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Classification Tomatoes on Machine Vision with Fuzzy the Mamdani Inference, Adaptive Neuro Fuzzy Inference System Based (Anfis-Sugeno)

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Abstract: In this paper, an efficient and accurate method for tomatoes sorting will proposed. first we extract features from inputted tomato image and then accurate and appropriate decision on Classification tomatoes using fuzzy the mamdani inference, adaptive fuzzy neural network (anfis) methods for each of that image. In our proposed system adaptive fuzzy neural network (anfis) has less error and system worked more accurate and appropriative than prior methods.

Key words: Image Processing, Fuzzy, Tomato, Anfis.

INTRODUCTION

Automatic fruit sorting using machine vision can improve the quality of the product, abolish inconsistent manual evaluation, and reduce dependence on available manpower. Machine vision is known to be a useful tool for external features measurement (e.g. size, shape, color and defects) (Hassan Asadollahi, 2009). For example, qualification classify of potato, pepper, cucumber, tomato and etc., (S. Nimesh, 1993; Y.Gejima, 2003).

Computer vision is a relatively young discipline with its origin traced back to the 1960s (Baxes, G.A., 1994).

Timmermans (Timmermans, A.J.M., 1998) states that it encloses the capturing, processing and analysis of two-dimensional images, with others noting that it aims to duplicate the effect of human vision by electronically perceiving and understanding an image (Sonka, M., 1999).

Computer vision has been recognized as a potential technique for the guidance or control of agricultural and food processes (Tarbell, K.A., 1991). Traditionally, quality inspection of agricultural and food products has been performed by human graders. However, in most cases these manual inspections are timeconsuming and labor-intensive. Moreover the accuracy of the tests cannot be guaranteed (Park, B., 1996). By contrast it has been found that computer vision inspection of food products, was more consistent, efficient and cost effective (Lu, J., 2000).

Efforts are being geared up towards the replacement of human operator with automated systems, as human operations are inconsistent and less efficient. Automation means every action that is needed to control a process at optimum efficiency as controlled by a system that operates using instructions that have been programmed into it or response to some activities. Automated systems in most cases are faster and more precise (Narendra V.G., 2010). There is increasing evidence of computer vision systems being adopted at commercial level. This is indicated by the sales of ASME (Application Specific Machine Vision) systems into the North American food market, which reached 65 million dollars in 1995 (Locht, P., 1997). Kanali *et al*., (Kanali, C., 1998) reported that the automated inspection of produce using machine vision not only results in labor savings, but can also improve quality inspection objectivity.

Neural networks (Miller, W.T., 1995) and fuzzy logic are soft computing techniques that have been used for pattern recognition and decision making problems with good results (Castillo, 1998; Jang, J.4. R., 1997; Ruan, D., 1996). For this reason, these techniques are a good alternative in manufacturing applications (Castillo, 2001; Melin, 2001).

The paper is organized in five sections. After the introduction in Section 1, Section 2 which also introduces the existing methods of the existing methods of the tomatoes Classification. Section 2 continues with explanations of proposed fuzzy system in section 3.in Section 4 is proposed adaptive fuzzy neural network(anfis) for tomato sorting. It continues with discussions on the architecture of hybrid learning and fuzzy model validation, the error of observations for training data sets. Section 5 presents the conclusions of the research.

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Literature Review:

Dealing with simple ‘black’ and ‘white’ answers is no longer satisfactory enough; degree of membership (suggested by Prof. Zadeh in 1965) became a new way of solving problems by treating data as imprecise or in a fuzzy form, there by allowing the fuzzy system to handle certain degree of randomness without compromising on the efficiency of the system.

Neuro-fuzzy systems are one of the most successful and visible directions of that effort. Neuro fuzzy hybridization is done in two ways (S. Mitra, 2000) a neural network equipped with the capability of handling fuzzy information (termed fuzzy neural network) and a fuzzy system augmented by neural networks to enhance some of its characteristics like flexibility, speed, and adapt-ability (termed neuro-fuzzy system(NFS) or ANFIS). An adapted neuro-fuzzy system (NFS) is designed to realize the process of fuzzy reasoning, where the connection weights of network correspond to parameters of fuzzy reasoning (H.R., Berenji, 1992; S. Mitra, 2000). These methodologies are thoroughly discussed in the literature (S. Mitra, 2000).

Devrim UNAY, Bernard GOSSELIN (Devrim UNAY, 2002) have shown the initial analysis of a quality classification system for ‘Jonagold’ and ‘Golden Delicious’ apples. Color, texture and wavelet features are extracted from the apple images. Principal components analysis was applied on the extracted features and some preliminary performance tests were done with single and multi layer perceptrons.

Wen and Tao, (1999) introduced automated rule-based system by near-infrared images to classify ‘Red Delicious’ apples as defected or not. They reached a speed of 50 apples per second with high recognition rates, but had problems in identification of stem/calyx.

Computer vision has also been used in the assessment of tomato seedling quality as a classification technique to ensure only good quality seedlings were transplanted (Ling, P.P., 1996). The classification process adopted an adaptive thresholding technique, the Oust method. The disagreement between canopy areas measured by manual examination and machine vision segmented, canopy portion boundaries, had a range from -2.6 to +2.3%.

Marius. Buzera, applied the proposed algorithms to 20 tomatoes and 20 apples belonging, to the same type as those used during the training period, 10 of that being mechanical damage and stains due to disease and other causes. As a result of the test, out the analysis of the data obtained, the identification process precision of the damage degree for tomatoes was set to be 90%, while for the apples, 85%.

Oscar Castillo, Raul Cardona and Patricia Melin in (2002) describe in their paper a new hybrid intelligent approach for automated quality control combining Learning Vector Quantization (LVQ) and fuzzy logic(mamdani).

Problem Description and Method:

The tomato is taken from the fields to the food processing plants, in which according to their quality a classification is performed. Tomato is classified in to four categories: export quality, national quality, regional, and salsa quality. This classification is very important because the net profit from tomato production depends on the quality evaluation been done appropriately (Oscar Castillo, 2002).

Tomatoes are directed through a rail to the camera section. In this stage, because of the reduction in reflected light, RGB color photo is taken from the tomatoes on black background (Figure 1). Then these photos are given to the image processing subsystem, and after the pre-processing operations, including reflection reduction, improved contrast and obtaining features of tomatoes are measured and their defects are analyzed. The device of video-inspection has been carried-out around transporters with a belt activated by an electric engine, which ensures the moving of the product in face of the video-inspection system, made of two video cameras with manual focusing (Marius Buzera, 2008). The cameras are disposed in the same frame, realizing an angle of 600, towards the analyzed object. These allow the acquisition of colored RGB pictures of 1024*768 pixels, which they transmit in a real time, to the analyzing mechanism represented by a PC of Centrino 1.7 MHZ type.

Fuzzy sets theory provides a framework to materialize the fuzzy rule-based (or inference) systems which have been applied to many disciplines such as control systems, decision-making and pattern recognition (J. Yen, 1989). The fuzzy rule-based system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface (Sivanandum, S.N, 2007).

In this paper, we took into 7 factors. Then, we have created the linguistic variables corresponding to the values. Output is categories of tomatoes to 9 classes.

7 factors obtained from tomato images are as follows:

A. maximum radius:

a1: low: less than or equal to 130 pixel
a2: medium: greater than 130 and less than or equal to 150
a3: high: greater than 150

Class 1 Class 2 Class 3 Class 4

Class 5 Class 6 Class 7 Class 8

Class 9

Fig. 1: Output Classes For Tomatoes.

B. difference between green average intensity and red average intensity (rg)
bl: low: less than or equal to 98
b2 : high: greater than 98

C. difference between red average intensity and blue average intensity (rb)
cl: low: less than or equal to 109
c2 : high: greater than 109

D. difference between green average intensity and blue average intensity (gb)
dl: low: less than or equal to 34
d2 : high: greater than 34

E. ratio of maximum radius over minimum radius (rratio)
e1: low: less than or equal to 1.22
e2: high: greater than 1.22

F. image entropy
Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as: -sum(p.*log2(p))
where p contains the histogram counts returned from imhist.
f1: low: less than or equal to 1.2
f2: high: greater than 1.2

G. Length of the boundary of the largest defect on the tomato
g1: low: less than or equal to 20
g2: high: greater than 20

output classes are :

class 1:large circular red tomato
class 2:medium circular red tomato
class 3:small circular red tomato
class 4:decayed tomato
class 5:non-red tomato

class 6:red tomato with bad texture
class 7:large non-circular red tomato
class 8:medium non-circular red tomato
class 9:small non- circular red tomato

According to terms of 7 above factors The fuzzy inference rules are designed as follow :

Rule 1 : If (rmax is high) and (rg is high) and (rb is high) and (gb is low) and (rate is low) and (entropy is low) and (defect-bound is low) Then output is 1.
Rule 2 : If (rmax is medium) and (rg is high) and (rb is high) and (gb is low) and (rate is low) and (entropy is low) and (defect-bound is low) Then output is 2.
Rule 3: If (rmax is low) and (rg is high) and (rb is high) and (gb is low) and (rate is low) and (entropy is low) and (defect-bound is low) Then output is 3.
Rule 4 : If (rmax is high) and (rg is high) and (rb is high) and (gb is low) and (rate is high) and (entropy is low) and (defect-bound is low) Then output is 7.
Rule 5 : If (rmax is medium) and (rg is high) and (rb is high) and (gb is low) and (rate is high) and (entropy is low) and (defect-bound is low) Then output is 8.
Rule 6: If (rmax is low) and (rg is high) and (rb is high) and (gb is low) and (rate is high) and (entropy is low) and (defect-bound is low) Then output is 9.
Rule 7: If (rg is high) and (rb is high) and (gb is low) and (entropy is high) and (defect-bound is low) Then output is 6.
Rule 8: If (rg is low) and (gb is high) and (entropy is high) and (defect-bound is low) Then output is 4.
Rule 9: If (rg is high) and (rb is high) and (gb is low) and (defect-bound is high) Then output is 4.
Rule 10: If (defect-bound is high) Then output is 4.
Rule 11 : If (gb is high) and (entropy is low) and (defect-bound is low) Then output is 5.
Rule 12: If (rg is low) and (rb is high) and (gb is high) and (entropy is low) and (defect-bound is low) Then output is 5.

Figures 2 Shows the functions for input,output variables based mamdani fuzzy system.

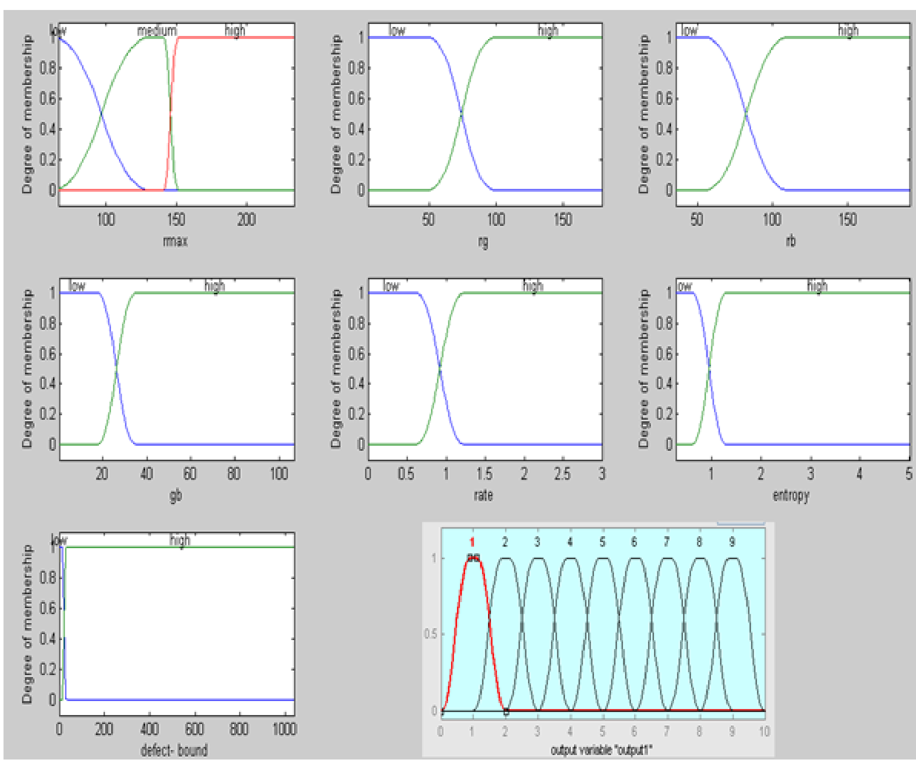

Fig. 2: Membership Functions For Input, Output.

The result of implementation and testing for a image tomato in Matlab environment when the input factors values are rmax = 126.8, rg = 61.54, rb = 137.5, gb = 75.95, rratio = 1.6, entropy = 0.69, Length of defect = 17 output reached 4.8 that correct class was 5.

Designing by Neuro Fuzzy:

It immediately comes to mind, when looking at a neural network, that the activation functions look like fuzzy membership functions. Indeed, an early paper from 1975 treats the extension of the McCulloch-Pitts neuron to a fuzzy neuron (Lee & Lee, 1975; see also Keller & Hunt, 1985).

The one neuron in the output layer, with a rather odd appearance, calculates the weighted average corresponding to the center of defuzzification in the rule base. Backpropagation applies to this network since all layers are differentiable. Two possibilities for learning are apparent. One is to adjust the weights in the output layer, i.e , all the singletons wi until the error is minimized. The other is to adjust the shape of the membership functions, provided they are parametric

Anfis Classfier:

Consider the fuzzy neural network in figure 8. The output of the first layer nodes are the degree of membership of linguistic variables. Typically, in this layer bell- shaped functions are used. Bell-shaped function is shown in Relationship 1. The purpose of learning in this layer is adjusting the parameters of membership function of inputs.

$$f(x) = \exp\left[\frac{-1}{2}\left(\frac{x - a_{i_1}}{b_{i_1}}\right)^2\right] \tag{1}$$

The second layer is 'rules layer'. In this layer, the condition part of rules is measured by usually Min fuzzy logic operator, and the result will be the degree of activity of rule resultant. Learning, in this layer, is the change of the amount of activity of rules resultant, regarding to the 'training data', given to the network. In the third layer, we'll get the linear combination of rules resultant rate, and in order to determine the degree of belonging to a particular category, Sigmund function is used in layer 4 [29k]. If a series of training vectors is given to the network in the form of the formula 2:

$$\{(x^k, y^k), k = 1, ..., K\} \tag{2}$$

where x^k refers to the K-th input pattern, then we have:

$$y^k = \begin{cases} (1,0) \\ (0,1) \end{cases} \text{ belongs to class 1 if } x^k$$

if x^k belongs to class 2

The error function for K pattern can be defined by relationship 4:

$$E_k = \frac{1}{2}[(O_1^k - y_1^k)^2 + (O_2^k - y_2^k)^2] \tag{3}$$

where y^k is desired output, and O^k is computed output.

Design Classification System by Anfis:

We took into 7 factors. Then, we have created the linguistic variables corresponding to the values. Output is categories of tomatoes to 9 classes. 7 factors obtained from tomato images are as section 3.1.

Discussion and Conclusion:

We implemented Our proposed system at a farm in Toskola, a village in Neka city for 126 tomato images. To implement article matlab 7.1 were used.

In anfis system number of membersip function of maximum radius factor 3 and other factors 2, function type primf, output membership function linear, fis type gride partition and optim.method type hybrid Were considered. 3×2^6 rules a weight was created. After training by training data, network with 20 epochs the root mean squared errors value(rmse) reaches 0.6309 (Figure 5,6).

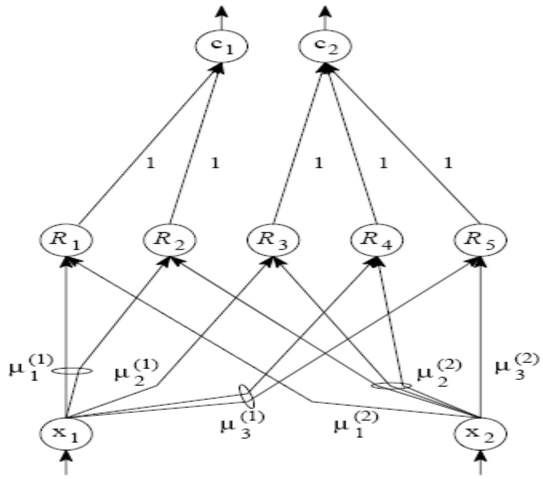

Fig. 3: Adaptive Neuro Fuzzy Network(Anfis).

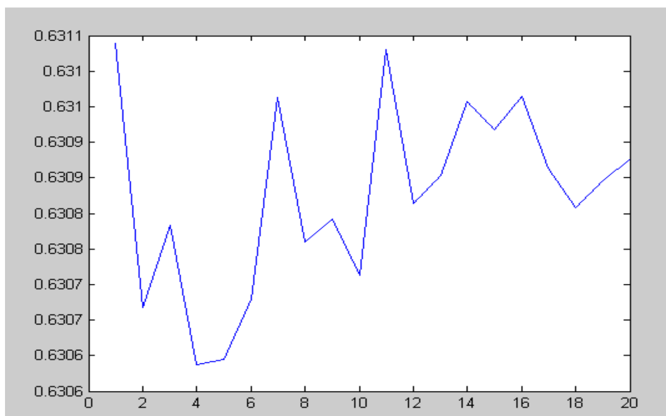

Fig. 4: Anfis Root Mean Squared Errors.

In fis system number of membership function of maximum radius factor 3 and other factors 2, function type primf, 12 rules, output membership function primf, fis type mamdani were considered. The root mean squared errors value (rmse) reaches 1.068 (Figure 8).

Thus anfis proposed system rmse is less and Anfis accuracy further. For future work can be other color space, features, different types of membership functions, different types of neural network and optimization algorithms like PSO algorithm considered.

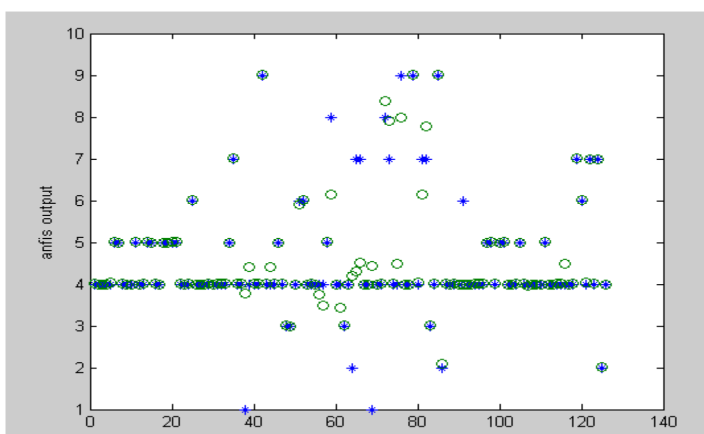

Fig. 5: Anfis Output.

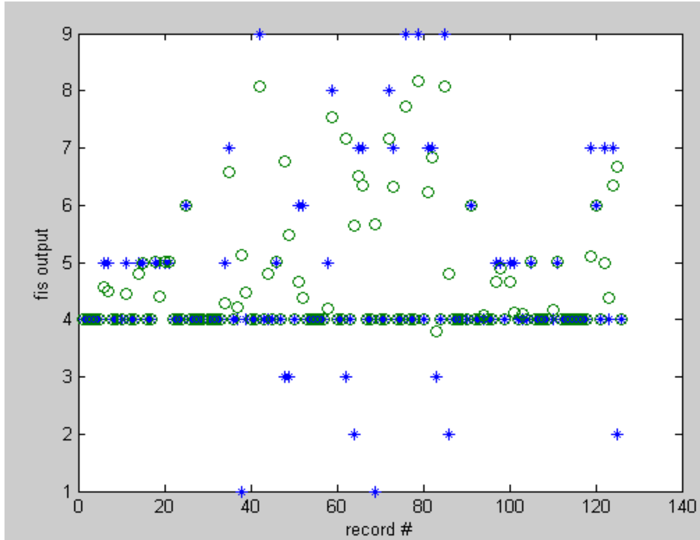

Fig. 6: Fis Output.

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