Fuzzy Techniques and Internal Models for Sensors

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Abstract: - The paper proposes a new architecture for a sensor with data fusion and internal model estimators. Fuzzy logic is used as an effective tool for data processing. The fusion process of information conducts to the improvement of the measurements accuracy. We focused our attention on industrial systems, implemented with such sensors and we discussed on limits and perspective of these techniques.

Key-Words: fuzzy logic, uncertainty, information fusion, internal model, fuzzy-interpolative, smart sensor.

1 Introduction

In any measurement or control action the uncertainty raises a fundamental obstacle. The errors due to inertial processes or to break down of the sensors may produce important damages. The precision of the measurements and the performance of the control process can be improved if we dispose of more knowledge about the system. Lotfi A. Zadeh affirmed that the main weakness of the Question-Answering Systems is the absence of the world knowledge. World knowledge WK, a term introduced by Lotfi A. Zadeh [1] is referring to the knowledge acquired through experience, education and communication.

Nowadays the WK learning by machines is a current research topic of the knowledge based systems. Our objective in [2] and other previous papers is to bring the WK paradigm into the industrial and applicative systems, implemented with low level devices (controllers, sensors, actuators).

Close loop controllers can benefit of general system theory knowledge, embedded into expert control rules, as well as of specific technical knowledge of the controlled plant, represented by planners. The designing of planners is assisted by computer simulations, using deterministic models of the plant. The Fuzzy-Interpolative methodology that makes feasible such approaches is presented in other previous papers [3, 4, etc.]. The fuzzy-Interpolative Controller FIC is a fuzzy controller that has an interpolative equivalent that can be implemented with piecewise interpolation look-up-tables. The linguistic representations and the computing with words can be translated into the world of low level devices.

2 Internal Models

The internal model can be used for the on-line identification of the real plant, like in the Fig. 1 block diagram [5].

Fig. 1 The process identification by internal model

R(s) = controller
G(s) = plant
M(s) = internal model
C(s) = corrector
θ̂ = the real parameters of the plant
θ̃ = estimated parameters of the plant
R(s) = imposed value
y = controlled output of the plant
yM = output of the model
e = control error
ε = correction error
u = control
p = perturbation

This idea can be applied only if we dispose of a structural deterministic model of the plant.
The set of estimated parameters will follow the evolution of the real plant parameters. A special attention must be paid to the correction algorithm, which must have an acceptable convergence and must not produce instability in the M(s) – C(s) loop.

3 Internal model adaptive sensors

The fusion of sensors and the internal model technique can merge into a natural architecture, called Internal Model Adaptive Sensor IMAS and presented in Fig. 2 [5]. The constitutive elements of IMAS are the following:

- **Plant** – The output y is hardly measurable or affected by uncertainties having different origins. In order to measure y in a redundant manner the plant includes n primary sensors S1, S2, ..., Sn. The input of the plant is the perturbation p.
  - Input: the perturbation p;
  - Outputs: the outputs of the primary sensors y1, y2, ..., yn;
  - State variables: the parameters \( \tilde{\theta} \).
- **Internal model** – It includes all our deterministic knowledge about the plant
  - Input: the perturbation p;
  - Output: \( \hat{y}_m \) the estimation of the model;
  - State variables: \( \hat{\theta} \) the estimations of the parameters of the plant.
- **Fusion** – It is computing the estimation of the plant’s output \( \hat{y} \), using the confidence degrees of each primary sensor, \( \mu_1, \mu_2, ..., \mu_n \) and of the confidence degree of the model \( \mu_m \).
  - Inputs: \( y_1, y_2, ..., y_n \) the outputs of the primary sensors and \( \hat{y}_m \) the output of the model;
  - Output: the estimation of the output of the plant \( \hat{y} \);
  - State variables: the confidence degrees \( \mu_1, \mu_2, ..., \mu_n \) and \( \hat{y}_m \).

Different fusion mechanisms can be applied. The simplest variant is just the weighted sum:

\[
y = \frac{\sum \mu_i(y_i) \cdot y_i}{\sum \mu_i(y_i)}
\]  

where the weights of each sensor (and model) \( \mu_i(y_i) \) are nonlinear, depending of the current measured value. A normalized fusion will respect the condition:

\[
\mu_m(y(t)) + \sum_{i=1}^{n} \mu_i(y(t)) = 1
\]

If precise \( \mu(y_i) \) dependencies are not available, fuzzy ones can be introduced:

\[
y = \frac{\sum \mu_i(fuzzy(y_i)) \cdot y_i}{\sum \mu_i(fuzzy(y_i))}
\]

Fuzzy linguistic degrees of confidence, inspired by [7], were tested with positive results [5, 6].

- **Corrector** – It has two crucial roles:
  o The on-line adaptation of the model’s parameters \( \hat{\theta} \), such that the model follows the real plant as close as possible;
  o The validation of the primary sensors and of the model, through their confidence degrees.

The main advantages of IMAS are:

- A very good reliability
- Very good steady performance
- Very good dynamics

The main disadvantage of IMAS relies into its complexity. Linear interpolative look-up tables could offer good implementation perspective [3].

4 Applications

4.1 A temperature IMAS for furnaces

The temperature measurement of the furnaces is an application where all the advantages of IMAS are welcomed is. The imprecision, during both steady
and dynamic regimes and failures has very expensive consequences in the temperature treatments of the metallic products.

The Temperature Internal Model Adaptive Sensor TIMAS, presented in Fig. 3, and introduced in [5], [11] includes an internal model of the furnace and three primary high temperature sensors:

- TR – a Pt thermo resistance;
- TC – a thermocouple;
- TP – a radiation pyrometer.

The internal model of the furnace (5) takes in account the next parameters [6]: \( V \) the internal volume of the furnace \([m^3]\), \( V_m \) the volume of the metallic parts \([m^3]\); \( \rho_m \) the density of the metal \([kg/m^3]\), \( \rho_a \) the density of the air \((\rho_a = 1,293 kg/m^3)\), \( c_a \) the specific heat of the air \((c_a = 1000 J/kg·°K)\), \( \theta_i \) the internal temperature \([°C]\), \( \alpha \) the mean thermal transfer coefficient of the furnace \([W/m^2·°K]\), \( S \) the radiant surface of the furnace \([m^2]\), \( \theta_e \) the external temperature \([°C]\), \( P \) the power of the heating device \([W]\) and \( \tau \) the dead time \([s]\). The input is \( P \) and the output is \( \theta_i \).

\[
[\bar{V}' \cdot \rho_m \cdot \bar{V}' + (\bar{V}' - \bar{V}) \cdot \rho_a \cdot c_a] \frac{d\bar{\theta}}{dt} = P(\theta - \bar{\theta}) - \alpha \cdot S \cdot [\bar{\theta}(\theta - \bar{\theta})] 
\]

\[
(4)
\]

4.2. Estimating the velocity of an vehicle when the wheels are sliding

The wheels of the vehicles begin to slide when the braking force exceeds the adherence offered by the wheel-rail/road contact. If the force is not immediately reduced, the wheel will be finally locked by the friction elements of the brake and the wheel will skate. The sliding \( s \) is defined as:

\[
s = \left( v_{\text{car}} - v_{\text{wheel}} \right) / v_{\text{car}} 
\]

where \( v_{\text{car}} \) [km/h] is the velocity of the car and \( v_{\text{wheel}} \) [km/h] is the tangential velocity of the wheel. The ABS (Anti-lock-Braking System) action consists in keeping \( s \) inside of an optimal dooming \((0.2 \div 0.25)\), by modulating the braking force. Each wheel is equipped with a speed sensor, but during the sliding regime of the wheels the sensors are not indicating \( v_{\text{car}} \) anymore, but \( v_{\text{wheel}} \) [8].

The approach presented in Fig. 4 can be applied here. The speed sensors of the wheels are fusioned with an piezoelectric accelerometer and a computer model of the vehicle and its ABS braking equipment [4].

\[
v_{\text{car}} = \sum \frac{\mu_i(t)}{\sum \mu_i(t)} u_i(t) 
\]

\[
(6)
\]

4.3. The on-line estimation of the adherence

The on-line evaluation of the rail-wheel adherence is achieved using for a second time the same computer model, because the on-line measurement of the
adherence is impossible. The model has as inputs the cylinder pressure and the estimated adherence and as output an estimated acceleration. The actual adherence is obtained by backpropagation, as shown in Fig. 5 [4].

![Diagram](image)

**Fig. 5 The estimation of the adherence**

### 4.4. Estimating the weariness for disk brakes and wheels’ tread

A method of real-time estimation of the weariness of these parts, based on the internal model technique was proposed in two previous papers [9] and [10]. This method is based on the time integration of the weariness ratio during the braking periods, because the final weariness is the result of all the braking actions performed during exploitation. The weariness ratio \( w \) [\( \mu m/km \)] can be measured by the lost thickness produced along the braking distance. In the disk brake case, \( w \) is highly non-linear, depending mainly of the relative speed between the disk brake and the friction set \( v \) and the braking force \( f \). A generic behavior of \( w \), determined by laboratory measurements, is shown in Fig. 6. \( w \) is constantly shifting during braking, therefore the manual calculus of the weariness is impossible. The precise estimation of \( w \) is achieved with the help of a computer model of the railway vehicle, oriented towards the estimation of \( v \), \( f \) and finally of \( w \) [9]. This method can be easily extended for the wheels’ treads weariness [10].

![Diagram](image)

**Fig. 6 The generic influence of \( v \) and \( f \) over \( w \)**

### 5 The internal model techniques: discussions

The examples presented are demonstrating the huge potential of the internal model techniques that are able to improve all the functional parameters of the control systems. The internal models can be considered as our main tool for providing control systems with knowledge.

A major limitation of this approach is the dependence of computing resources demanding software. Sophisticated control solutions can not be implemented in the usual industrial control systems, with microcontrollers, DSPs or ASICs!

Based on the fuzzy sets theory, linguistic knowledge and expert systems can now be easily represented into computers. The neural networks, the fuzzy-interpolative methodology or other similar methods can do the same job. The problem is that when implementing mathematical models into low level devices we do not dispose of an adequate theoretical apparatus able to standardize and to simplify the procedures and to secure the results.

A partial solution is represented by the planned systems. Planners that are designed with the help of functional computer models are indirectly embedding the model’s knowledge, but they are working essentially in an off-line manner.

The implementation of the functional models with minimal computing resources is a rewarding research direction that will fully open the way of the on-line internal model applications.

### 6 Conclusions

The paper is presenting our theoretical researches on the internal model sensors and actuators.

For applications depending of measurements or estimations affected by uncertainty the internal model adaptive sensors IMAS offer good perspectives. They are merging the advantages of two basic techniques that can operate in the presence
of notable uncertainties: the internal model and the fusion of redundant sensors. Their advantages are:

− High reliability (due to the redundancy of the fusion and to the validation of the primary sensors by comparing them to the model);
− Good precision (the confidence degree of the fusion sensors can be adjusted along the operation domain according to their best precision);
− Good dynamics (during the transient regimes the confidence degree of the model is raised, because the model has no notable time delays);
− They offer the possibility to estimate unmeasurable parameters.

Some applications are illustrated by simulations: on-line estimators for the velocity of the vehicles during wheels’ sliding, for the adherence, for the weariness of the disk brakes and for the weariness of the wheels’ treads.

A discussion on the limits and on the perspectives of the internal model technique is trying to identify different ways to implement internal models into low level devices: sensors, controllers, actuators.

References


