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Inspection process for dimensioning through images and fuzzy logic

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Abstract

This paper presents a hybrid methodology based on a type 1 fuzzy model in singleton version using a 2k factorial design that optimizes the model of the expert system and serves to perform in-line inspection. The factorial design method provides the required database for the creation of the rule base for the fuzzy model and also generates the database to train the expert system. The proposed method was validated in the process of verifying dimensional parameters by means of images compared with the ANFIS and RBFN models which show greater margins of error in the approximation of the function represented by the system compared with the proposed model. The results obtained show that the model has an excellent performance in the prediction and quality control of the industrial process studied when compared with similar expert system techniques as ANFIS and RBFN.

Keywords: Neural networks, irrigation control, instrumentation and image analysis, micro-greenhouse.

1. Introduction

Machine vision systems used industrially, particularly in Supervisory Control And Data Acquisition (SCADA) systems need to evolve to be more reliable. In addition, multiple factors affecting their performance must be addressed, since they generate variations in the magnitude of the data inputs [1]. For this reason, uncertainty can

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emerge from different sources such as characteristics of raw materials, production, machinery, production scheduling, data acquisition systems (sensors) and the environment [2]. Particularle, data acquisition systems constitute a fundamental part for the evaluation, monitoring and control of manufacturing processes, which are continuously affected by uncertainty [3]. In this sense, the Taguchi model takes into account uncertainty and classifies it into three forms: internal, external and production [4]. Based on these two perspectives, the following classification can be defined [4][5][6]:

- Internal uncertainty, which comes from the raw materials and the main cause of this kind of uncertainty consists of two elements: a) physical properties of the materials, b) chemical properties. This section refers to the formulation of the material.
- Production uncertainty, which is due to the process operation having as main components the operators and working methods, machinery, maintenance, among others.
- External uncertainty, which usually comes from nature. Among the most common factors are: environment, temperature, lighting, humidity, radiation.

This paper is based on an inspection process for image-based dimensioning and aims to generate a hybrid model with factorial design and singleton type 1 fuzzy logic (T1 SFLS) which will be validated against similar models of expert systems such as: Adaptive Neuro-Fuzzy Inference System (ANFIS) designated in this case as T1 ANFIS and Radial Basis Function Network (RBFN) to verify its performance and accuracy.

2. Methodology

The methodological process required by the image inspection system needs an adaptation process to generate the evaluation in a single layer because most of the current cameras performing the color acquisition require removing the additional layers [7]. In the case of RGB (Red, Green and Blue), 2 layers, 3 layers for YUV (Yellow and Ultraviolet) matrices to generate a single matrix instead of a matrix array, this will be converted to an 8-bit grayscale matrix that must be processed to generate a binary matrix needed for segmentation and evaluation. The process requires the following steps [8][9][10][11][12]:

1. Acquire a series of images of n samples.
2. Filter each image. By means of a threshold, convert the image to a binary matrix.
3. Establish a counter to evaluate the quantity present in the sample in the segmented matrix.
4. Obtain the specification limits.
5. By means of an interpolation of the value obtained by the counter (generated in step 3) and obtain the limits of the specification according to what was obtained in step 3.
6. Obtain the specification limits by sampling images at the specification limits. (repeating the methodology several times. One for each sample).
7. Obtain the limit scales for each variable from the data obtained from steps 5 and 6.
8. With the values obtained from step 7, generate a multiple input system and an output (MISO) that will serve to create the rule base of the expert system.
9. Generate a uniform partition space by interpolating the high and low states of each variable, that is, establish the DF vertices as the means for the fuzzy sets and their dispersion.
10. Use the DF database as training data for the expert system.
11. Generate the evaluation by approximation.

With the previous points developed, the expert system is obtained with the approximation (T1 SFLS, T1 ANFIS and RFBN) of reduced rule base by means of the methodology called expert system (SE) SE/DF/2k.

3. Application of the expert system (T1 SFLS T1 ANFIS, RBFN)

The application established in the experiment consists of generating dimensioning by means of images, requiring the calculation of two control parameters within a production process of base plates or supports, which consist of 1/16" thick aluminum plates with the specification shown in Figure 1 [13]. The image obtained by means of the vision system produces an image affected by the reflection that causes brightness altering the dimension. This can be observed in Figure 2 in which zones in different tones of gray appear in the background of the image. For eliminating this characteristic, it is necessary to make a pre-processing by means of a filter which works by using a threshold that performs the processing required for make the conversion to a binary matrix (Fig. 3). Later, an interpolation of the image is generated, and this is converted into a vector from which the representative values of each characteristic will be obtained (table 1). That is to say that for generating the interpolation of the numerical matrix that represents the image, it is necessary to use the equation (1), which represents the characteristic that dimensions the width of the sample [14].

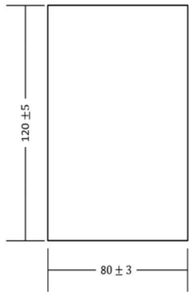

Fig 1. Specification of the sample.

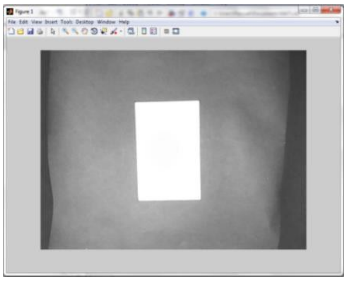

Fig 2. Sample image for inspection.

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} \qquad \forall x \in X \tag{1}$$

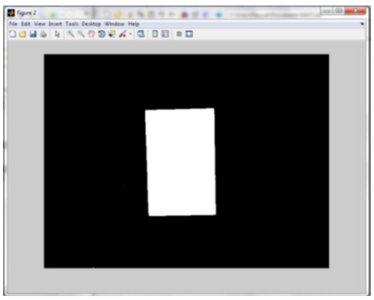

Fig 3. Filtered image.

The experimental phase for this application was assembled as follows: All the experiments were performed in a rectangular prism shaped cabin with dimensions of 35 X 35 cm. for the base and 55 cm. high. The image acquisition equipment is a Logitec web camera model C110, and the analysis was made by means of the MatLab software version R2009a in a laptop with Windows 7 professional and an Intel Core i-5 @ 2.5 GHz processor. The lighting provided to the system is as follows:

The tests of the expert system (T1 SFLS, T1 ANFIS and RBFN), use a set of 2 General Electric (GE) brand lights placed 10 cm. from camera 1 on each side, these 75 w incandescent lights with factory light intensity of 1070 lumens per piece and the lens at 43 cm. from the camera [15] [16].

The values used for the output of each fuzzy rule are determined by evaluation expertise either through a procedure or an interpretation of data from the quality department. The model output will be generated with the hybrid model (SE/DF/2k). The DF is used to create the reduced rule base of the expert system by generating a simplified form and having a specific methodological model for the creation of a composite inference base by means of factorial design.

The database shown in Table 1 can be used to model the fuzzy system based on an individual inference base that would create a base of 13 rules where each test or data pair would represent one rule. This is reduced using the limits shown in Table 2. This inference base represents the process without the need for the uncertain knowledge of one or more people [2]. The fuzzy system created uses a Mamdani type model (T1 SFLS), with a Gaussian fuser and a product implication, with an average center defuser and 4 rules for the reduced model.

Table 1. Factorial design.

Samples	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
X1	202	208	212	212	204	203	199	202	208	212	212	204	203
X2	141	143	137	144	144	143	139	141	143	137	144	144	143
Objective	**1.55**	**4.55**	**2.15**	**6.35**	**3.95**	**3.05**	**0.55**	**1.55**	**4.55**	**2.15**	**6.35**	**3.95**	**3.05**

Table 2. Basis for DF/ 2k/ applications of the expert system (T1 SFLS, T1 ANFIS and RBFN)

X1	**140**	**140**	**142**	**142**
X2	202	202	200	214
Y	**-5**	**0**	**0**	**5**

4. Results

The different experiments are based on comparing the performance of different intelligent systems such as T1 SFLS, T1 ANFIS and the RBFN, showing that the performance of the proposed hybrid model is viable for use with the benefit that only requires the establishment of four rules derived from the axial points of the factorial design, which in turn, is obtained from the manufacturing specifications. The labels for the establishment of the partition of the data propagation universe can be obtained from the different treatments of the DF. The results of the different experiments are presented in Table 3.

The samples 3 and 4 present the case of a variable close to the limit of the specification. Due to this condition, the output values are smoothed or pronounced, that is to say, the peaks of the function are eliminated or become more pronounced depending on the point where they are located in the data distribution. As a consequence, the generated approach will present variations against the objective causing an error rate of the model (see Figure 4).

The samples that are in the interval 0.5 to 2.5 standard deviations show a displacement proportional to the real value because the normal distribution in this interval presents a linear behavior. These variations produce small changes in the output when the changes in the input are significant. The samples found between the mean and 0.5 standard deviations and the interval between 2.5 and 3 standard deviations show significant changes when small variations in the input occur. These variations are produced due to the shape of the curve after the turning points, which present an exponential behavior (see Figure 5).

Table 3. Samples evaluated by the application of the expert system.

Sample	X1	X2	Objective	T1 SFLS	ANFIS	RBFN
1	210	136	1.1	0.087	0.1115	0.65187681
2	216	138	4.1	3.2209	2.4398	1.64909782
3	220	132	1.7	1.2841	-1.5267	-1.39949782
4	220	139	5.9	4.6555	3.7779	2.09301401
5	212	139	3.5	3.4291	2.6488	2.09301401
6	211	138	2.6	1.6753	1.7555	1.64909782
7	207	134	-1	-1.208	-1.6821	-0.40227681
8	220	140	6.5	4.5878	4.5523	2.48561604
9	210	136	1.1	0.087	0.1115	0.65187681
10	216	138	4.1	3.2209	2.4398	1.64909782
11	220	132	1.7	1.2841	-1.5267	-1.39949782
12	220	139	5.9	4.6555	3.7779	2.09301401
13	**212**	**139**	**3.5**	**3.4291**	**2.6488**	**2.09301401**

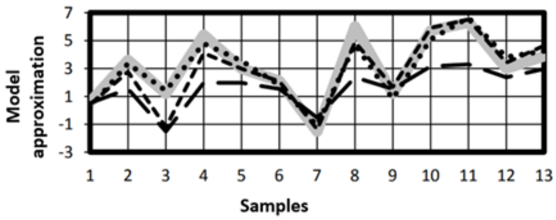

Fig 4. Results of the approach generated by the expert system (___) Objective, (. . .) RBFN, (- - -) T1 SFLS, (_____) T1 ANFIS

The method developed improves performance of similar models such as: fuzzy system with DCC [4][17], which consists of 11 rules and individual inference base for the fuzzy model version. On the other hand, the model (ANFIS/Compound Central Design) with compound inference base, only operates with 4 rules obtained from the treatments of the compound central design [14] and optimizes the fuzzy system modeling reducing it in more than 60% because 7 of the 11 rules are eliminated (63.63%).

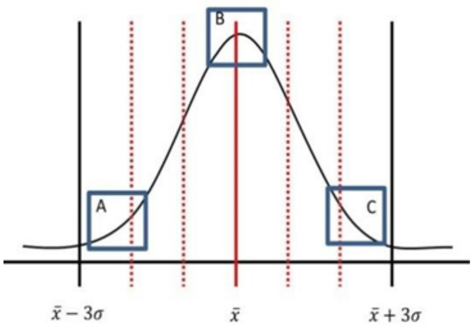

Fig 5. Inflection points in a normal distribution (diffuse set).

5. Conclusions

The proposals presented as hybrid models based on DOE and soft-computing operate with a base of rules obtained from multiple states based on the combinatorics of the evidence and data thrown by the DOE itself.

The proposed model can reduce the number of rules, allowing the inspection system to work online. Since the rule base only requires 4 rules for this particular case, the system can be delimited within a specific universe without the restrictions of a system with internal partition boundaries within the fuzzy space. The approximation can be generated at any point within this universe without the need to activate multiple rules that provide variations for the fit and rounding that could cause the fuzzy base function with the limitation of performing multiple calculations for each rule and without having to wait for a delay time in the approximation.

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