A Hybrid Intelligent Approach for Automated Quality Control Combining Learning Vector Quantization Neural Networks and Fuzzy Logic

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Abstract

We describe in this paper a new hybrid intelligent approach for automated quality control combining Learning Vector Quantization (LVQ) and fuzzy logic. In our approach, LVQ neural networks are used for image processing and classification. Also, a set of fuzzy rules are used for solving the problem of automating the decision making for quality control. The fuzzy system contains the expert knowledge for quality evaluation. The new approach has been tested with the specific case of automating the quality control of tomato in a food processing plant with excellent results.

1. Introduction

Automating quality control in manufacturing applications is very important because there is always a need of reducing times and costs of production [2, 3]. Also, traditional quality control relies on human experts and as a consequence has the following problems [7]:

a) Lack of objectivity due to several factors as illumination, mud changes, humans being tired, etc.
b) Lack of homogeneity due to similar factors as before.
c) Lack of accuracy as a consequence of the previous problems.

The use of artificial vision in classification processes, not only helps in reducing the time of identification, also helps in giving greater consistency to the classification, and this implies more homogeneity in quality evaluation [7]. Neural networks [9] and fuzzy logic are soft computing techniques that have been used for pattern recognition and decision making problems with good results [1, 4, 11]. For this reason, these techniques are a good alternative in manufacturing applications [3, 8].

The approach proposed in this paper is to use LVQ neural networks [6] to perform image processing and classification, and then use a set of fuzzy if-then rules [12] to decide on the quality based on the results of the LVQ network. The LVQ network enables the classification of an arbitrary geometrical object based on its digital image. However, the classification outputs discrete values only, and therefore fuzzy logic [11, 12] is needed to model the uncertainty associated with this classification process. In this case, a digital video camera is used to capture the images of the objects subject of the classification. The images are then processed to compute the area or volume. These images are then classified using the LVQ network. Finally, a set of fuzzy rules are used to decide on the quality of the product.

Neural networks with local activation functions, for example Radial Basis Functions (RBF) Networks, have the merit of excellent generalization capabilities [5]. So they have been widely used in function approximation [4]. Learning Vector Quantization (LVQ) networks also have the characteristic of local activation functions. Each output node is given a prototype label, which is its associated output value. For each output node, through LVQ learning, an appropriate local region is found where the output is approximated by the label value. Thus the partition of the input space is done based on the output information. The LVQ network, however, outputs discrete values only, and therefore can not approximate real-valued functions. For this reason, fuzzy sets are used to cope with the uncertainty in the classification done by LVQ.

2. LVQ Networks and Function Approximation

Kohonen's LVQ network is a supervised learning algorithm associated with the competitive network shown in Figure1. The network consists of an input layer and an output layer. A weight vector wi is associated to the i-th node in the output layer. In learning phase, the LVQ network selects a weight vector closest to a given input vector and then compares the output of LVQ network with the output of training data [6]. If they match, the selected weight vector is updated so that it approaches the input vector. Otherwise, the selected weight vector is updated so that it moves away from the input vector. After the learning, the LVQ network chooses the nearest weight vector to a given input vector, and outputs its 'label' as the network output. Thus, a weight vector can be regarded as the center of a local region in the input space.

In function approximation problems, a certain fixed real value must be assigned to each weight vector as its 'label'. So, if there are a sufficient number of weight vectors with various 'label' values, they found their proper locations by their learning. This realizes the partition of the input space based on the output values of the training data.

However, when the LVQ algorithm is used in function approximation, it has some problems. The LVQ training algorithm drives a weight vector closer to a training input vector when the 'label' value of the weight vector matches the training output value. But, there are only a finite number of 'labels' while the training output data can take any real number. So, there are an infinite number of data that do not match any weight vector 'label', and thus the LVQ learning algorithm sometimes does not work well in function approximation problems. Another problem occurs when the output is calculated after learning. The LVQ network output can take a value among the finite set of 'label' values only.

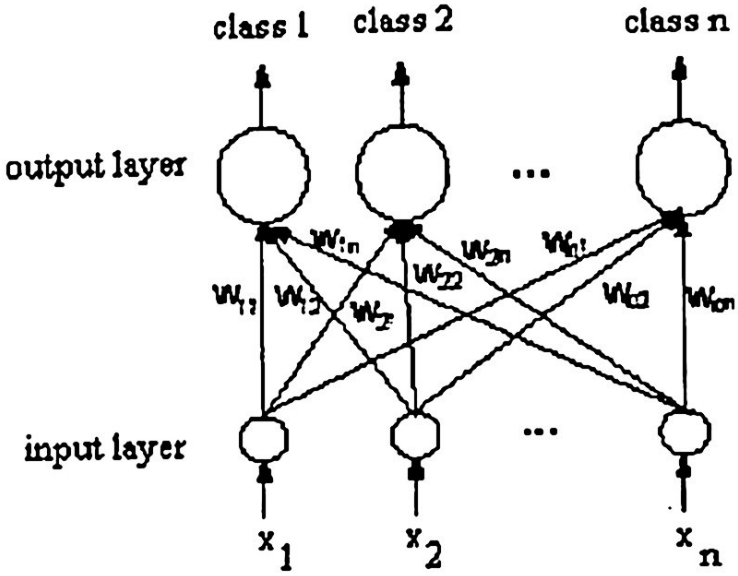


Figure 1 Structure of LVQ network

3. Problem Description

The San Quintin valley is a region of Baja California, Mexico in which tomato is the main export product. 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.

Traditionally quality control of tomato production has been done by manually selecting the good quality tomatoes from production lines. Human workers visually classify the tomatoes from the production line. The tomatoes move on a belt, as shown in Figure 2, and are classified according to their size and to their appearance. Human experts know how to do this job very well. However, they usually have the problems of objectivity, homogeneity, and accuracy, mentioned before. Also, there is a need of performing quality control in less time.

For this reason, automating the quality control process was decided to reduce costs and times of production.

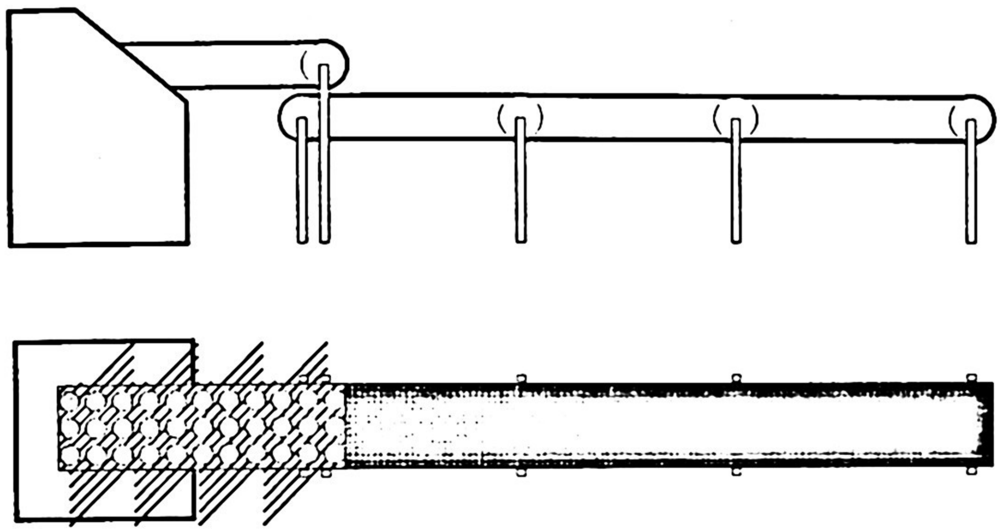


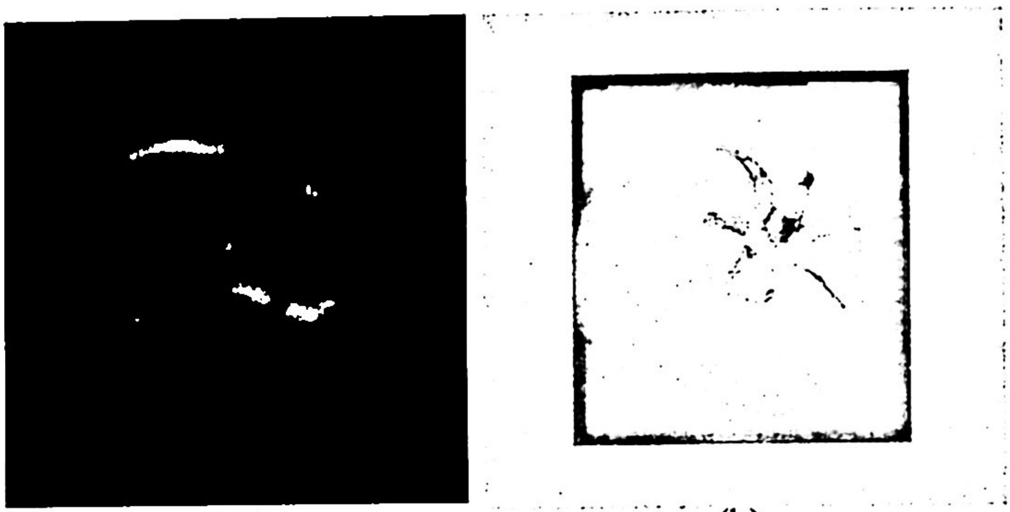
Figure 2 Belt of a tomato production line.

A window of opportunity was recognized for the application of soft computing techniques for achieving automated quality control of tomato production. A LVQ neural network was selected to perform image processing and classification. Also, fuzzy logic techniques were used to deal with inherent uncertainty in deciding the final quality of the product.

4. Image Acquisition and Processing

There are several techniques for processing digital images. For example, in the MATLAB language there are several functions for image analysis and processing [10]. To begin the process, we first need to define the method for image acquisition. This method has to acquire the digital image with less noise as possible. Of course, any acquisition method adds noise to the image, but we need to use a method that minimizes this noise.

For a real time system, like for tomato classification, image acquisition has to be done with a digital camera, but the scene has to be reflection free and with uniform illumination. We show in Figure 3(a) the image of a tomato acquired with a digital camera. Figure 3(b) shows the same image, but with intensity values adjusted for better processing. After the image is acquired, then we perform processing operations to calculate the area of the image and estimate the size of the tomato.

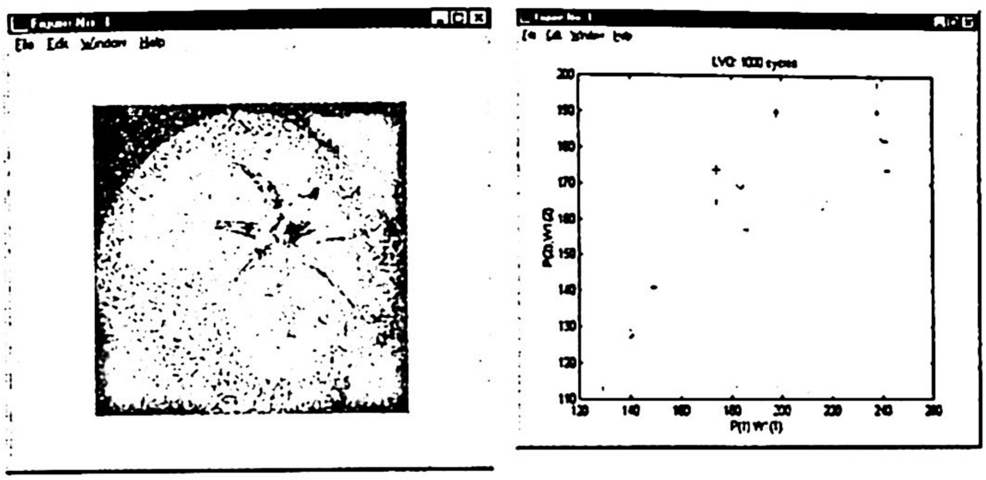


(a) (b)

Figure 3 (a) Image acquired by digital camera, (b) Image with intensity values adjusted.

5. Application of LVQ Neural Network for Image Classification

In this section, we describe how the LVQ network was applied to achieve image classification. First, we did make a choice about which pixels of the image to use. For tomato image we used ten pixels as input to the network. We show in Figure 4(a) the tomato image with the pixels used as input. Of course, the final choice of pixels was achieved after experimentation, and comparison of results. We consider that the final choice of pixels is representative of the image, or at least this was true for the purpose of this work. We also show in Figure 4(b) the final training of the LVQ network after 1000 cycles of learning.



(a) (b)

Figure 4 (a) Image with the choice of pixels, (b) Final training of the LVQ network.

The LVQ neural network basically classifies the tomato images according to their similarities. However, there exists uncertainty in this classification. For this reason, the use of fuzzy logic is justified to complement the LVQ network.

6. Fuzzy System for Automated Quality Evaluation

We formulated a set of fuzzy if then rules to automate quality evaluation of the tomato according to the results of the LVQ network. We used as input linguistic variables the area of the image (size of the tomato), maturity of the tomato, and defects of the tomato. We used as output linguistic variable the class of the tomato. We used a Mamdani type fuzzy system with seven fuzzy rules, which were formulated to model experts in this task. We show in Figure 5 the general architecture of the fuzzy system for automated quality control. In this figure it is clearly shown the use of the three inputs and one output.

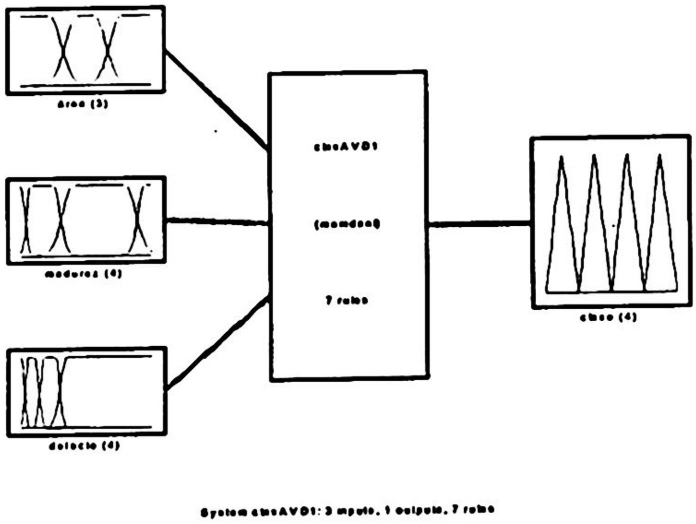


Figure 5 General architecture of the fuzzy system for quality control.

Now we describe the choice of the linguistic terms and membership functions for each of the linguistic variables in the fuzzy system. First, for the area input variable we decided to use three linguistic terms: small, medium, and large. The numerical value of this area is calculated from the tomato image (in millimeters) and this is used to calculate the membership degree to these linguistic terms. We show in Figure 6 the membership functions for the area input variable. On the other hand, for the maturity input variable we used four linguistic terms: very mature, mature, less mature, and, green. In this case, the numerical value of maturity is obtained from the LVQ network. We show in Figure 6 the membership functions of the maturity input variable. Finally, for the defect input variable we used four linguistic terms: few, regular, many, too many. In all the cases, we used generalized bell membership functions to obtain more approximation power.

For the output linguistic variable of the fuzzy system, we decided to use four linguistic terms to classify the quality of the product. The quality linguistic variable was classified as: export, national, local and salsa quality. In this case, we considered sufficient to use triangular membership functions for the output variable because we only needed to do the classification. We show in Figure 7 the membership functions for the quality linguistic variable.

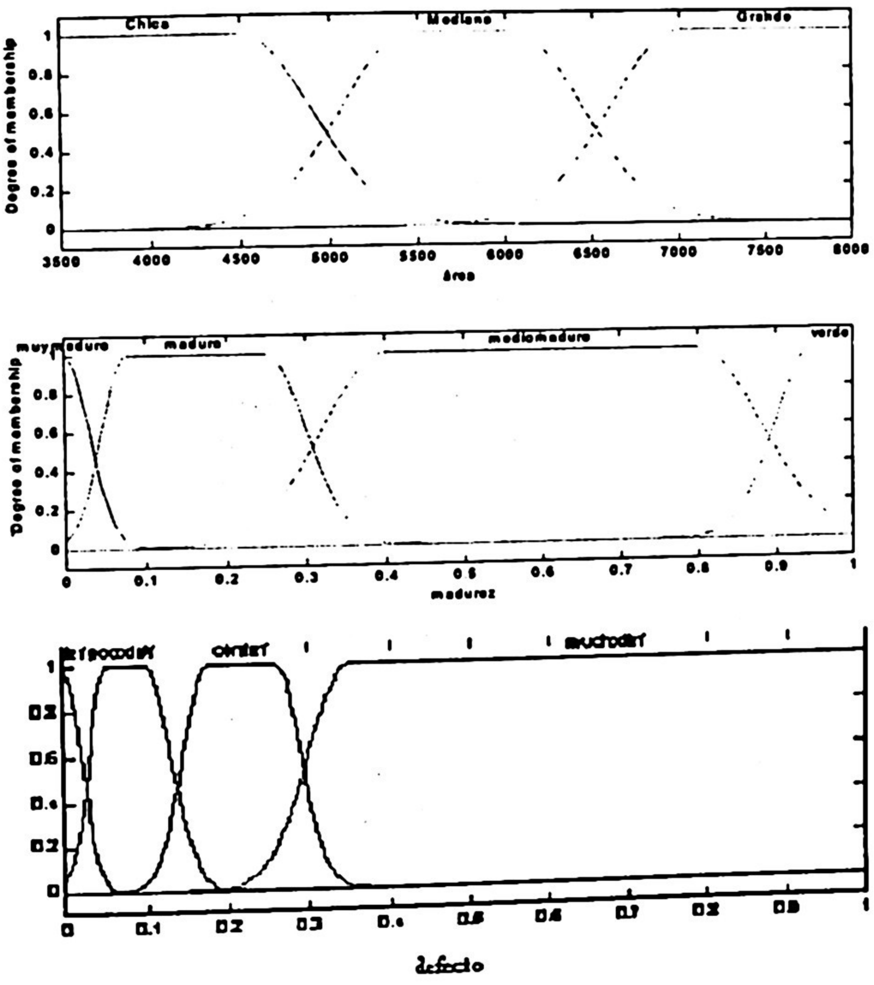


Figure 6 Membership functions for the input linguistic variables of the fuzzy system.

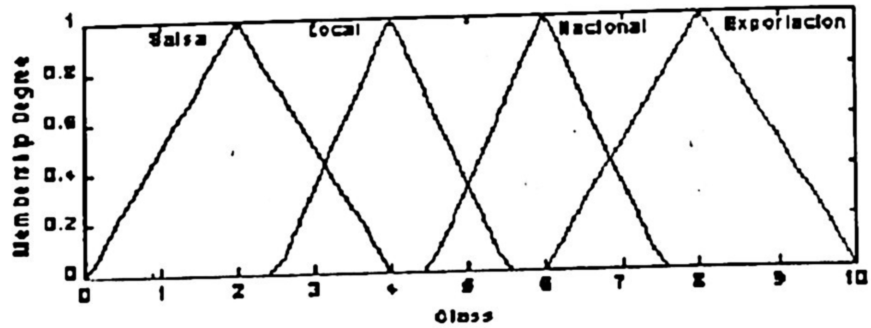


Figure 7 Membership functions for the output linguistic variable of the fuzzy system.

7. Conclusions

We described in this paper a new hybrid intelligent approach for automated quality control combining LVQ neural networks and fuzzy logic. In our approach, LVQ networks are used for image processing and classification. Also, a fuzzy system is used for solving the problem of automating the decision making process for quality control. The fuzzy system contains the expert knowledge for quality evaluation of a specific product. The new approach has been tested with the specific case of automating the quality control of tomato in a food processing plant with excellent results. The accuracy of the classification has been improved, using the hybrid approach, from 85% to approximately 95%. On the other hand, the time required to perform this classification process has been reduced more than 15% with the automation of the process. Finally, we have to say that this hybrid approach can be used for similar problems in quality control.

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