Unhealthy Poultry Carcass Detection Using Genetic Fuzzy Classifier System

Reza Javidan and Ali Reza Mollaei

***Abstract*—** In this paper automatic unhealthy detection of poultries in slaughter houses is discussed and a new real-time approach based on genetic fuzzy classifier for classification of textural images of poultries is proposed. In the presented method, after segmentation of the image into the object (poultry) and background, the size (area), shape (elongation) and the color of the object are calculated as features. Then, these crisp values are converted to their normalized fuzzy equivalents, between 0 and 1. A fuzzy rule base system is then used for inferring that the poultry is normal or not. The parameters of the fuzzy rule based system are optimized using genetic algorithm. Finally, if the output of the optimized fuzzy classifier system shows any abnormality, the carcass of the poultry should be omitted from the slaughter. Experimental results on real data show the effectiveness of the proposed method.

***Keywords*—** classifier, fuzzy, genetic, poultry.

I. Introduction

THE problem of quality control is concerned with sampling, specifications and testing which ensure that the necessary and relevant tests are carried out, and that materials are not released for use, nor products released for sale or supply, until their quality has been judged satisfactory. It is an important aspect of today's highly competitive industry. One important way to improve the quality of the end product is to inspect the output of each manufacturing process. However, manual inspection of end products slows down the entire process as it becomes costly, time consuming. It also may impact the effectiveness of human labor due to the hazardous atmosphere of industry. The inspection system should be designed to be an efficient composition of human intelligence and experience along with the fastness of a machine.

There are many kinds of popular diseases in poultries which carried on slaughter house for poultry sticking operation. Mycoplasma gallisepticum (Mg) infection has existed in chickens for many years. Infectious bursal disease, IBD, (Gumboro) is also an important viral disease of poultry throughout the world. Both diseases result down-grading of carcasses of chickens (thinning) and inclining the skin color to red. Other infections usually make the skin to seem yellow. In any case, for the safety and healthy reasons, these kinds of infected poultry should be recognized and omitted from the slaughter.

In slaughter houses, poultries move continuously on the conveyer belt at high speed. Thus, it is a tough job for the inspection system to acquire and effectively process large amount of data in a short quantum of time. In a traditional method, an inspector, usually a veterinarian or his/her assistant, inspects visually the line of slaughter, and omits the poultries which look to be unhealthy due to their thin body or unusual skin color. Even this method may look to be enough safe, but increasing demand on daily and fresh poultry meat in the market, direct us to enhance the inspection method by using an automated machine vision system. Substitution of human inspection with a machine has many benefits including: decreasing the overall payment cost, increasing safety and quality of the meat production process and finally, applying a fast and consistent inspection rule over all the slaughter houses of the country.

In this paper, the problem of automatic segmentation and classification of the poultry images using fuzzy logic [1] is discussed. We also used a genetic paradigm [2] to tune the fuzzy rule base system. We would like the classification task to be computationally inexpensive and enough fast to be applied in a real-time environment. As a result a genetic fuzzy classifier system [3] is designed and trained to do the task.

In the presented method, after segmentation of the image into the object (poultry) and background, the size (area), shape (elongation) and color of the object are calculated. Then, these crisp values are converted to their normalized fuzzy equivalents, usually between 0 and 1. A fuzzy rule base system then is used for inferring that the poultry is abnormal (positive) or not. Genetic algorithm is applied for better optimization of the parameters of fuzzy rule based system. If the output of the fuzzy system becomes positive, it means that the poultry has some kind of disease and should be omitted form the slaughter. Experimental results show the effectiveness of the proposed method.

Even there are many professional vision systems developed in the industrial environment, however, our inspection showed that the proposed approach in this article is the first practical vision instrumentation that is used in a slaughter house. Therefore this system can be thought as a new application in the field of machine vision.

Reza Javidan is with the Department of Computer Engineering, Islamic Azad University – Beyza Branch, (e-mail:reza.javidan@gmail.com).
Ali Reza Mollaei is with Islamic Azad University- Beyza Branch (e-mail: mollaie.2020@gmail.com).

The organization of the rest of the paper is as follows: In Section 2 genetic fuzzy classifier systems are briefly explained. The proposed approach for automatic unhealthy detection based on genetic fuzzy classifier system is discussed in Section 3. In Section 4 the experimental results are outlined. Finally the conclusion and remarks is the subject of Section 5.

II. Genetic Fuzzy Classifier Systems

Computational Intelligence techniques such as fuzzy logic and genetic algorithms (GAs) are popular research subjects, since they can deal with complex engineering problems which are difficult to solve by classical methods [3]. Fuzzy systems are fundamental methodologies to represent and process linguistic information, with mechanisms to deal with uncertainty and imprecision. With such remarkable attributes, fuzzy systems have been widely and successfully applied to control, classification and modeling problems. One of the most important tasks in the development of fuzzy systems is the design of its knowledge base. An expressive effort has been devised lately to develop or adapt methodologies that are capable of automatically extracting the knowledge base from numerical data. Fuzzy systems are particularly suitable for modeling and classification problems as a human expert is able to analyze and comprehend the knowledge stored in the form of linguistic variables and rules. Although fuzzy systems have been successfully applied in a large number of applications, they lack the ability to extract knowledge from a set of training data. Therefore, over the past years more research has been devoted to augment the approximate reasoning method of fuzzy systems with the learning capabilities of neural networks and evolutionary algorithms [4].

Over the past decade, there has been an increasing interest in evolutionary algorithms that adapt the knowledge base of a fuzzy system. Genetic algorithms have demonstrated to be a powerful tool to perform tasks such as generation of fuzzy rule base, optimization of fuzzy rule bases, generation of membership functions, and tuning of membership functions. These approaches are described by the general term Genetic Fuzzy Rule Based Systems (GFRBS) [4]. The role of the evolutionary algorithm is to either tune the parameters of a fuzzy rule based system or to completely automate the fuzzy knowledge base design. A Genetic Fuzzy System (GFS) [5] is basically a fuzzy system augmented by a learning process based on evolutionary computation, such as genetic algorithms [6]. The first step in designing a Genetic Fuzzy System is to decide which parts of the knowledge base (KB) are subject to optimization by the GA. The KB of a fuzzy system does not constitute a homogeneous structure but is rather the union of qualitatively different components. This topic has attracted considerable attention in the Computation Intelligence community in the last few years. Fig. 1 shows the fundamental block diagram of a GFS [3].

A DataBase (DB), containing the linguistic term sets considered in the linguistic rules and the membership functions defining the semantics of the linguistic labels. Each linguistic variable involved in the problem will have associated a fuzzy partition of its domain representing the fuzzy set associated with each of its linguistic terms. A rule base (RB), comprised of a collection of linguistic rules that are joined by a rule connective

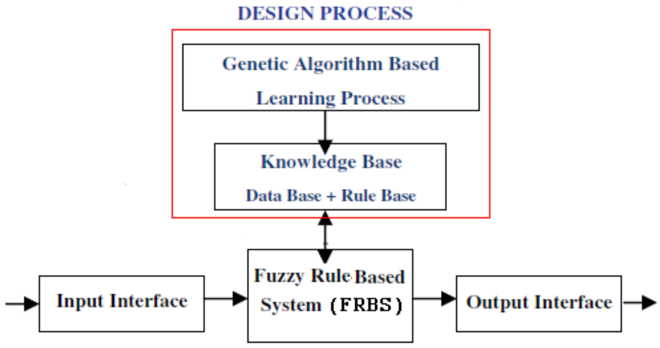

Fig. 1 Genetic fuzzy systems (GFS)

The essential part of FRBSs is a set of IF-THEN linguistic rules, whose antecedents and consequents are composed of fuzzy statements, related by the dual concepts of fuzzy implication and the compositional rule of inference. An FRBS is composed of a knowledge base (KB) that includes the information in the form of IF-THEN fuzzy rules:

IF a set of conditions are satisfied
THEN a set of consequents can be inferred

and an inference engine module that includes a fuzzification interface, which has the effect of transforming crisp data into fuzzy sets; an inference system, that uses them together with the KB to make inference by means of a reasoning method; and a defuzzification interface, that translates the fuzzy rule action thus obtained to a real action using a defuzzification method. Fig.2 shows the fundamental block diagram of a FRBS.

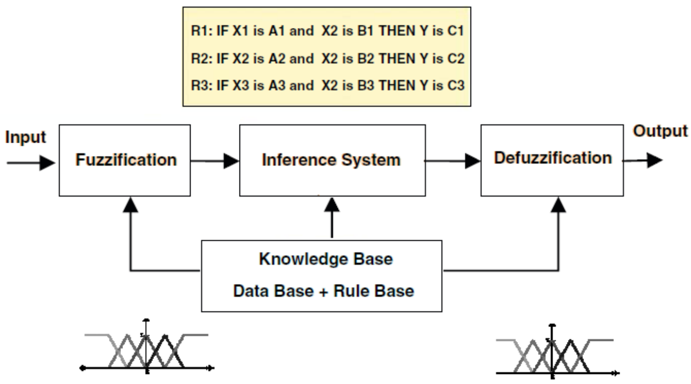

Fig. 2 Fuzzy Rule Based System (FRBS)

Fuzzy rule based systems have been widely applied to the classification problems. Each fuzzy rule covers a particular region of the attribute space described by the rule antecedent, for which it proposes the classification specified in the rule consequent.

Assume a training set of K instances $T = \{(x^1, c^1), \ldots, (x^K, c^K)\}$ and $x^k = \{x_1^k, \ldots, x_N^k\}$ is an instance taken from some attribute space $\{X_1, \ldots, X_n\}$, and $c^k \in \{C_1, \ldots, C_m\}$ is the class label associated with x^k. We use upper indices k to denote the k-th training examples, and lower indices n to denote the n-th attribute x_n^k of a training example x^k. Fuzzy rules are of the form

$$R_i : \text{if } X_1 \text{ is } A_{1i} \text{ and} \ldots X_N \text{ is } A_{Ni} \text{ then } Y = c_i \tag{1}$$

in which X_n denotes the n-th input variable, A_{ni} the fuzzy set associated to X_n and $c_i \in \{C_1, \ldots, C_M\}$ represents the class label of the rule. For a particular instance $x^k = \{x_1^k, \ldots, x_N^k\}$, the rule activation

$$\mu_{R_i}(x^k) = \mu_{R_i}(\{x_1^k, \ldots, x_n^k\}) = \min_{n=1}^{N} \mu_{A_{ni}}(x_n^k) \tag{2}$$

describes to what degree the rule matches the instance. For each possible classification C_m the degree of activation of fuzzy rules with a matching consequent $c_i = C_m$ is aggregated. The instance x^k is classified by the class label

$$C_{max}(x^k) = \text{argmax}_{C_m} \sum_{R_i/c_i = C_m} \mu_{R_i}(x^k) \tag{3}$$

that accumulates the majority of rule contributions [7].

The role of the evolutionary algorithm is to discover fuzzy rules that cover a large number of positive examples and at the same time contain only a small number of negative examples. The central aspect on the use of GAs for automatic learning of FRBSs is that the design process can be analyzed as a search problem in the space of models, such as the space of rule sets, by means of the coding of the model in a chromosome. Even GA can be used for multi-objective optimization of FRBS [8], however, in this article it was used for generation of optimized rule base system.

To do this, a population of candidate solutions by means of genetic operators such as mutation, recombination and selection evolves over time. The detail design of such population is described in next section.

III. THE PROPOSED APPROACH

In this section we proposed a new method for automatic unhealthy detection in a slaughter house based on genetic fuzzy classifier system. Fig. 3 shows the basic setup for the proposed approach.

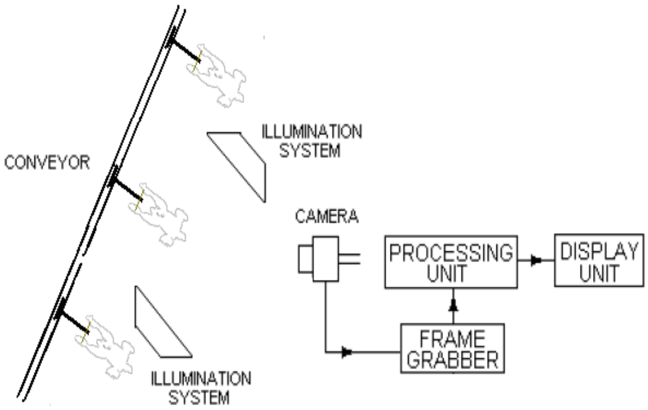

Fig. 3 The imaging setup system for unhealthy detection in poultries of slaughter houses

A vision system [9] for poultry inspection consists of two main parts: an imaging system for taking an image from the poultry body (after sticking and without head and feathers) and analyzing it, and an actuator for omitting the unhealthy corpse from the line. The imaging setup itself consists of a camera unit, illumination system and computing hardware for unhealthy detection in the acquired image as shown in Fig. 3. To reduce the segmentation complexity process, the background of the conveyor, in front of the camera, is covered with a black screen. This ensures that the evaluation algorithm will be enough fast for real-time processing.

Abnormality detection in a two dimensional picture is not a straightforward process. Usually size and shape of the poultry in conjunction with the skin color should be considered. Small carcass size, i.e. thin poultry, and unusual skin color incline to red or yellow, direct the machine to reject the inspected body. Normal and abnormal color and size are not crisp concepts. They can be viewed as fuzzy concept [10]. So a fuzzy inference rule base system [11] can be used for the detection process.

The general architecture of our approach is illustrated in Fig. 4. A digital camera takes a picture from the carcass of poultry. After preprocessing including contrast stretching, the image should be segmented into the object and background.

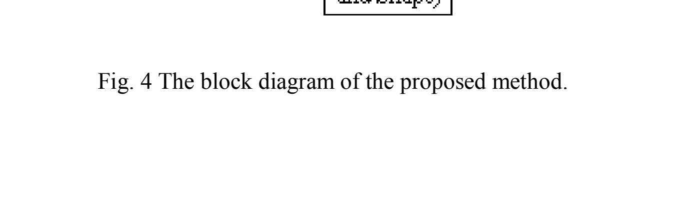

Fig. 4 The block diagram of the proposed method.

Segmentation is a challenging problem in the field of computer vision [12]-[14]. However, since the background of our camera is black, we used a simple threshold to discriminate the object from the background.

A. Feature Extraction

A general pattern recognition paradigm performs this task in two stages: first feature extraction and then, classification. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Size (Area) and skin color are two important features for accepting or rejecting the poultries in a manual system. However in an automated system, in addition to size and color, elongation of the body (shape) is also important. The object area is defined as the area in square pixels inside the line joining the center of the border pixels [15]. This is a normal approach for image processing [16]. In a crisp approach, the lower size limit is set according to the smallest object that could be positively identified in the image. However selecting such a threshold is not a straightforward work. In addition, it is not independent from the shape feature. This all yield us to apply fuzzy approach.

Ones unrealistically sized objects have been ruled out, a study is made on the shape of the objects with acceptable size. This will ensure that the poultries with unusual body (narrow) will be rejected even with enough size. Clearly, it is important to use a shape measure which is position and orientation invariant. This can be achieved using a form of moment analysis. The generalized formula for central moment m_{ij} is as follows [9]:

$$m_{ij} = \iint_R (x-\bar{x})^i (y-\bar{y})^j f(x,y)dxdy \tag{4}$$

Where R is a finite region over which $f(x,y)$ exists and *i* and *j* are integers. A combination of low-ordered moments has been used as a measure of object elongation. Because only the shape is being considered, it is simplify equation (4) by setting $f(x,y)=1$ inside the object and $f(x,y)=0$ outside. Central moments are translation invariant but not rotation invariant. It can be shown that, if the (x,y) axis is rotated through an angle θ, the rotated moment is given by equation (5).

$$\mu_{ij} = \iint_B ((x-\bar{x})\cos\theta + (y-\bar{y})\sin\theta)^i + (-(x-\bar{x})\sin\theta + (y-\bar{y})\cos\theta)^j \tag{5}$$

Since m_{10} and m_{01} are zero by definition, so too are μ_{10} and μ_{01} for all values of θ, therefore the second ordered moments in terms of m_{ij} can be written as:

$$\begin{aligned}\mu_{20} &= 1/2(m_{20}+m_{02}) + 1/2(m_{20}-m_{02})\cos 2\theta - m_{11}\sin 2\theta \\ \mu_{02} &= 1/2(m_{20}+m_{02}) + 1/2(m_{02}-m_{20})\cos 2\theta - m_{11}\sin 2\theta\end{aligned} \tag{6}$$

If μ_{02} is minimized, then the resulting angle θ, θ_p should define the axis from which the edges of the shape deviate least. This angle can be found by computing $\frac{d\mu_{02}}{d\theta}$ and set equal to zero:

$$\tan 2\theta_p = \frac{2m_{11}}{(m_{20}-m_{02})} \tag{7}$$

The axis defined by θ_p is called the principal axis [17] and the second order moments μ'_{02} and μ'_{20} for any object are size, position and orientation independent. A good measure of elongation is the ratio μ'_{02}/μ'_{20} where μ'_{ij} is μ_{ij} when $\theta=\theta_p$ and θ_p is set to $\theta_p + \pi/2 \;\; if \;\; \mu'_{02} > \mu'_{20}$. Again the selecting best threshold value can be seen as a fuzzy concept.

Another important feature is color. We used the approach for color composition texture features that take into account both image characteristics and human color perception. An important characteristic of human color perception is that the human eye cannot simultaneously perceive a large number of colors. In addition the number of colors that may be represented in the poultry skin is limited. The compact color representation in terms of dominant colors for image analysis consists of dominant colors along with the percentage of occurrence of each color:

$$f_c = \{(c_i, p_i), i = 1,...N, p_i \in [0,1]\} \tag{8}$$

where each of the dominant colors, c_i, are in approximately perceptually uniform color space (Lab), and p_i are the corresponding percentages [18]. The distance between color spaces of the unknown object with a good prototype based on a threshold is a criterion for color matching. This difference threshold can also be expressed in fuzzy logic.

The final part of the block diagram of Fig. 4 is decision process that will be explained in the next subsection.

B. Genetic Fuzzy System

The genetic fuzzy system and fuzzy rule based system in our approach are the same as showed in Fig.1 and Fig. 2, respectively.

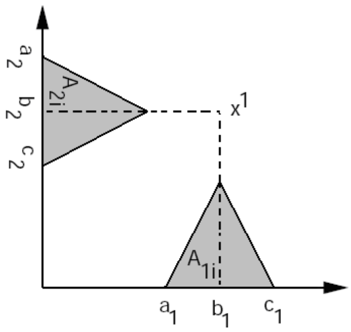

Fig. 4 Initialization of triangular fuzzy sets A_{ni}

The calculated features (Size, Shape and Color) should be normalized and fed to the FRBS through the fuzzification process according to the curves drawn in Fig. 4. The dynamic behavior of a fuzzy system will be model using a set of rule base in the form of (1).

Based on similar method proposed in [4], our classifier employs an approximate fuzzy knowledge base, in which each rule employs its own definition of fuzzy sets, rather than being composed of linguistic labels that refer to a commonly defined set of membership functions. The triangular fuzzy sets A_{nj} are described by the three characteristic points a_n, b_n, c_n. The chromosome encodes the left most point a_n and the distances between successive points $\delta_n^1 = b_n - a_n$, $\delta_n^2 = c_n - b_n$. This representation ensures that the order of points is maintained as long as the δ_n^i remain positive.

The entire rule chromosome is formed by a real-valued vector that is the concatenation of the individual fuzzy set code segments $a_1, \delta_1^1, \delta_1^2, \ldots, a_N, \delta_N^1, \delta_N^2$. As the number of rules required covering the entire input space grows rapidly with the number of input dimensions the coding scheme provides for general rule antecedents that only refer to a subset of attributes. The chromosome contains an additional bit-string $S = \{s_1, \ldots, s_N\}$ in which the bit s_n indicates whether the input clause "X_n is A_{ni}" occurs or is omitted in the rule antecedent. Adaptation of the bit-string S enables the evolutionary algorithm to generate fuzzy rules with those attributes that best discriminate among the different classes.

The training instances are used as prototypes to initialize the membership function parameters. The initialization scheme randomly picks a pair of training instances (x^1, c^1) and (x^2, c^2) that share the same class label $c^1 = c^2$. The parameters of the fuzzy sets A_{ni} are selected such that the two training examples span the core of the fuzzy sets:

$$
\begin{aligned}
a_n &= b_n - \frac{x_n^1}{2} \\
c_n &= b_n + \frac{x_n^1}{2}
\end{aligned}
\tag{9}
$$

as depicted in Fig. 4. The fitness function is defined as:

$$
f = \frac{\sum_{k|c^k=c_i} \mu_{R_i}(x^k)}{\sum_{k|c^k=c_i}} \left(1 - \frac{\sum_{k|c^k \neq c_i} \mu_{R_i}(x^k)}{\sum_k \mu_{R_i}(x^k)}\right) \tag{10}
$$

The fitness function considers two objectives, namely the number of training instances covered by the rule R_i compared to the number of training instances that have the rule class label c_i; and the frequency of negative examples covered by a

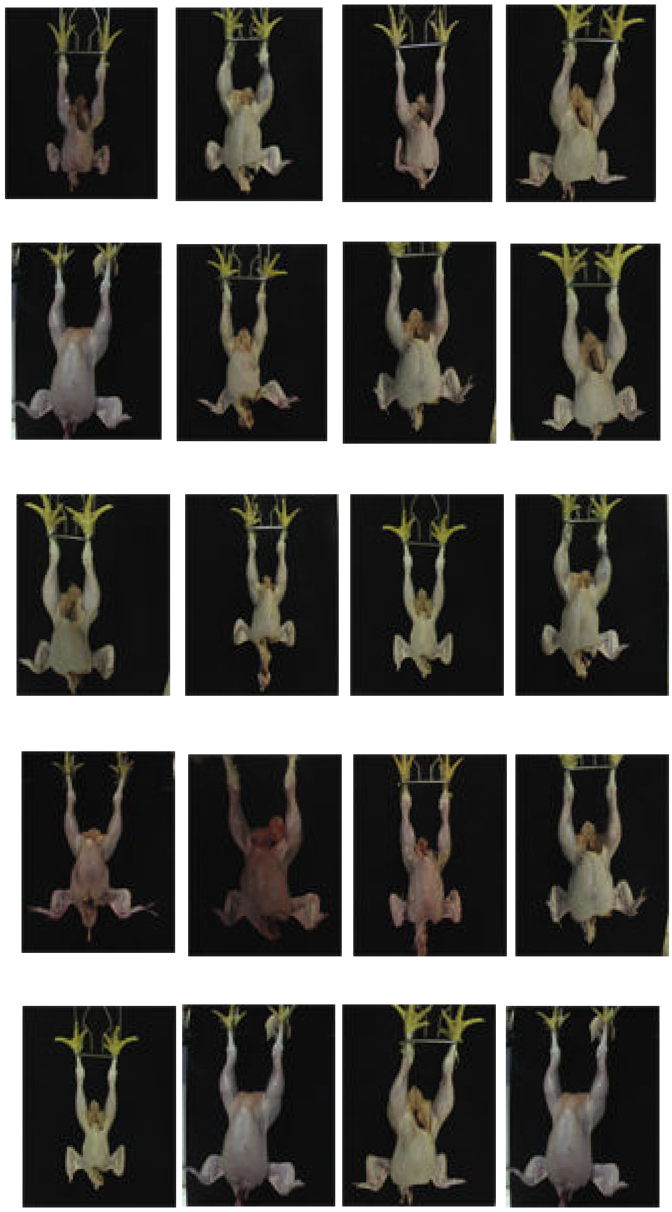

Fig. 5 Some of the real images acquired from a slaughter house

rule. After enough iteration of genetic algorithm, the remaining individual with the best fitness value will produce the optimized fuzzy rule base system which will be used for the classification purpose.

IV. Experimental Results

For testing the proposed approach, 125 images covering both healthy and unhealthy poultries acquired from a modern slaughter house. Fig. 5 shows some of these images. For getting better results, the background of the conveyor at the imaging point covered with a black screen. Ten images covering both healthy and unhealthy poultries are selected as training instances. After preprocessing of the acquired images, including contrast stretching and color level adjustment, the images were segmented using a simple threshold. Just as an example, Fig. 6 shows two real sample images and the segmented results; the left one for acceptable poultry (healthy) and the right for unacceptable one (unhealthy).

(a)

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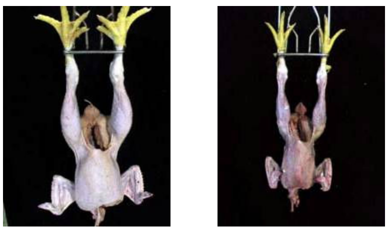

(b)

(c)

Fig. 6 An acceptable (left) and unacceptable (right) samples.
(a) original images (b) preprocessed and (c) segmented results

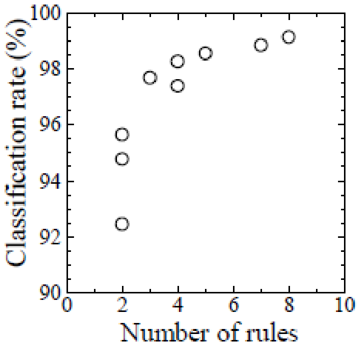

Fig. 7 Classification rate versus number of rules

Size (area) and shape (elongation) features from the segmented images and color feature from the original images before segmentation were extracted and after normalization, are used for training of fuzzy classifier system. Based on the learning approach mentioned above, a genetic algorithm with population size 100 and mutation rate 0.2 and Rolette Wheel reproduction method is used for optimization. Finally, the best individual is selected for construction of the fuzzy rule based system. The learning fuzzy classifier system was able to classify the 100 instances correctly in the rate of %92.4. Experimental results on these real data show the effectiveness of the proposed method (see Fig. 7).

V. Conclusion

The hybridization between fuzzy systems and GAs in GFSs became an important research area during the last decade. At the present, it is a mature research area, where researchers need to reflect in order to advance towards strengths and distinctive features of the GFSs, providing useful advance in the fuzzy systems theory [19].

In this article, as a new application of fuzzy logic, a machine vision system for automatic classification of the poultry images in slaughter houses is introduced. In a traditional method, an inspector, usually a veterinarian or his/her assistant, inspects visually the line of slaughter, and omits the poultries which look to be unhealthy due to their thin body or unusual skin color. Substitution of human inspection with a machine has many benefits including: decreasing the overall payment cost, increasing safety and quality of the meat production process and finally, applying a fast and consistent inspection rule over all the slaughter houses of the country.

In the proposed approach, size (area), and shape (elongation) from the segmented image and color form the original image are three main extracted features. The normalized features are used in a genetic algorithm for optimization of the learning process of a fuzzy classifier system. The optimized fuzzy rule base system is then used as a classifier system for acceptation or rejection of an object under inspection. The system is designed to be enough fast for real time processing. Experimental results on 100 real sample images from both healthy and unhealthy images, showed the fidelity of the proposed approach with accuracy rate of %92.4.

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Reza Javidan received the B.Sc degree in Computer Engineering (hardware) from Isfahan University in 1993. He received M.Sc. and Ph.D. degree in Computer Science and Engineering (Artificial Intelligence) from Shiraz University in 1996 and 2007, respectively. He currently is an assistant professor at the Department of Computer Engineering of the Islamic Azad University –Beyza Branch. His research interests include Pattern Recognition, Image Processing, Artificial Intelligence and Computer Vision.