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Research Paper

Computer Vision System Coupled with an Artificial Neural Network to Rainbow Trout Eggs Quality Evaluation

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ABSTRACT

Rainbow trout in most of the proliferation and breeding sites of cold-water fishes has been propagated and inbred. One of the proliferation steps of this type of fishes is the separating fertile and living fish eggs from the infertile or dead ones and counting them for sale. In spite of various apparatuses and methods of proliferation, the recognition of fertile from dead fish eggs is essential. In this study, the ability of machine vision system coupled with soft computing methods such as Artificial Neural Networks (ANN) was examined to quality assessment of fish eggs. In this regard, the captured images were transferred to the LAB color domain, because this domain is less affected by the camera and lighting conditions then several color and textural features were extracted from the images of rainbow trout fish eggs. Finally, extracted features were introduced to ANN as an input layer. As a conclusion, results showed that with an optimum adjustment of ANN, the live and dead fish eggs were classified with 99% accuracy. The outcome of this investigation can be used in the fish egg quality assessment.

Key words: Fish eggs, image processing, texture analysis, color analysis, artificial neural network.

INTRODUCTION

Traditionally, the separation of the dead eggs from the live fish eggs has been performed manually. Currently, some semi-automated apparatuses for separating and counting of fish eggs are also available. Most of such devices are slow in operation and low accuracy. This is mainly because of their unsuitable and old technology. Moreover, they need to be supervised by some operators to increase the accuracy of separation and complete their job. Due to the inherent characteristics and unique advantages of image processing techniques, it can be adapted for fish industry, specifically for fish eggs evaluation such as counting and sorting process. Also, the fish egg separator devices equipped with image processing technology will have fewer repair and maintenance problems compared to the devices and methods using light and optics to separate the dead and live fish eggs (Skala, 2005). Such devices can also benefit from computer programming and pattern recognition methods to control the system.

A basic machine vision system consists of an image-capturing device, the appropriate computer hardware and software, and a lighting system. Quality of the captured image can be greatly affected by the lighting conditions and a high quality image can help to reduce the time and complexity of the subsequent image processing steps (Du and Sun, 2004, 2006). For rapid prototyping of a machine vision system, artificial intelligence programming can be incorporated into the system. Novel tools such as artificial neural networks and fuzzy logic as expert systems can be applied to learn meaningful or nontrivial relationships automatically in a set of training data and produce a generalization of these relationships that can be used to interpret new, previously unseen test data (Mitchell et al., 1996).

The so called machine vision system is increasingly employed in various branches of science and technology. This technique can be utilized to replace visual assessment of many agricultural and food materials for different purpose of quality assessment and characterization (Yud-Ren et al., 2002, Yam et al., 2004, Kiani and Jafari, 2012). Zhao-Yan and Fang (2005) attempted to identify some rice varieties, using image processing and incorporating neural network techniques. From the images of the varieties, 7color features and 9 morphological features were extracted. For each variety, 200 samples were selected for network training and 60 samples were used for testing the network. Finally, they stated that the classification accuracy with this algorithm is about 88%. Because this classification accuracy was under laboratory setting and had some limit it was decided that in future work, large quantity of rice seeds should be investigated.

Pydipati et al. (2006) examined the quality of seeds and fruit using machine vision system. They used some structural properties of leaf color for recognizing citrus disease. Abbasgholipour et al. (2010) determined a system for grading healthy raisin from unhealthy using image processing technique. This technique was also employed for classifying and dirt inspecting of eggs (Ibrahim et al. 2000). They stated that this technique and designed system can classify the eggs with the accuracy of 80 to 90% on the basis of the respective grade and this system can also successfully specify the cleanliness of the eggs.

Machine vision in combination with learning techniques was used for the assessment of honey quality and prediction of its chemical parameters based on color quantification (Shafiee et al., 2014). Early work in the area of image processing for beef grading based on reflectance characteristics, was done in the early 1990s (McDonald and Chen, 1990). Muscle tissue was successfully discriminated from fat by generating and processing binary images of the muscle. In the case of fish, machine vision has demonstrated its potential for automation of several operations in fish processing. Sizing, weighing, counting, grading, classification, recognition, and monitoring are some of the applications of machine vision in fishery industries (Gumus et al., 2011; Dowlati et al., 2012).

Lunadei et al. (2012) developed an off-line system based on image processing and artificial vision that automatically detected defective eggshells. They used MATLAB software for analyzing images to classify samples as clean and dirty. Eliminating the background, detection of the dirt stain and classification were three steps of their work. The algorithm classified eggs correctly to nearly 98% with a fairly short time (0.05 s). Also Dehrouyehl et al. (2010) presented algorithms based on image processing for detecting the dirt of the eggshell and internal blood spots. They used a machine vision system in HSI color space. Blood spots detection was used from hue histogram and defect detection were selected from maximum value of two ends of the histogram. They created a hardware system including roller conveys, illumination box, camera and PC that transform the egg images to the MATLB software. At least with an average of 85.66% accuracy, their algorithms detected eggs defect.

According to what have been stated above, it has been proved that image color and texture information can be utilized for the objective quality assessment of many types of food products with various applications ranging from fruits, grains, vegetables to meats and fish. Despite extensive existing research works regarding to employing machine vision system on the literature, unfortunately, computer vision has not been developed for inspection and grading of fish egg. Thus in this study, image processing techniques coupled with an artificial neural network have been applied to determine and separate the live and dead fish eggs of rainbow trout.

MATERIALS AND METHODS

Image acquisition

To get the best result, 200 photos (100 photos of live fish eggs and 100 photos of dead ones) were captured. These images were collected from the Ghezel Danesh fish proliferation and breeding farm in Nahavand region, Hamedan, Iran. Image capturing was done in April 2014 with a Canon Digital Asus 500 VHS. Since the fish eggs were small, the size of images was selected to 280*280 pixels. To analyze the images, a PC Pentium 5 tooling with MATLAB software, with image processing and neural networks toolbox, was used. As an example, Figure 1 shows a sample of a dead and a live fish egg. To get the best result, the Camera was fixed at 40 cm above the plate containing the samples.

Feature extraction

For each images of the fish egg samples, 26 features were extracted. Nine of them were from color features (mean, rang and standard deviation for every element of LAB) and 17 of them were texture features. Texture features included 5 Gray Level Co-occurrence Matrix (GLCM) features (energy, contrast, correlation, homogeneity and entropy), 6 Local binary pattern (LBP) features and 6 Fuzzy local binary pattern (FLBP) features (mean, smoothness, skewness, kurtosis, entropy and standard deviation).

Color Features

Before processing of the images, their backgrounds were omitted. The RGB color space is formed from three color components: red, green and blue. Since this color space is

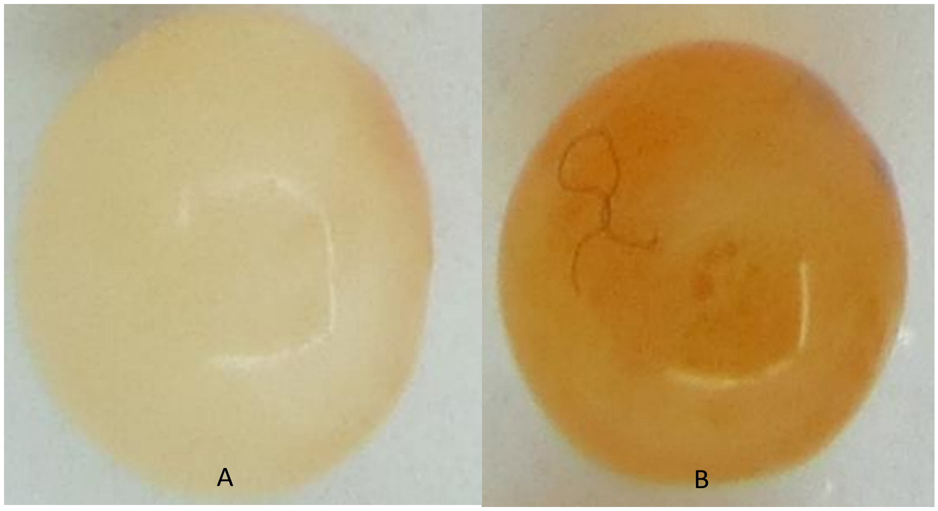

Figure1. Samples of rainbow trout eggs, A) a dead and B) live fish egg.

Table 1. The statistical features of the LAB color domain.

Statistic	Formula
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Standard deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Range	$range = \sqrt{(x_{max} - x_{min})^2 + (y_{max} - y_{min})^2}$

strongly affected by imaging instrument and condition, in this work the RGB color space transferred to LAB space. Unlike the RGB, this system is similar to the human eye. Also it is not affected by the instrument (Shafiee et al., 2014). In this space, L is the equivalent brightness, A has an unlimited amount such that the positive values represent the red and the negative values are green. The positive value of B is equal to yellow and the negative equal to blue. Today, for the majority of researches related to the food industry, LAB space is used frequently (Katherine et al., 2006). For this purpose, statistical properties were extracted. These features are shown in Table 1. For each element of the LAB space, the statistical properties were extracted and therefore totally nine color features were provided.

Texture's features

For analysis of each image based on texture features, they were converted from a color images into a gray level images and then functions GLCM, LBP, and FLBP have been applied to extract texture features from them.

Gray Level Co-occurrence Matrix (GLCM): In this method, the images were converted into a two-dimensional matrix as a GLCM, where each element was the probability of getting color intensity i and j in the neighborhood of the distance d and the angle θ (0, 45, 90, 135°). Finally, by using the function, similarities shown in Table 2, five features were extracted. Before calculating the function on the co-occurrence matrix, each element of the matrix should be normalized. Data were normalized by dividing each element by the total numbers of pairs of pixels considered. From the co-occurrence matrix, it was first (Haralick et al., 1973) used to extract texture features of images to troubleshoot from grapefruit. However the closer the amount of pixels together, the more concentration on the main diagonal matrix will be created in comparison to a simple histogram of pixels in the location information,

Table 2. Features extracted from GLCM function.

Statistic	Formula
Energy	$\sum c^2(i,j)$
Contrast	$\frac{\sum_{i,j}(i-j)^2 * (i,j)}{(j-1)^2}$
Entropy	$\sum_{i,j} c_{i,j} \times \log_2 c_{i,j}$
Homogeneity	$\sum \frac{1}{i+(i-j)^2} c(i,j)$
Coloration	$\frac{cov(i,j)^1}{std(i) * std(j)}$

which is lost and only the frequency of pixel gray values is calculated and location of the pixel matrix are considered, so that the wider the distribution of gray values, the more variance will be seen in the matrix.

Local binary pattern (LBP): One of the effective methods in the texture analysis is LBP. In this method, the most important properties include ease of computation and tolerance against illumination changes (Pietikainen et al., 2005). For each image, a 3×3 neighborhood was considered. For them, central pixel is a threshold. If the value of the element was greater than the value of the central pixel, the new value becomes one, otherwise it will be zero. New value of 3×3 matrix element will be zero or one. By multiple threshold neighborhood values and by resulting bit matrix, the numbers will be converted to decimals. LBP index is the sum of the decimal numbers (Ojala et al., 1996, 2002). Figure 2 shows the rotation invariant LBP for a 3*3 matrix and Table 3 shows features which were extracted by use of LBP function.

Fuzzy local binary pattern (FLBP): Also in this method, after computing the histogram of the possible pattern, one pixel position, may contribute to several bins of a histogram (Iakovidis et al., 2008). If g_b be the neighboring value and g_c be the center value, the difference between those, encodes with 3 values is:

$$m_0(p,f) = \begin{cases} 0, & g_p \geq g_c + f \\ \frac{f - g_p + g_c}{2 - f}, & g_c - f \leq g_p \leq g_c + f \\ 1, & \text{othrewise} \end{cases}$$

$$m_1(p,f) = 1 - m_0(p,f)$$

Where f belongs to the interval fuzzy. Membership function in FLBP, is shown in Figure 3.

The contribution for a pixel position (x,y) to a bin i in the histogram H is defined as follows:

$$FLBP_{N,R(x,y,i)} = \prod_{p=0}^{N-1} [b_p(i) m_1(g_c - g_p) + (1 - b_p(i) m_0(g_c - g_p)]$$

$$H_{flbp}(i) = \sum_{x,y} FLBP_{N,R}(x,y,i)$$

Where p is the number of bits and $b_p(i) \in \{0,1\}$ is defined as the value of the pth bit of the binary representation of pattern i. Table 3 show five FLBP features which were extracted with by this function.

Data analysis

Artificial Neural networks (ANN), particularly the multilayer Perceptron (MLP), are among the most practical. These networks are able to choose the appropriate number of layers and neurons, which aren't often too high, a nonlinear mapping arbitrary precision does. It is a linear model that is used in various fields, such as pattern classification and detection. It is composed of elements

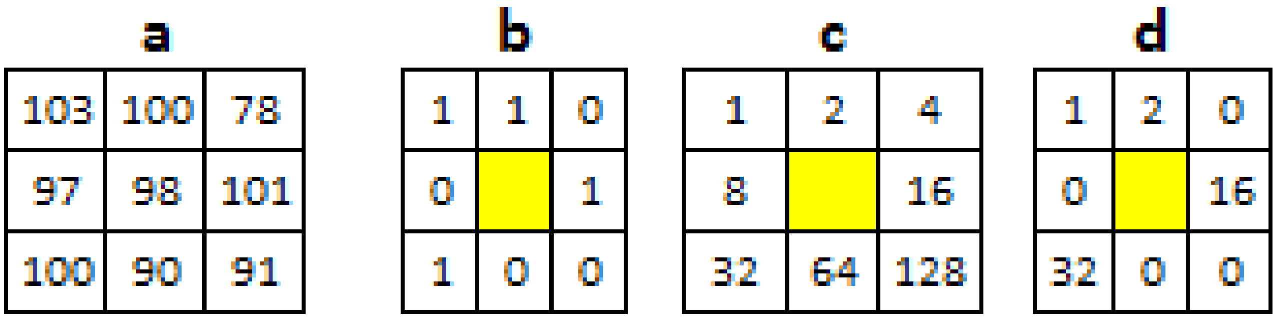

Figure 2. LBP calculation, a: a sample neighborhood, b: resulting Bit-String, c: LBP mask and d: b*c; LBP=1+2+16+32= 49.

Table 3. Features extracted from LBP and FLBP.

Statistic	Formula
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Standard deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Smoothness	$S = 1 - \frac{1}{1+\sigma^2}$
Kurtosis	$k = \frac{E(x-\mu)^4}{\sigma^4}$
Entropy	$E = -\sum_{i,j} c_{i,j} \times \log_2 c_{i,j}$
Skewness	$S = \frac{E(x-\mu)^3}{\sigma^3}$

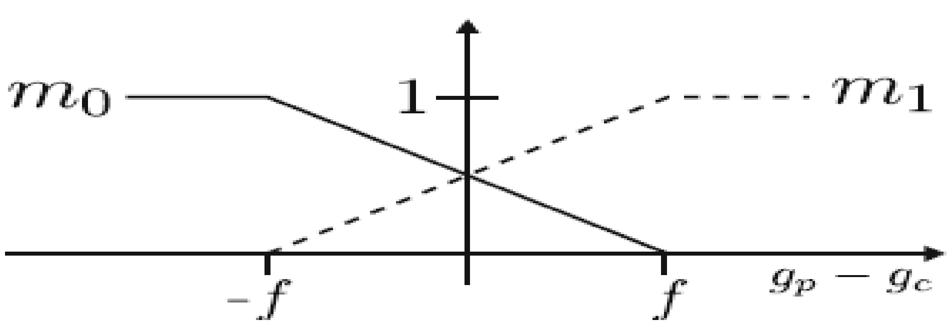

Figure 3. Membership function in FLBP. The x-axis is difference between gray level g_b-g_c and y-axis is function value.

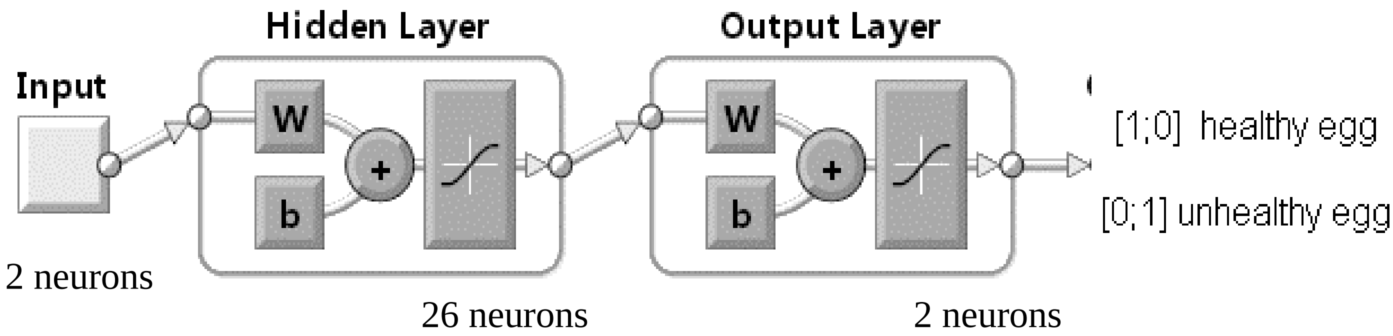

Figure 4. Schematic topologic for neural network.

Table 4. MLP architecture and training parameters.

Architecture	Parameter	Training	Parameter
Number of layers	3	Initial weight and biases	Random
		Activation function	Tangent sigmoid
	Input: 29	Training parameter	Rule= Levenberg-Marquardt (training)
Number of neurons in each layers	Hidden: 20	Performance	Mean Squared Error(MSE)
	Output: 2	Train function	Tangent sigmoid

such as the human brain. By comparing the output and the target of the network, the weights are adjusted. The schematic of neural network is shown in Figure 4.

The trained network consists of three layers, input, hidden and output layers. Twenty six features that had been extracted from feature extraction phase were defined as an input vector. For hidden layer, 20 neurons was defined (it gets by examination) and at least, for output layer, 2 neurons were defined according to the dead ([0,1]) and live ([1,0]) fish eggs. To obtain the best result, some adjustments must be applied. Table 4 shows some parameters of ANN architecture.

RESULTS AND DISCUSSION

When the network started to train, over fitting has occurred. It is the tendency to memorize the training examples without learning how to generalize it into new situations. To improve the network generalization, stop learning method is used. In this way, the data were divided into three categories: training, validation and testing. From the training data (160 samples), the gradient was calculated and the weights and bias were updated. Data validation (20 samples), with increase of error in these data, training become stop. From the test data (20 samples), segmentation data quality was checked. Fig.5 displays the trends of training, validation, and test errors as training iterations passes.

Training stop occurs when the validation error starts to increase. It was at epoch 42 (Figure 5). Also confusion matrixes were used for showing the results (Figure 6). In that, diagonal cells show correct cases and the off-diagonal cells show misclassified cases. It is determined from the matrix that network was able to separate the live and dead fish eggs from each other with 99% accuracy. Also, we can see from this matrix, accuracy of network for train, validation and test, separately. According to the mentioned results it was concluded that the algorithm (Combination of the color and texture with artificial neural network) for quality assessment and distinguishing two types of dead and live fish egg, has a very high efficiency.

Conclusion

Computer vision has the potential to become a vital component of automated food processing operations. The flexibility and nondestructive nature of this technique helps to maintain its attractiveness for application in various facets of the food industry. Also advances in machine vision technology have made vision systems accurate, robust, and low cost which renders them suitable for characterization of fish eggs quality evaluation. Recent application of machine system in the fish industry presented in this paper has been used to separate dead and live fish eggs. Considering the results obtained from this study, it will be founded that this system coupled with ANN have a good

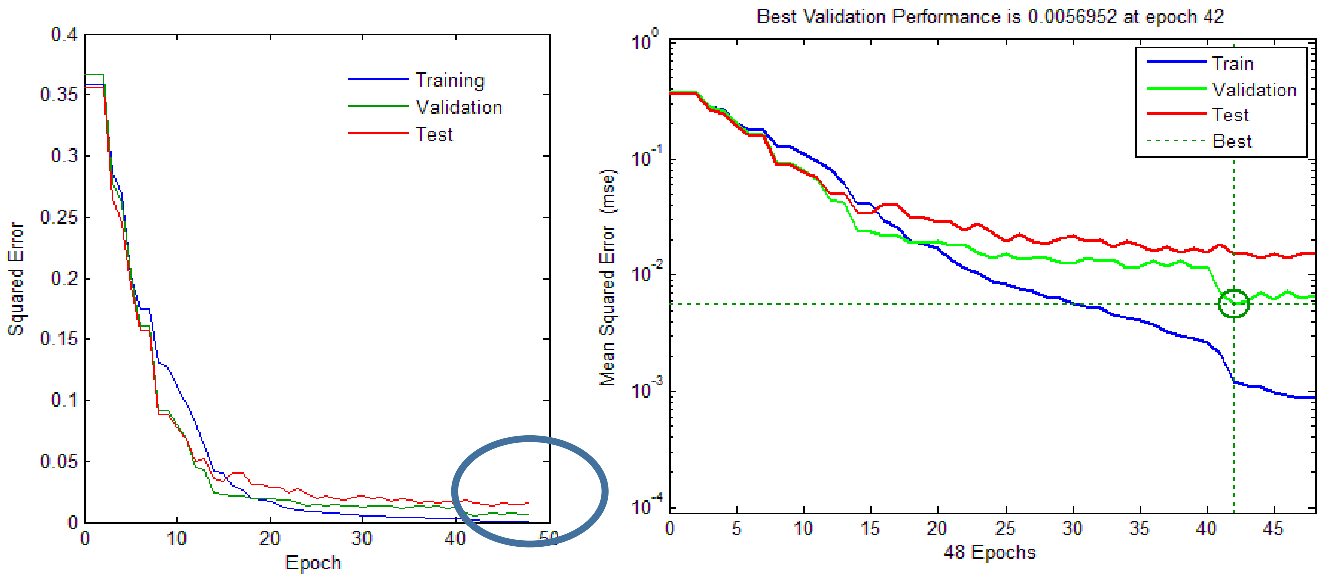

Figure 5. Trends of training, validation, and test errors as training iterations passes.

Figure 6. Confusion matrixes.

potential to separate the live and dead fish eggs with 99% accuracy.

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