T1 Singleton Hybrid Soft Computing Techniques (T1 SFLS/CCD; ANFIS/CCD) Applied To Industrial Image Processing Under Noisy Data

Md. Rakibul Hoque
University of Dhaka
Bangladesh
afshar0506@gmail.com

ABSTRACT: *Measurements are the core of quality systems; the calibration of the measurement devices is a form of evaluating it. The variability of these measurement devices is verified to know the variation inherit in the measurement tool. Additionally the dynamics of the actual production systems cannot be satisfied by the classic approaches of the human visual inspection because they exceed the human capacities and this phenomenon causes the loss of reliability at the outputs of the system. The exposed topics above presents a hybrid model of adaptive Neuro-fuzzy inference system (ANFIS) to evaluate quality features, also this purpose, offers a knowledge based expert system able to do the quality assurance tasks by learning and adaptation. The obtained results provide an acceptable error rate for this class of systems to run at the speed of a manufacturing system.*

Keywords: Neuro-fuzzy System, Knowledge Based System, ANFIS, Image Processing

Received: 20 December 2014, Revised 17 January 2015, Accepted 21 January 2015

1. Introduction

The actual manufacturing systems need to evolve to faster, more reliable, and more precise systems. To do this, the use of the new scientific approaches are needed, such as: the Soft Computing (SC) techniques in the form of expert systems which can simulate human behavior by the use of the human knowledge. The new quality process turns to the use of artificial vision to improve their performance. An artificial vision system may be defined as: the assembly of a light source; a device that captures the image; and an algorithm able to process the acquired image [1]. Data mining is an important element that helps to eliminate non-necessary information in order to reduce the complexity of the model and the computational time needed to produce an evaluated approximation of the sample quality [2].

In the acquisition, there exist some factors that cause noise and contribute to increase the uncertainty at the inputs of the model. The quality of the components of the acquisition devices such as defects in the lens produces refraction on the images. Also, the source of light produces bright spots in the image. Those factors produce variations after the pre-processing (filtering) that contributes to increase the error rates in the output of the system.

The SC methods, particularly the fuzzy logic and the neural networks, or the hybrid models, of both techniques brings the chance to evaluate infinite combinations of the inputs and outputs on the universe. This universe is created by the limits of the data used as knowledge (obtained by sampling or by technical specifications). Those classes of systems are not restrictive and it may be simplified by some states or patterns presented in the samples used as knowledge. The missing or eliminated states may be obtained by an extrapolation of the present states because in general those states present linear dependency to the known states.

A survey of literature shows some approaches of pure and hybrid techniques of these models such as: Type-1 singleton fuzzy logic system (T1 SFLS) [3-5], Type-1 Non-singleton fuzzy inference system (T1 NSFLS) [6-9], T1 SFLS & Genetic algorithms (GA) [10-11], Fuzzy cognitive maps [12], ANFIS & GA [13], T1 SFLS for control [14], T1 NSFLS & GA [15], the ANFIS model [16] was presented as an option to model inference systems as an Artificial neural network (ANN), this is approached the best by part of fuzzy logic and ANN [17]. There exist some adaptations of the original Jang's model with the using of different training models: back propagation [18], least squares [17], morphological gradient [19], and decision trees [20]. Also the quality assurance tasks were used to fault detection [21-22]. The ANFIS model is used to detect edges as an alternative to manage the uncertainty in the edges of the samples [23, 24]. Is used as a filtering technique after the edge detection with the preservation of the original edges after the application of the noise [25], as is mentioned by several authors the elimination of the noise, the usual types of noise presented are: Gaussian, salt and pepper, Poisson and speckle, this noise changes the saturation of a pixel and produces variations on the dimension of the sample piece. This is a crucial step in the image processing, the elimination of the noise is a very complicated task and the ANFIS technique is implemented to eliminate them [27-29], but the proposed methods are only theoretical proposals, also the noise that affects these images are too large to realistically present in an industrial process or a real life process. Demant et al in [30] presents the typical variations presented in the digital image processing that corresponds to a one standard deviation, less than 2.5 %. The final proposals are not tested or implemented in real processes to compare their performance with low levels of noise (> 2.5 %) of variation. Exist a couple of proposals with the implementation of these soft computing techniques in an industrial process [9, 31].

Also, the mentioned factors above are needed to deal with other factors that produce variations on the performance of the system, particularly those factors that affect inputs [33]. The uncertainty, as is mentioned in [34], comes from different places such as: materials, methods, machines, environment, among others. The supervisory control and data acquisition (SCADA) are the base for the quality systems because it evaluates, controls and monitors the process [35]. On the other hand, the design techniques mentioned in Taguchi's model take into account the uncertainty [36] says that uncertainty comes from 3 main sources such as: Intern, production and external.

The case of study for this paper is based on an inspection process where need evaluates the dimension of support plates based on industrial image processing with the use of ANFIS model and compares their performance versus a pure system T1 SFLS to validate the proposal.

2. Fundamentals

2.1 Type-1 Fuzzy Logic

The fuzzy logic was created to study the properties of certain samples that portion a set and determinate the membership grade to the set. [37] Presents a mathematical algorithm to create approximations via iterations with vectors, these kind of evaluations is done in a continuous universe with several values in a place of a discrete universe that presents Boolean membership [38].

The design of a fuzzy logic application may use linguistic or crisp inputs [39-41], as this system is based on a propositional and conditional sentence in the form (1). Those sentences are called rules and are evaluated by the T-norm (2) or T-conorm, to establish a normalized evaluation that is named firing level after the activation of the rules that are needed to assemble a Fuzzy basis function (FBF) given by (3) that brings a fuzzy output that need to be defuzzified or converted to a crisp number,

$$Rule n: \text{ } if\ x_1 \text{ is } A_1 \text{ and ... and } X_n \text{ is } A_n \text{ then } Y_n = B_n \qquad i = 1,2...,n \tag{1}$$

where: X_i represents the input variables, A_n represents the crisp input, Y_n represents the fuzzy output of the rule and B_n represents the crisp output,

$$\mu_{R\circ S}(x,z) = \sup_{y\in v}[\mu_R(x,y) * \mu_R(y,z)] \tag{2}$$

where: * denotes the product and μ_R, μ_S represents the membership functions of the variables and $\mu_{R\circ S}$ represents the firing of the rule or the activation grade of the rule,

$$FBF = \frac{\sum_{j=1}^{M} Z^{j}\left(\Pi_{i=1}^{n}\ \mu_i^{j}(x_i)\right)}{\sum_{j=1}^{M} Z^{j}\left(\Pi_{i=1}^{n}\ \mu_i^{j}(x_i)\right)} \tag{3}$$

where: $\bar{z}^{j}$ is the output of some rule in the space R, $\mu_i^{j}(x_i)$ represents the firing of the rule.

2.2 ANFIS

The original model of ANFIS [15, 17] established by Jang's cannot evolve before their creation. The architecture of this model is based in an ANN with 5 layers, where the first layer is used to fuzzify the inputs and the next 3 layers are dedicated to the processing and inference that are hidden while the final layer brings the output. (Figure 1).

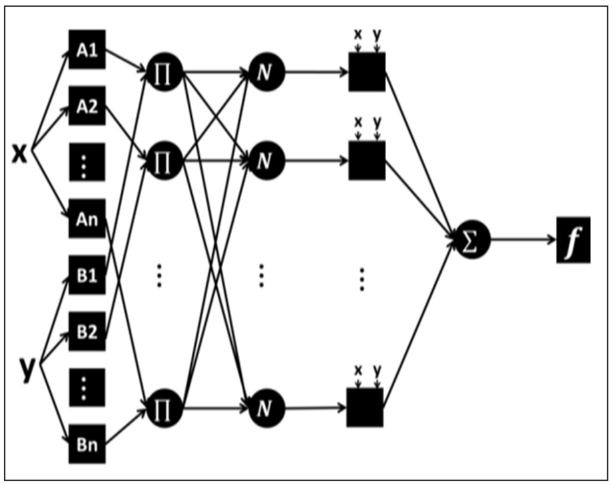

Figure 1. Basic architecture of ANFIS model

This architecture uses the fuzzification and the implication of the T1 SFLS but eliminates the defuzzification. Nevertheless, the rule base and the fuzzifier that were designed to simplify the mathematical formulation and the complexity of a classic fuzzy system are still needed. In the model presented in Figure 1 every layer is dedicated to accomplishing a particular function because of the simplicity of the artificial neurons, also called the simple perceptron (Figure 2). They only can perform a simple mathematical calculation such as: sum, subtraction, product, etc. From there the ANFIS model requires multiple layers of neurons.

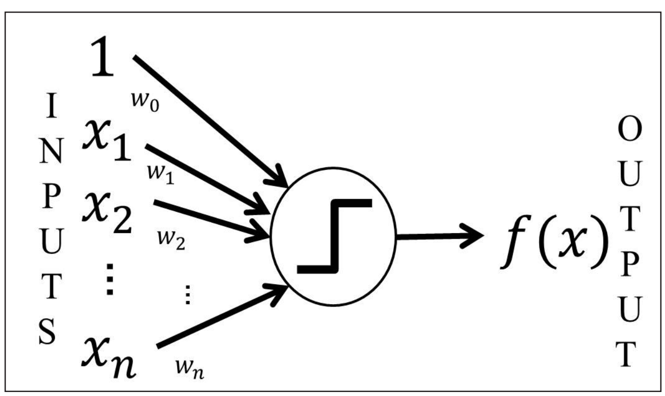

Figure 2. Artificial Neuron

2.2.1 ANFIS Algorithm

Layer 1, every node of this layer obtains the membership values for the inputs. In an FLS the number of activated rules depends on the spread of the fuzzy sets. In the case of the activation of only one rule; this can be done if and only if the value of the antecedents is centered on the mean value of a fuzzy set. The rule activation is done as follows,

$$\text{Rulen: if } X_1 \text{ is } A_1 \text{ and ... and } X_n \text{ is } A_n \text{ then } Y_n = p_n x_n + q_n y_n + r_n \tag{4}$$

where: p, q and r are the coefficients of the inputs and output of the fuzzy rule. The output of this layer is given by (5 and 6) that yields the fuzzy values of the rule,

$$O_{1,i} = \mu_A(x), for: i = 1,2,...,n \tag{5}$$

$$O_{1,i} = \mu_{B_{i-n}}(y), for: (n+1),(n+2),...,m \tag{6}$$

where: $\mu_A(x)$ and $\mu_B(y)$ yields (7).

$$gauss(x;c,\sigma) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2} \tag{7}$$

Layer 2, yields the weight (w_i), that shows the activation value of the rule and may be obtained with the T-norm of membership functions for the antecedents and is given by (8). All nodes in this layer are fixed,

$$O_{2,i} = w_i = \mu_A(x) \cdot \mu_B(y), for: i = 1,2 \tag{8}$$

This layer value is the fuzzified value for the output in every rule.

Layer 3, gives a vector where the output fuzzy values for every rule where grouped for the general output in i that is given by (9),

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, for: i = 1,2 \tag{9}$$

Layer 4 gives the output values that are equivalent to an output function in a Sugeno system that yields (10).

$$O_{4,i} = \overline{w}_i(p_i x + q_i y + r_i) \tag{10}$$

Layer 5, is a sum of the vector $\overline{w}_i f$ generated in layer 4 and is the equivalent value of the function and gives (11) that is the crisp output approximation.

$$O_{5,i} = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{11}$$

3. Case of study

The purpose of this work is to test and implement the automation in a quality assurance process, later is carried out the exploration of the best technique of SC in the quality process to enhance the measurement inspection method. In there was used the proposals of [9, 42] and evaluate them to determine which of them provide better results with uncertain data input.

The characteristic of the pieces is placed in Table 1 and are based on the technical specifications of the piece.

Characteristic	**Noise**	
	Specification	***Tolerance***
Material	Medium Density Fiberboard (MDF)	
Width (mm)	80	3
Height (mm)	120	5
Caliber (mm)	3	0.2

Table 1. Technical data sheet

4. Methodology

Due the nature and simplicity of the singleton systems, such as T1 SFLS and ANFIS, pre-processing to simplify the complexity of the process is required; also an adaptation from a color image to grayscale image to get a one layer matrix with 8-bit definition in a place of an array of 3 matrices such as in Red, Green and Blue (RGB) is needed. The 8-bit grayscale matrix is used to be transformed in a binary matrix in order to get the scalars needed in the quality process. The technical data of the images are described in table 2.

Characteristic	**Description**
Resolution	640X480
Bit Depth	8
Color	Gray scale
Format	JPG

Table 2. Image technical data

The system needs the following steps:

1. Obtain a series of *n* images.
2. Filter the image to get the binary matrix by a threshold.
3. Count the activated pixels.
4. Obtain the limits of the design by a pattern sample.
5. Interpolate the values obtained in step 3 to get the limits of specification in pixels.
6. Obtain the values for every sample.
7. Obtain the limits for every variable on every sample by steps 5 and 6.
8. With the database obtained in the step 7 generate a Multiple input, single output (MISO) system with the limits of specification in pixels.
9. Generate the rule base with the permutations of the limits of every variable.
10. Use the database obtained in the sampling to generate the knowledge base to train the system.
11. Run the system to obtain the dimensions of the piece (width and height).

5. Proposed Method

This application is based on a MISO system with two input variables (height and width) and one output as a quality standard; these parameters are used to check the quality of the process.

The data used for the tests were obtained from a set of 30 samples. The process presents variations in the quality parameters that cause noisy measurements of 2.5% or one standard deviation on every side of the population The objectives of this application are:

· Get a standard evaluation without variability caused by the instruments, people, environment, etc.

· Optimize the operation cycles based on an approximation system.

6. Experimental Procedure

All tests were done on a laptop provided with an intel® CORE™ i5 @ 2.5 GHz, 4 MB RAM y Windows® 7 Professional and MatLab (2009a) for the algorithm. To validate the system we used the Square root mean error (SMRE). The data was corrupted with a signal to noise ratio (SNR) of 40 dB to get variations around about of 5%, also, is applied a SNR of 90 dB. To generate 2.5 % of variation, this variation is the usual error rate for this class of system as is mentioned by [32]. The noisy images are shown in Fig. 3, the variations caused by noise are presented on the insets.

The ANFIS system uses a Gaussian fuzzifier and a reduced rule base to compare with a T1 SFLS of the same characteristics, that system consists in: Gaussian fuzzifier, a) Product inference, Centroid defizifier, and the optimization of the rule base of central composite design/ANFIS proposed by [42].

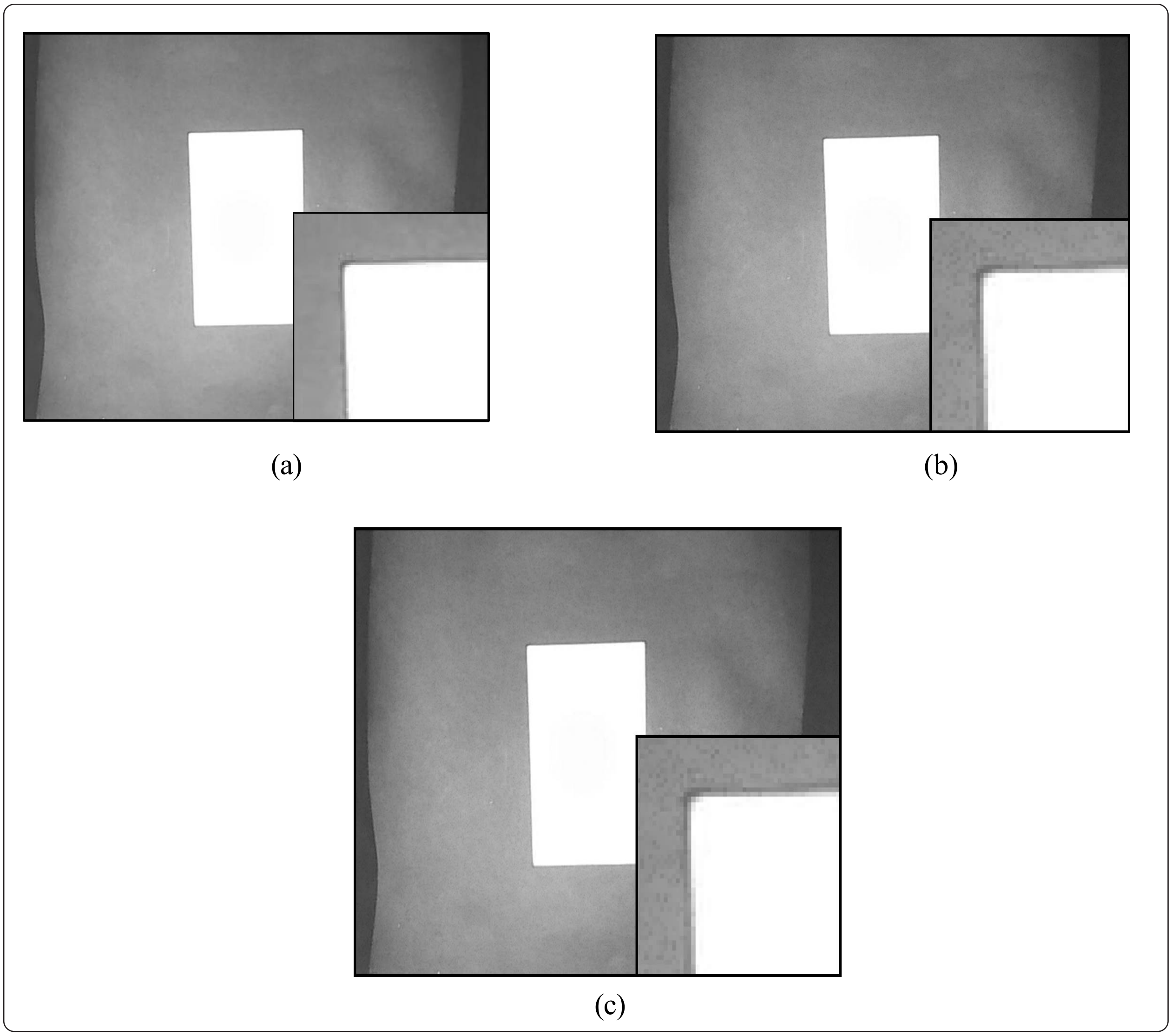

Figure 3. Sample Image (Support Plate) After Filtering. A) Original Image, B) Image With 40 Db. Snr Added, C) Image With 90 Db. Snr Added

7. Results

The exposed results below, shows that the industrial image process may be evaluated with the use of SC techniques, these techniques also may be used to the quality assurance in the forms of: measuring (dimensioning, shape checking), visual inspection (assembly, feature evaluation, presence, etc.).

The obtained images after filtering shows small variations that should be tolerated by the specification in a stable process. The insets in (Figure 4) show variations in the form of missing pixels in the border of the image because the pixels are not saturated or changed by the noise but, these missing pixels do not change the dimension of the evaluation phase. The expert system ANFIS is capable to adapt and adjust these variations and evaluate the sample by knowledge.

The noise in the image is eliminated in two phases: first some of the pixels affected by noise are eliminated by the threshold filter. Second the variation caused by the pixels that not be eliminated on the filtering phase are adapted from training.

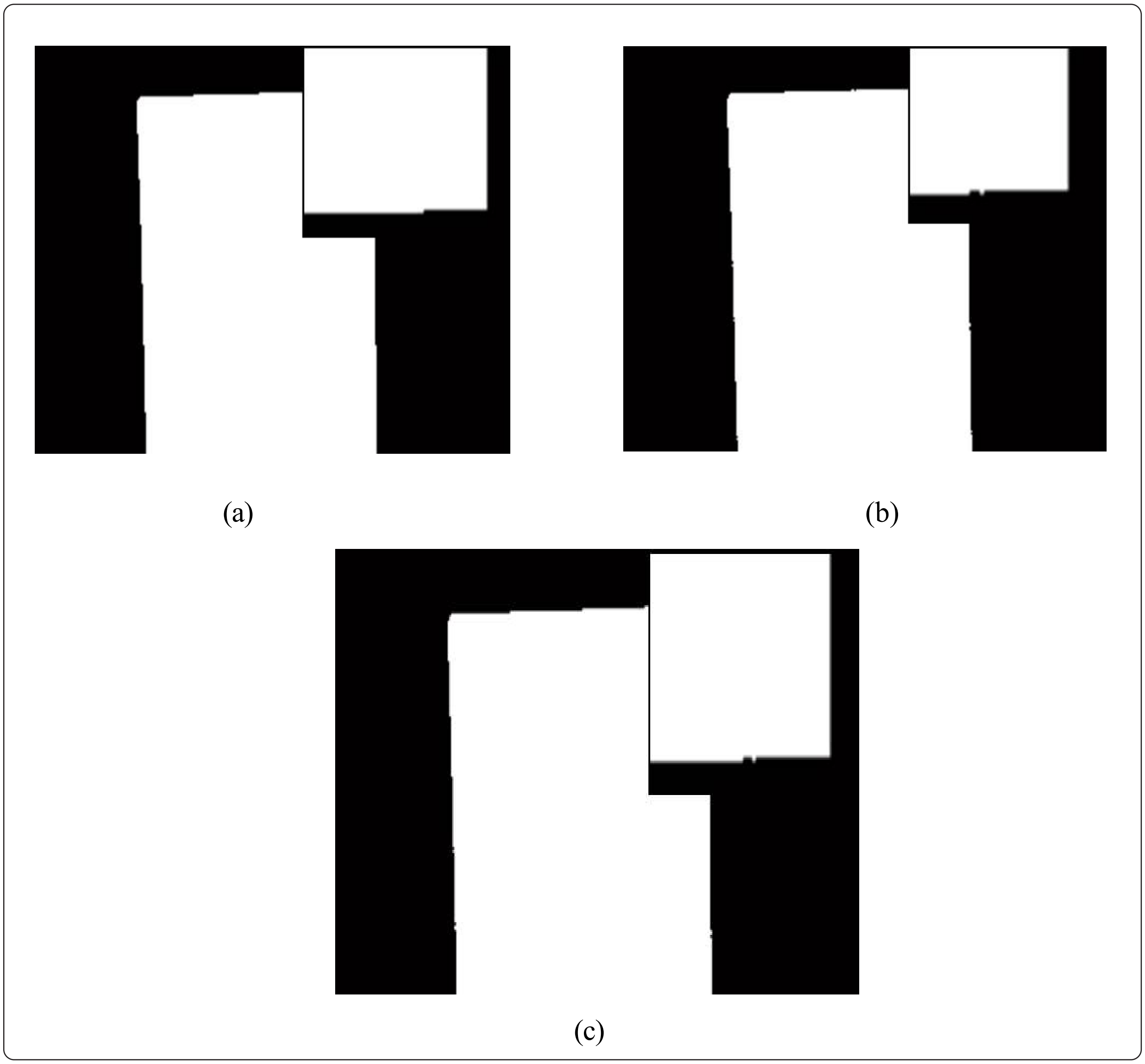

Figure 4. Sample Image After Filtering. A) Original Image, B) Image With 40 Db. Snr Added, C) Image With 90 Db. Snr Added

The singleton models are useful but, require a lot epochs of training and still have a significant error when the inputs are corrupted by significant levels of noise ($\approx \sigma$), e.g. Samples (1,5,8,10) as shown in Figure 5. Also the uncertainty cannot be filtered with this model. If the training data is corrupted by noise, as is in this case, the output values cannot be adjusted by the model. In this particular case the evaluation is done by image acquisition processing.

The Figure 6 presents the approximation of corrupted input data with uncertain values that have a rate of error in an interval of ± 5%, The Figure below shows the prediction of the model after 100 epochs of training and we can say that the number of epochs that must train the system depends on the amount of uncertainty in the input, at least in this case. On it one can see variations in the samples (4, 6, 7) that cannot be adjusted by the training because they appear in the limits of the specification.

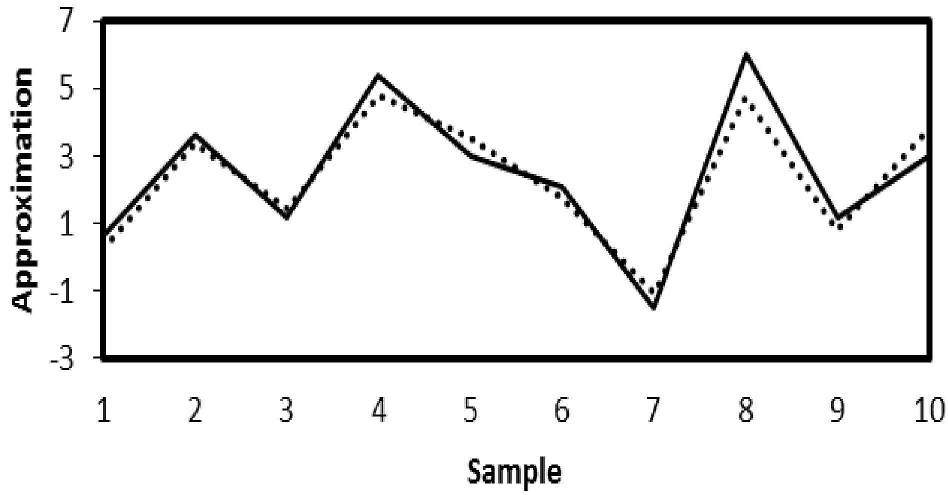

Figure 5. T1 Singleton FLS model output after 100 epochs of training. (___) goal, (...) Uncertain inputs with SNR of 90 dB

Figure 6. T1 Singleton FLS model output after 100 epochs of training. (___) goal, (...) Uncertain inputs with SNR of 40 dB

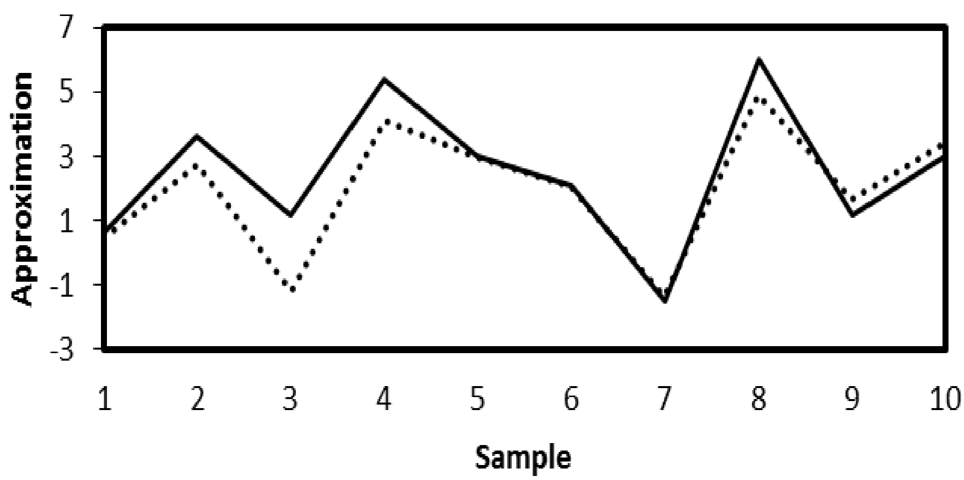

Figure 7. ANFIS model output after 100 epochs of training. (___) goal, (...)Uncertain inputs with SNR of 40 dB

Figure 7 presents the approximation of ANFIS model with a noisy measurement with a SNR of 40 dB, this process takes many epochs to get adaptation; the system after 100 epochs of training shows two patterns: a) Shows the adaptation in the first 2 standard deviations on both sides of the mean and small error rate at extreme points in the values as softening because of the training cycles. E.g. In the case of one of the features evaluated, it is near the specification limits or out of the limits and the difference between the prediction and the goal value grows and the prediction value increases the error rate. Some points at the extreme limits have over trainning e.g. Sample 3. On the other hand the noise at 90 dB. Shows a fast adaptation and an accuracy near about 90% as shown in table 3.

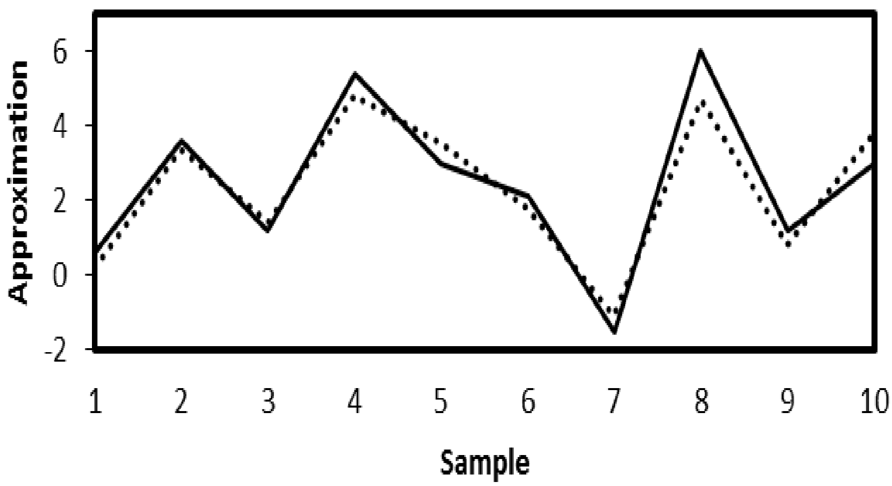

Figure 8. ANFIS model output after 100 epochs of training. (___) goal, (...) Uncertain inputs with SNR of 90 dB

Model	Noise	
	95 dB SNR	40 dB SNR
T1 SFLS	0.081733354	0.37854377
T1 ANFIS	0.125857261	0.08144897

Table 3. Comparison between methodologies (T1 SFLS, ANFIS, with Gaussian membership functions after 100 epochs of training)

7. Conclusions

The results obtained show that the ANFIS system is not reliable for small uncertainty at the inputs because the training adaptation moves the objective and increases error rate.

The exposed results in table 3 show that the error rate is less than 1 pixel in the approximation that gives around of 0.5 mm for this particular case. That error is tolerable as a regular variation in the industrial image processing.

References

[1] Santos y, J. F., Rodrigues, L. F. (2012). Applications of a computer visión techniques in the agriculture and food industry: a review, *European Food Research and Technology*.

[2] Czarnowski Ireneusz. (2012). Distributed learning with data reduction. Lecture Notes in Computer Science, *Transactions on Computational Collective Intelligence* IV. 6660, 3-124.

[3] Martínez, R., Castillo, O., Aguilar, L. T. (2009). Optimization of interval type-2 fuzzy logic controllers for a perturbed autonomous wheeled mobile robot using genetic algorithms. *Information Sciences*. 179 (13), 2158-2174.

[4] Maity, S y Sil, J. (2009). Color Image Segmentation using Type-2 Fuzzy Sets. IEEE, *International Journal of Computer and Electrical Engineering,* 1 (3) 376-383.

[5] Nedeljkovic, I. (2004). Image classification based on fuzzy logic. (2004). *In*: Proceedings. Geo-Imagery Bridging Continents XXth ISPRS (Sociedad Internacional de Fotogrametría y Teledetección) Congress. [Internet] [Viewed at November 5 of 2011. Available at: http://www.isprs.org/proceedings/XXXV/congress/comm6/papers /685.pdf

[6] Nogales-Bueno, J., Hernández-Hierro, J., Rodríguez-Pulido, J., Heredia, F. (2014). Determination of technological maturity of grapes and total phenolic compounds of grape skins in red and white cultivars during ripening by near infrared hyperspectral image: *A preliminary approach, Food Chemistry*, 152, 586-591.

[7] Lelandais, B., Gardin, I., Mouchard, L., Vera, P. (2014). Dealing with uncertainty and imprecision in image segmentation belief function theory, *International Journal of Approximate Reasoning*, 55, 376-387.

[8] Ciocca, G., Cusano, C., Santini, S., Schettini, R. (2014). On the use of supervised features for unsupervised image categorization: An evaluation, *Computer Vision and Image Undersatanding*, 122, 155-171.

[9] Montes Dorantes, P. N., Nieto González, J. P., Méndez, G. M., Praga Alejo, R., Gujardo Cosio, K. L. (2014). Sistema inteligente para procesamiento de imágenes en control de calidad basado en el modelo singleton tipo 1. Modelado computacional de habilidades lingusiticas y visuales. *Research in Computing Science*, 74, 117-130.

[10] Ghasemi, M. J., Tajozzakerin, H. R., Omidian, A. R. (2010). An Iranian National Number Plate Localization and Recognition System for Private vehicles. *International Journal of Academic Research*. 2 (6)13-19.

[11] Zhang, F y Zhang, X. (2011). Classification and Quality Evaluation of Tobacco leaves Based in Image Processing and Fuzzy Comprehensive Evaluation. Sensors. 11 (3) 2369-2384.

[12] Papakostas, G. A., Boutalis, Y. S., Koulouriotis, D. E., Mertzios, B.G. (2008). Fuzzy Cognitive Maps for Pattern Recognition Applications. *International Journal of Pattern Recognition and Artificial Intelligence*.Vol. 22(8) 461-1468c.

[13] Tahmasebi, P. y Herzarkhani, A.(2012). A Hybrid Neural networks-fuzzy logic-genetic algorithm for grade estimation. *Computers & Geosciences*. 42, 18-27.

[14] Malhotra, R., Singh, N., Singh, Y. (2010). Fuzzy Logic Modeling, Simulation and Control: A Review. *International Journal of Computer Science and Technology*. 1 (2) 183-188.

[15] Chua, T. W. y Tan, W. W. (2011). Non-singleton genetic fuzzy logic system for arrhythmias classification. *Engineering Applications of Artificial Intelligence,* 24 (2) 251–259.

[16] Jang R.S. (1993). ANFIS:Adaptive-Network-Based Fuzzy Inference System, *IEEE Transactions on systems*, *Man and Cybernetics*, 23 (3), 665-685.

[17] Kabini, S. K., Ikua, B. W., Nyakoe, G. N. (2011). Review of ANFIS and its Application in Control of Machining Processes. 2011 Sustainable Research and Innovation Conference Proceedings 3.

[18] J.-S. R. Jang, C. -T. Sun, E. Mizutani. (1997). Neuro-Fuzzy and Soft Computing: *A Computational Approach to Learning and Machine Intelligence*, Prentice-Hall, Upper Saddle River NJ.

[19] Hosseini, M. S., Zekri, M. (2012). Review of Medical Image Classification using the Adaptive Neuro-Fuzzy Inference System. Journal of Medical Signals & Sensors. 2 (1) (2012). 49-60.

[20] González, M. A., Ballarin, V. L. (2008). Segmentación de imágenes utilizando la transformada Watershed: obtención de marcadores mediante lógica difusa IEEE Latinamerica Transactions, 6 (2) 223-228.

[21] Silvestri G., Verona F. B., Innocenti M., Napolitano M. (1994). Fault detection using neural networks. *In*: Proceedings of IEEE World Congress on Computational Intelligence, 1994, IEEE International Conference on Neural Networks, 27 Jun-2 Jul, 1994, 6, 3796-3799.

[22] Fei, S., Zhang, X. (2009). Fault diagnosis of power transformer based on support vector machine with genetic algorithm. *Expert Systems with Applications*, 36 (8) 11352–11357.

[23] Zhang, L., Xiao, M., Ma, J., Song, H. (2009, October). Edge detection by adaptive neuro-fuzzy inference system. In *Image and Signal Processing, 2009. CISP'09. 2nd International Congress on* (p 1-4). IEEE.

[24] Anwar, S., Raj, S. (2014, September). A Neural Network approach to edge detection using Adaptive Neuro-Fuzzy Inference

System. In *Advances in Computing, Communications and Informatics (ICACCI, 2014 International Conference on* (p. 2432-2435). IEEE.

[25] Pushpavalli, R., Sivaraman, A. (2013). Image Enhancement Using Adaptive Neuro-Fuzzy Inference System. *International journal of scientific & technology research (IJSTR)*, 2 (6) 256-262.

[26] Saradhadevi, V., Sundaram, V. (2011). An enhanced Two-stage impulse noise removal technique based on fast ANFIS and fuzzy decision. *International Journal of Computer Science Issues (IJCSI)*, 8 (5).

[27] Pushpavalli, R., Sivarajde, G. (2013). A hybrid filtering technique for eliminating uniform noise and impulse noise on digiral images. *Signal & Image Processing: An international journal* (SIPIJ), 4 (2) 76-89.

[28] Kumari, R., Asthana, A., Kumar, V. (2014). Detection and reduction of impulse noise using neuro-fuzzy system and dilation rule. In *Information and Automation for Sustainability (ICIAfS), 2014 7th International Conference on* 1-5.

[29] Xiao, M., Zhang, L., Hou, Y., Song, C. (2013). A novel noise filter for removing impulse noise from digital images. *Advances in information sciences and service sciences* (AISS). 5 (3). 81-90.

[30] Demant, C., Bernd, S., Waszkewitz. P. (1999). Industrial Image Processing. Springer-Verlag, Berlin, Heidelberg, New York

[31] Montes Dorantes, P. N., Jiménez Gómez, M. A., Méndez, G. M., Nieto Gonzalez, J. P., dela Rosa Elizondo, J. (2015). One-step models for soft computing techniques in quality assurance process. *International Journal of Advanced Manufacturing Technology*.

[32] Demant, C., Bernd, S., Waszkewitz, P. (1999). Industrial Image Processing. Springer-Verlag, Berlin, Heidelberg, New York.

[33] Vale, Z., Morais, H., Faria, P., Ramos, C. (2013). Distribution system operation supported by contextual energy resource management based on intelligent SCADA. *Renewable Energy* 52, 143-153.

[34] Méndez, G. M. y Hernández, M. A. (2013). Hybrid learning mechanism for interval A2-C1type-2 non-singleton type-2 Takagi–Sugeno–Kang fuzzy logic systems. *Information Sciences*, 220, 149–169

[35] NCS TIB 04-1. (1994). National Communications System, Technical Information Bulletin 04-1, Supervisory Control and Data Acquisition (SCADA) Systems, October 2004, *Office of the Manager National Communications Systems*. Arlington, Virginia, 4-9.7

[36] Tomiyama T., Gu P. Jin, Y., Lutters, D., Kind Ch., Kimura, F. (2009). Design methodologies: Industrial and educational applications. *CIRP Annals - Manufacturing Technology*, 58. 543–565.

[37] Zadeh, L. A. (1965). Fuzzy Sets. *Information and control*, 8, 338-353.

[38] Morales-Luna, G. (2002). Introducción a la lógica difusa, Centro de Investigación y Estudios Avanzados del IPN, (CINVESTAV-IPN), [Internet][viewed in October 8th of 2011]. Available at: http://delta.cs.cinvestav.mx/~gmorales/ldifll/ldifll.p

[39] Zadeh, L. A. (1975).The concept of a linguistic variable and its application to approximate reasoning - I, *Information Sciences*, 8 (3) 199-249.

[40] Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning - II, *Information Sciences*, 8 (4) 301-357.

[41] Zadeh, L. A. The concept of a linguistic variable and its application to approximate reasoning - III, *Information Sciences*, 9 (1) 43-80.

[42] Montes Dorantes, P. N., Praga-Alejo, R., Nieto González, J. P., Méndez, G. M. (2013). Modelado de Sistemas Adaptativos de Inferencia Neuro-Difusa Usando Diseño Central Compuesto. Avances en Inteligencia Artificial, *Research in Computing Science*, 62, 259-269.