(x) \tag{4}$$

Almost all sensors have non-linear transfer characteristics. Producers of sensor present their sensor transfer characteristics in the catalogue sheet in some of the following ways: polynomial functions on intervals of measured quantity, tables of reference points, etc. The knowledge of TCH is mainly important for conversion of the measured signal value to the measured quantity value. There are several methods of approximation of sensor transfer characteristics [6,7]. The important task of sensor producers is to ensure high time stability (large repeatability) of sensors. Additional improvement of the metrological parameters can be achieved in the digital sub-system of SSS using appropriate methods.

3.2 Scene or object status identification

Sometimes it is needed to identify the scene or object status. It means to evaluate a couple of physical quantities that characterize an identifiable status. For example, chemical transmitters can identify a gas mixture existing in environment. So a scene state could be also the existence of a gas substance in the environment, an obstacle location in the work area of a robot etc.

The sensor array is very appropriate for identification purposess. One approach of signal processing from the sensor array is to improve selectivity of the sensor by intelligent methods. In this case it would be ideal to use one sensor only for one of each of the measured quantities (as by process quantity probes). However, as it was said before, a sensor sensitive to only one physical quantity practically does not exist - the signal from the sensor is affected by more than one quantity (see the relation (1)). Since, the sensors have non-zero cross sensitivities, it is necessary to realize the disturbance correction. The cross sensitivities are reduced by complicated technological means, which, however, need not be enough. In addition, real sensor transfer characteristics are non-linear that usually requires more complicated mathematical operations to be applied, whereby demands on the computational power of intelligent unit are increasing.

Another, more effective solution (typical for sensor arrays) is based on exploitation of cross sensitivities. Non-zero cross sensitivities make it possibile to identify a lot of quantities with a smaller number of sensors and using a classification method. The non-linearity of sensor's transfer charakteristics need not be a significant problem for identification. If non-linearities were almost identical, they would be omitted.

The principle of classification consists in comparision of actual patterns

$$A_t, A_{t1}, \ldots, A_{tK}$$

and those from a group of reference patterns

$$R_1, R_2, \ldots, R_N.$$

Patterns are virtual signal vectors made from sensor signals obtained from a sensor array. The number of distinguishable patterns depends on the ability of the measuring transmitter to generate miscellaneous output signal levels. Now, the signal unification is not appropriate because of pattern count reduction.

Next, the main consideration will be taken of the identification principle that resides in comparison of the actually obtained pattern with several patterns that represent known identification targets. Such a way of identification is known as pattern recognition (PARC) or classification. Pattern recognition algorithms have been developed especially for chemicals to identify a substance in a mixture [8].

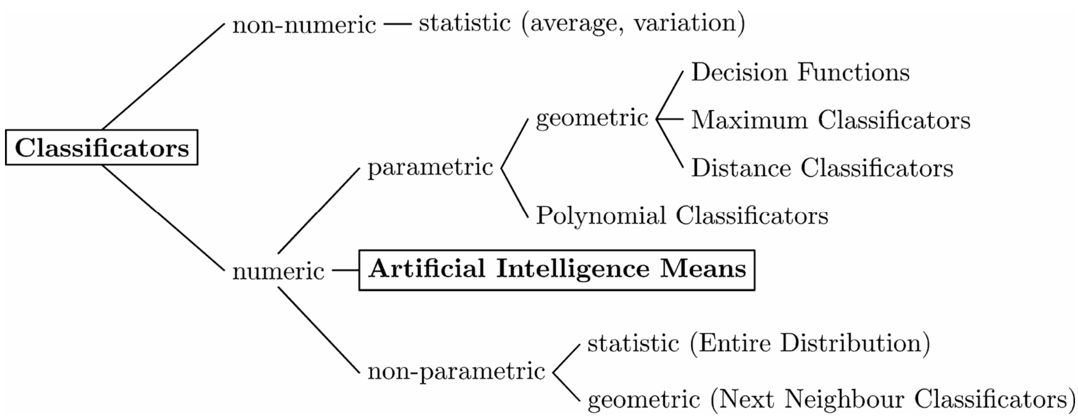

Fig.3 Various types of classificators

The smell as a one of human senses is a good example of multidimensional sensing and signal processing. A palette of smells can be recognized by receptors located at the end of nerve cells in the nose. Engineers have developed an "electronic nose" as a technical analogy of the nose, where the sensor array consists of *X* sensors and this sensor system has the ability to distinguish *Y* gases (it holds $Y > X$).

Figure 3 shows a tree diagram of several classificators used by PARC. Some classificator types are represented by *artifical intelligence means*, which are boxed and bold marked in the diagram. In the next article (part 2), there will be elaborated methods using neural network and fuzzy logic as a classificator in detail. All other methods are grouped in a special category. Let the category be called *classic method*, that can be exactly distinguished from those using artificial intelligence means. Classic methods will be discussed next.

4. Classic methods

Classic methods [8] of signal processing in sensor arrays are applied especially in chemical analysis sensor systems, where one of the tasks is to identify one or several chemical substances and indicate their concentrations. The way of identification is usually based on the pattern recognition principle by comparing reference and actual (real) patterns. The methods listed below consist of two phases: calibration process and evaluation process.

The best known classic methods:

- correlation method (CM),
- vector method (VM),
- partial least squares (PLS) method,
- transformed least squares (TLS) method.

The first two methods serve the purpose of identification only and evaluation of the concentration has to be done separately. The other two methods were developed for identification and evaluation of the concentration in one step. The way and process of signal evaluation using classic methods is presented on a practical example in section "Example for Identification". Because of available article range, there is presented only one of them. The correlation method was chosen as the representative. The use of this method is prety wide but in the article there will be mainly discussed with the use of scene or object status identification.

4.1 Correlation method

The correlation method [8] is one of the best known classic methods used for signal processing from sensor arrays, where the sensors have non-zero cross sensitivities. In general, let sensor array (see Fig.1) consist of K sensor elements dedicated to identify N scene statuses and stands $N>K$. The method is based on the pattern recognition principle and the matching of patterns is evaluated through the correlation coefficient. The correlation coefficient (CC) is evaluated in each measuring cycle. If CC is around 1, then the status is identified, else the scene or object is in an unknown status that was not considered in the calibration process. If more than one pattern is almost identical, then more values of the correlation coefficient might be around 1. In such a case identified status should be that with the CC value closer to 1.

The method consist of two parts:

- calibration process - preparation of reference patterns,
- evaluation process - realization of the algorithm of the method.

Calibration process

In the calibration process the reference patterns are generated and a specific meaning is assigned to each pattern. The patterns are preprocessed signal vectors $\boldsymbol{E_j}$ obtained from sensors used in the sensor array. Signals depend on the measurands characterizing an identifiable status.

Each element e_{ij} of the signal vector $\boldsymbol{E_j}$ can be, for example, preproceessed as an arithmetical average (5) of several sensor output values in certain range of measured quantities by equation

$$e_{ij} = \frac{1}{m}\sum_{k=1}^{m} e_{ijk} \tag{5}$$

for $i = 1,\dots,K$; $j = 1,\dots,N$

where e_{ijk} is the output of the i-th sensor while scene is in the j-th status during the k-th measurement,

m is the number of measurements of e_{ij} from the i-th sensor by j-th scene status.

The result is $K*N$ values divided by the index j into N vectors $\mathbf{E_j}$ each with K elements. Mostly, all elements contain a bias unwanted for identification, whereupon is eliminated. The bias value can be determined as an average of values of the elements of signal vector $\mathbf{E_j}$ by

$$\bar{e} = \frac{1}{K}\sum_{i=1}^{K} e_{ij} \tag{6}$$

where e_{ij} is the i-th element of signal vectorfor j-th medium status.

After removing the bias from the values of elements of signal vector $\mathbf{E_j}$, one obtains reference pattern $\mathbf{R_j}$

$$\mathbf{R_j} = \begin{bmatrix} r_{j1} \\ r_{j2} \\ \vdots \\ r_{jk} \end{bmatrix} = \begin{bmatrix} e_{1j} - \bar{e}_j \\ e_{2j} - \bar{e}_j \\ \vdots \\ e_{Kj} - \bar{e}_j \end{bmatrix} \tag{7}$$

for $j = 1,\dots,N$

Evaluation process

In the evaluation process the actual pattern $\mathbf{A(t)}$ is compared with reference pattern $\mathbf{R_j}$ for $j = 1,\dots,N$. If the patterns (the actual and any of the references) are not identical, then the actual pattern (status being identified) might be marked as non-identified or a specific meaning can be assigned to it and the pattern could be stored as a new reference pattern.

In order to compare patterns, it is necessary, that real patterns be preprocessed as the reference patterns. Hence, the bias is removed from the actual signal vector using the same procedure as in the calibration process by (6) and (7).

The correlation coefficient is calculated by

$$\rho_j = \frac{\sum_{i=j}^{K}\left[(a_i)(r_{ji})\right]}{\sqrt{\sum_{i=1}^{K}(a_i)^2 \sum_{i=1}^{K}(r_{ji})^2}} \tag{8}$$

for $j=1,\dots,N$.

The correlation coefficient value lies in the interval $< -1; 1 >$.

Practically, each measurement is affected by some unknown errors, which affect CC value too. Hence, value ρ is not always 1, but it is only close to 1. By this reason, it is necessary to specify an aperture or interval low boundary value for ρ (e.g. 0.85). If it stands $\rho \in < 0.85; 1 >$, then the status could be treated as identified.

5. Example for identification

In the next example there is demonstrated an approach of correlation method realization for identification of the scene status B_j for $j = 1,\dots,m$ using a transmitter with an array of sensors S_i for $i = 1,\dots,n$. For simplicity, let one scene status be characterized by just one physical quantity. Let sensors in the array have non-zero cross sensitivities and the number of the sensors be $n = 3$, so that it holds $n < m$. The sensor transfer characteristics are 2nd order polynomial functions given by

$$y_i = a_i + \frac{0.5}{100}x + \frac{1}{100^2}x^2 \tag{9}$$

where a_i is y-axis shift,

x is the measured quantity [\%],

so the non-linearities are identical.

The graphical interpretations of transfer characteristics of sensors S_i in dependence on the scene statuses B_j are depicted in Figures 4 to 6.

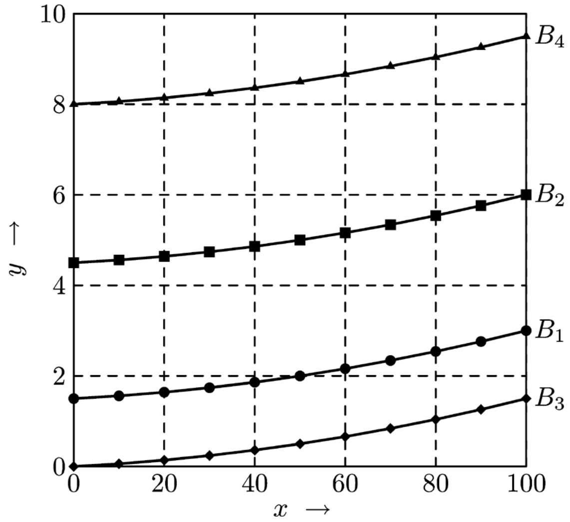

Fig.4 Transfer characteristics of sensor S_1

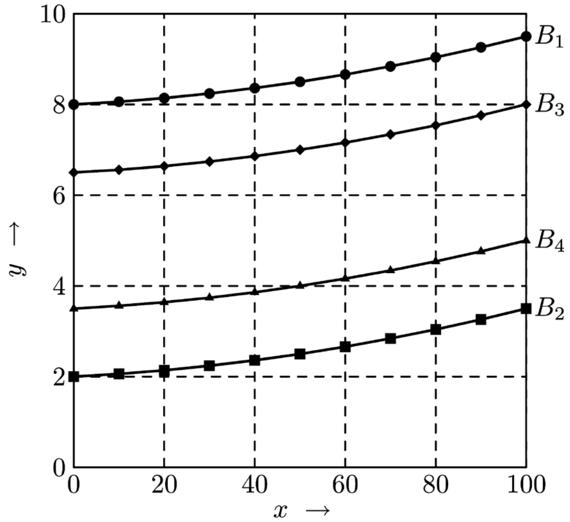

Fig.5 Transfer characteristics of sensor S_2

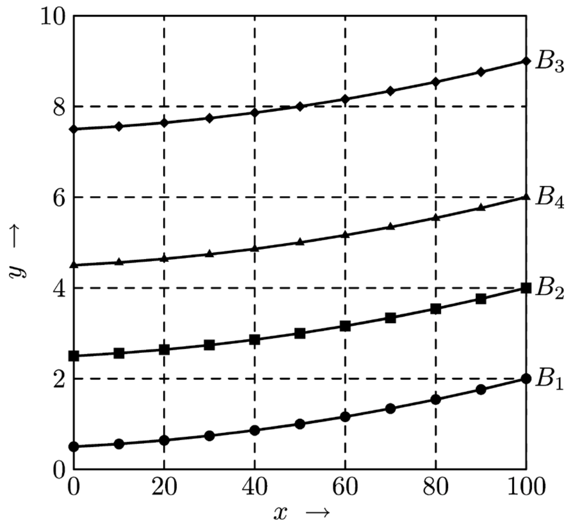

Fig.6 Transfer characteristics of sensor S_3

Calibration process

At first, it is necessary to choose all scene statuses that should be identified. All other scene statuses will be evaluated as unidentified. The result of the calibration process is a group of reference patterns that will be correlated with the actual pattern. The reference patterns (Tab.1) are achieved following the approach presented in section "Correlation method".

For example, let us take a look at creating the reference pattern for status B_1 in 11 measurements:

Sensor S_1:

$$e_{11} = \frac{1}{11}\sum_{k=1}^{11} e_{11k} = 2{,}1$$

Sensor S_2:

$$e_{21} = \frac{1}{11}\sum_{k=1}^{11} e_{21k} = 8{,}6$$

Sensor S_3:

$$e_{31} = \frac{1}{11}\sum_{k=1}^{11} e_{31k} = 1{,}1$$

Consequently, it is necessary to remove the bias from the vector elements calculated above. The value of the bias is calculated following (6) and the result is

$$e_1 = \frac{1}{3}\sum_{i=1}^{3} e_{i1} \cong 3{,}933$$

Such a signal vector with elements without bias is the reference pattern needed for identifying status B_1. In this manner, the other patterns are created too.

Tab.1 The reference patterns for scene status B_i

	S_1	S_2	S_3
$\boldsymbol{R_1}$ (B_1)	-1,833	4,667	-2,833
$\boldsymbol{R_2}$ (B_2)	1,500	-1,000	-0,500
$\boldsymbol{R_3}$ (B_3)	-4,667	1,833	2,833
$\boldsymbol{R_4}$ (B_4)	2,667	-1,833	-0,833

The graphical representation of reference patterns is shown in Figure 7.

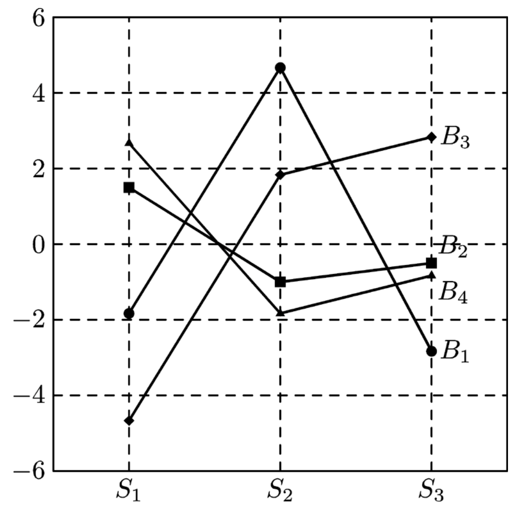

Fig.7 The reference patterns for the states B_i

Evaluation process

For example, let the scene be in status B_2 and the quantity characterized this state be in 20% of its range. Let signals from sensor array be measured with precision 2%. These signals represent signal vector

$$\mathbf{A} = [4{,}69 \quad 2{,}12 \quad 2{,}67]$$

The elements of this vector contain a bias that has to be removed by the known approach listed above

$$a = \frac{1}{3}\sum_{i=1}^{3} a_{i2} = 3{,}16.$$

Now, if all needed parameters are known, the correlation coefficient can be evaluated for all reference patterns and the actual pattern

$$\rho_1 \cong -0{,}568882,$$
$$\rho_2 \cong 0{,}999895,$$
$$\rho_3 \cong -0{,}946824,$$
$$\rho_4 \cong 0{,}999963.$$

If the aperture were 0.99, identification would be successfuly done after evaluation ρ_2. But according to the next evaluated coefficients, the result is fully else. Also coefficient ρ_4 meets the given criterion. Hence, it should be determined which coefficient value is closer to 1. The result is that scene is in status B_4. But that is a wrong result, because the scene has been in status B_2. The similarity of patterns $\mathbf{R}_2$ and $\mathbf{R}_4$ is so close that it causes wrong results. One of possible solutions, in order to avoid such cases, is providing a more precise measurement.

Conclusion

Undoubtedly, smart sensor systems find their wide range of use in automation of many industry sectors. Their qualitative properties are improved thanks to new methods for tasks of information pre-processing. The article on the presented example cannot, of course, find out all solutions for all possible problems that can arise here. But it is a good example for any solutions of identification purposes, where most of the methods can confirm their behaviours and be compared with each other. In this article there were presented only the so-called classic methods using classic mathematical operations, which take some advantages and disadvantages in sensor technology. The main disadvantage are large computational power demands prohibiting the application of classic methods in many of cases. Thus, limitation of realization of primary information processing tasks in smart sensor systems results from the intelligent unit computational power. Computational technology and microelectronics development therefore play an important role here. Requirements on a larger number of sensors and higher rate of sensing cause a need for much more efficient methods that have ability to process larger amount of data in real time. Some possible solutions using artificial intelligence means will be presented in the next part.

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Doc. Ing. Ján Šturcel, PhD.

Slovak University of Technology
Faculty of Electrical Engineering and Information Technology
Department of Automation and Control
Ilkovičova 3
812 19 Bratislava
Tel.: (+4212 6029 1678)
jan.sturcel@stuba.sk