Knowledge-Based System for On-line Grading of Herring Roe

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Abstract

Grading of herring roe is a tedious and labor-intensive task. This paper presents techniques developed by us for automating the grading process. Visual and ultrasonic sensors are used to obtain information related to the size, shape, color and texture of each skein of roe. Computer vision techniques are developed to analyse the images and generate parametric features. Fuzzy reasoning that mimics human-expert reasoning, has been used to make decisions through a fuzzy logic rule base, which provides for accurate and consistent grading of bulk herring roe.

1 Introduction

Canada has a significant herring roe fishery which is primarily driven by a Japanese market for high quality herring roe which is a luxury product that is in high demand during the new year season. Much of the commercial value of herring roe is related to the visual appearance and to the texture (firmness) of roe [1].

A major component of herring roe processing involves grading for quality assessment. The natural variation in the quality of roe, in addition to the effects of the early stages of processing, leads to a variation in appearance and texture, which poses considerable challenges in automating the grading process. In view of the very high volume of herring roe which has to be processed during a season that is short, manual extraction and grading is not practical in terms of providing a product at a competitive price. The objective of this research is to develop an automatic grading system that can extract roe belonging to well defined grades from the processing line reducing the volume of roe that needs to be manually graded.

Herring roe is assigned a grade according to its aesthetic properties including colour, texture, size, weight, and shape. Highest quality roe is typically light yellow in color, longer than 3 inches, firm to touch, and fully formed. Knowledge-based computer vision system is considered in this paper for automating the herring roe grading process. Visual and ultrasonic sensors are used to obtain information related to the size, shape, color and texture of each skein of roe, and the processed information drives a fuzzy decision module that is based on rules derived from the assistance of expert graders currently employed in the herring roe industry.

The remainder of the paper is organized as follows: Section 2 gives an overview of the system developed. Since the shape of roe represents the most difficult feature to assess using computer vision, Section 3 describes the feature extraction and classification algorithms developed for shape assessment. Section 4 discusses issues related to hardware/software implementation of the system. Finally conclusions are given in Section 5.

2 Overview of the System

As shown in Figure 1, the system contains five main modules: the shape grader, the color grader, the texture grader, the weight estimator, and the knowledge-based decision-making system. The basic principle behind each module is outlined as follows:

2.1 The Shape Grader

This module preprocesses an image captured on-line and analyses the shape of the particular roe skein. It then gives a grade index which can subsequently be used by

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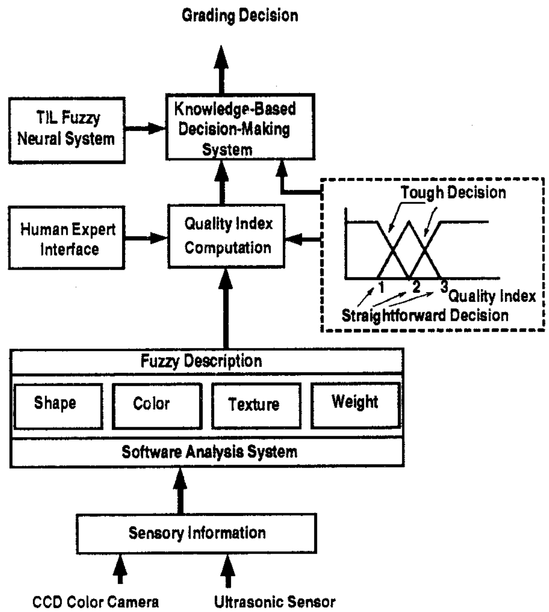

Figure 1: A Schematic Diagram of the Functional Components of the Grading System.

the knowledge-based decision-making system. The detailed algorithms are described in Section 3.

2.2 The Color Grader

The images from different RGB channels are processed by this module and a color grade index is generated. Several methods have been proposed for color feature extraction and classification. The current implementation uses information from the blue channel and the red channel. Information from the blue channel is used to identify the area of interest since the contrast here between the object and the background is much clearer. Once the area of interest is located, each object pixel found in the blue image is matched to the red channel. If the intensity value is above a certain threshold, it is accumulated. Finally the sum of the intensity values is normalized. Figure 2 shows the results of average intensity measurement for good and bad roe samples.

Since the grade of roe is dependent not only on the color, but also on shape, firmness, and other characteristics, a color feature which is in the form of numerical data, is used as one of the characteristic inputs to the fuzzy classification system [2].

2.3 The Texture Grader

After studying the material properties of herring roe and after discussing with experts in the fields of X-ray, ultrasound,

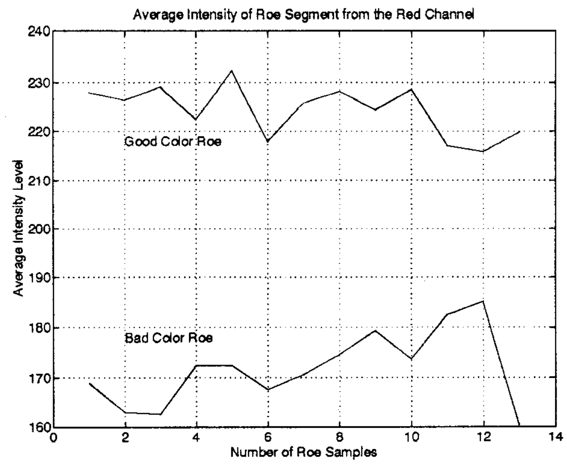

Figure 2: Average Intensity of a Roe Sample from the Red Channel.

and infrared, it was apparent that the acoustic impedance is related to the firmness of a material. To measure the firmness of herring roe, image analysis techniques have been developed in the present system that allow extraction of crucial features, from the acoustic depth images obtained using an ultrasonic probe.

The approach is to develop image analysis techniques that allow extraction of crucial features, from the acoustic video images, that can be used in a decision making system to derive a value for the firmness of herring roe. An initial examination of the ultrasound roe images have revealed that the images generated by soft roe are generally brighter than those of firm roe. This fact has been further investigated and algorithms have been established to obtain some statistical features of the brightness.

In order to extract the brightness feature, five rectangular patches covering the approximate linear region of the echoed ultrasound image obtained by the convex sector scanner, were selected. These rectangular patches, superimposed on the original image, are shown in Figure 3. The width of the patches is kept constant as the region covered by the probe is constant. However, the height of the patches was varied with the thickness of the roe being scanned.

In order to represent the brightness feature, five patches from each image were chosen and the gray-level histogram of each patch was plotted. It was clear from the histograms that the pixel values of firm roe had a less spread than that of the soft roe, and the average brightness value of pixels in a soft roe image was consistently higher than the firm roe. The mean values and the standard deviation values of each patch are computed using the equations given below.

$$M_i = \frac{1}{N} \sum_{X=c1}^{c2} \sum_{Y=r1}^{r2} I(X,Y) \tag{1}$$

$$SD_i = \sqrt{\frac{1}{N} \sum_{X=c1}^{c2} \sum_{Y=r1}^{r2} (I(X,Y)^2 - M_i^2)} \tag{2}$$

where $N = (r2 - r1)(c2 - c1)$ and $(r1, c1)$ and $(r2, c2)$ are the diagonal coordinates of the patches. These features are used in the decision-making system. An "intelligent" sensor for firmness measurement has been developed on this basis, and a theoretical foundation has been established for the associated data analysis [3].

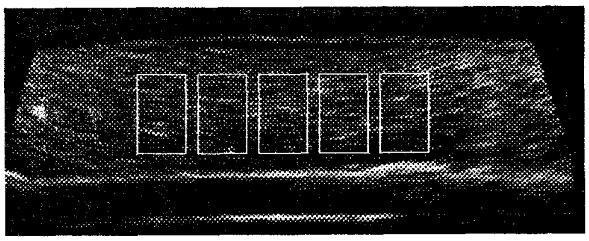

Figure 3: Selected Patches of an Ultrasound Image for Brightness Features

2.4 The Weight Estimator

Weight is also a very important factor in sorting herring roe into different packages. The weight of roe skeins can be measured by a weighing scale. However, installing a weighing scale on the grading system reduces the grading speed and increases the system cost. To overcome these problems, statistical and neural network based methods have been developed to correlate shape information with weight.

Neural Network Method

Neural networks can be effectively used to map a vector of input data to output data. In this case, the input data are geometric features, and the output from the neural network is weight. The geometric features considered consist of area, perimeter, ratio of area and perimeter, and thickness of herring roe. The architecture of the neural network is a feedforward multilayer perceptron. In training the neural network, a backpropagation learning algorithm is employed. The activation functions of the hidden layer nodes are nonlinear (sigmoid), while the activation functions of the output layer nodes are linear. Various combinations of the geometric features have been tried as the input to the neural network, and the results show that using the three features of area, perimeter and thickness as inputs of the neural network give better results than with the other combinations.

Multiple Regression Estimator

The multiple regression estimator is also employed for estimating weight. Again a number of combinations of various geometric parameters were tried in the experiment, and a similar conclusion as before was obtained. That is, the use of three parameters (area, perimeter, and thickness) as independent variables gives the most accurate estimation. In this case, the estimation formula is as given by equation (3):

$$w = -23.088 + 1.655a - 0.003p + 1.9h \tag{3}$$

where, w, a, and h represent weight, area, and thickness, respectively.

From these experiments, it was concluded that the weight of roe can be estimated using shape parameters. Therefore, such an estimator has been successfully incorporated into the prototype grading system. As will be seen from sample of the performance data that is included in Table 1, quite accurate estimation can be achieved from this approach. In a subsequent implementation, the entire thickness profile will be used using a non-contact sensor (ultrasound or laser), which would lead to still better accuracy.

2.5 The KB Decision-Making System

The final grading decision is generated by a knowledge-based decision-making system. The knowledge-base is established with the assistance of roe grading experts, and incorporating other forms of knowledge. Considering that the information is fuzzy in nature, fuzzy logic has been effectively used in the decision-making process [4]. The following paragraph gives some of the rules developed for the rulebase.

cl: color *fm*: firmness *sh*: shape *grd*: grade

If *cl* is *med*	**and** *fm* is *med*	**and** *sh* is *med*	**then** *grd* **is** *med*
If *cl* is *med*	**and** *fm* is *med*	**and** *sh* is *hgh*	**then** *grd* **is** *med*
If *cl* is *hgh*	**and** *fm* is *med*	**and** *sh* is *med*	**then** *grd* **is** *med*
If *cl* is *med*	**and** *fm* is *hgh*	**and** *sh* is *hgh*	**then** *grd* **is** *hgh*
If *cl* is *hgh*	**and** *fm* is *med*	**and** *sh* is *hgh*	**then** *grd* **is** *hgh*
If *cl* is *hgh*	**and** *fm* is *hgh*	**and** *sh* is *med*	**then** *grd* **is** *med*
If *cl* is *hgh*	**and** *fm* is *hgh*	**and** *sh* is *hgh*	**then** *grd* **is** *hgh*
	... ...		... ...

The reasoning and inference making are performed by the compositional rule of inference, i.e., the following three steps are implmemented [4]:

Fuzzification:

Match the crisp reading to its corresponding fuzzy variable by finding the matching membership function value.

Compositional Rule of Inference:

The membership function of the rule base is formed;

$$\mu_R(\underline{e}, \underline{c}) = \sup_{i,j\,(i)} \min \{\mu_{\underline{E}^i}, \mu_{\underline{C}^j}(\underline{c})\}$$

where

$$\begin{aligned} \mu_{\underline{E}^i} &\triangleq \{\mu_{E_1^i}(e_1), \ldots, \mu_{E_n^i}(e_n)\} \\ \mu_{\underline{C}^j}(\underline{c}) &\triangleq \{\mu_{C_1^j}(c_1), \ldots, \mu_{C_p^j}(c_p)\} \\ \mu_R(\underline{e}, \underline{c}) &: \mathbf{R}^n \times \mathbf{R}^p \rightarrow [0, 1]. \end{aligned}$$

Then $\mu_{\underline{C}^j}(\underline{c})$ is obtained by using the *compositional rule of inference* as:

$$\mu_{\underline{C}^j}(\underline{c}) = \sup_{\underline{e}} \min \{ \mu_{\underline{E}^i}(\underline{e}), \mu_R(\underline{e}, \underline{c})\} \quad (4)$$

Defuzzification:

The centroidal defuzzification method;

$$\hat{c}_q = \frac{c_q \int c\mu_{C_q}(c)dc}{c_q \int \mu_{C_q}(c)dc} \quad \text{for } q = 1, 2, \ldots, p \quad (5)$$

may be employed here, where $\hat{c}_q$ is a vector of real valued outputs.

3 Shape Analysis Algorithms

The shape of roe represents the most difficult feature to assess using computer vision. This is because there are no quantitative definations for high and low grades of roe, and the grading decision is very subjective. This paper discusses two approaches developed for shape representation and classification:

- Direct measurement approach.
- Curvature-based approach.

3.1 Direct Measurement Approach

The captured image (from the blue channel) is first thresholded and labeled. The bounding box of the largest configuration in the image is then determined. Once the configuration of interest has been identified, its orientation (i.e., the angle of the principle axis of area) has to be calculated, and for future processing it should be rotated to the horizontal direction. The first moments, $\sum x$ and $\sum y$ of the configuration are calculated, which yield the centroid of area ($\bar{x}$, $\bar{y}$), where x and y form the bounding box coordinates. Next the second moments are calculated as:

$$\begin{aligned} M_{x^2} &= \sum (x - \hat{x})^2 \\ M_{y^2} &= \sum (y - \hat{y})^2 \\ M_{xy} &= \sum (x - \hat{x})(y - \hat{y}) \end{aligned}$$

From these, the angle of the major principal axis of area can be calculated as

$$\theta = \frac{1}{2} tan^{-1}(\frac{M_{xy}}{(M_{x^2} - M_{y^2})} \quad (6)$$

Having obtained the orientation angle, the contents of the bounding box are rotated around the centroid of the bounding box.

The subsequent steps of processing include:

- Identify the anterior end and ventral and dorsal edges of the sample.
- Take width measurements across the two edges of the samples, along the longitudinal axis.
- Smooth the measurements, differentiate, and determine the tangent angles.
- Use the magnitude of the vector difference of the tangent angle representations to compare different samples.
- Compare each test sample with an internal database of training samples which describe allowable variations in grade 1 roe.
- Assign a difference measure to the sample by averaging the distance to its closest K neighbours in the internal database.
- Use this difference measure as one of the inputs to the fuzzy decision-making system.

3.2 Curvature-Based Approach

Curvature variation provides important information about the shape of the roe boundary. For an ideal roe, the mean value of the curvature for the dorsal curve should be a small positive value, and that for ventral should be close to zero. The standard deviation of the curvature plot for the dorsal curve should be moderate, and that for the ventral curve should be small.

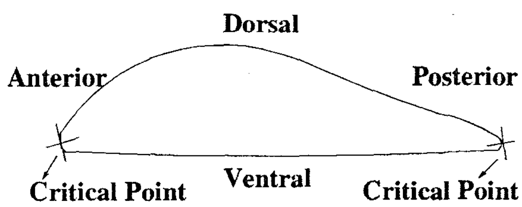

Figure 4: Diagram of Roe.

If a piece of roe is deformed, for instance, if a roe skein has a broken end or a bump, then there are more break points, i.e., more open curves, although the critical points can be identified based on a search in the vicinity of the principal axis. If a roe skein has a distorted boundary, there may be only two open curves detected, although the standard deviation of the curvature function for the distorted roe is expected to be significantly different from that of high-grade roe. This general grading information is compiled using fuzzy rules and used as a component of the complete knowledge base for making grading decisions.

The following image processing operations are implemented in order to obtain a curvature function of a shape:

1. Boundary extraction using contour following.

2. Curvature function estimation using the angle detection method: The curvature uniquely specifies a curve independent of translation and rotation. If the boundary function $\gamma(p) = x(p) + iy(p)$ is twice differentiable, the curvature function $\kappa(p)$ is given by

$$\kappa(p) = \frac{\partial}{\partial p} tan^{-1} \frac{\dot{y}(p)}{\dot{x}(p)}, \quad (7)$$

where $\dot{x}(p)$ and $\dot{y}(p)$ are the derivatives of x and y with respect to p. To overcome the problem arising from a digitized image in curvature calculation, the curvature is calculated as the angular difference between successive vectors on the boundary.

3. Critical-point detection: The critical points are detected as the local maximum points on the curvature function in the vicinity of interception points between the principal axis and the boundary.

4 Implementation and Testing

In order to simplify the image analysis algorithms, the incoming roe skeins are organized into a single file, without overlap, by a filing mechanism. Each roe skein is imaged by a CCD color camera and then the image is analyzed by a PC 486 equipped with a Sharp GPB image processing board. The grading decision is then made and passed to a sorting mechanism. The system is capable of computing estimates for shape, color and weight using the camera images (full color), and firmness using ultrasound depth images. The ultrasound probe interface has not been automated yet, in view of contact sensing that is needed.

The hardware system for image processing includes a CCD camera, a Sharp GPB image processing board, and a 486 host computer. The main part of the software system is for the image analysis algorithms. The software routines for shape, color, firmness, as well as the high-level knowledge-based system have all been developed in a modular structure so that integration of these various modules can be made easy. Parameter passing is used for communication between different software modules. The overall program can be run either in off-line mode or in on-line mode. When the off-line mode is specified, images from various stages of processing for shape, color, firmness, and the knowledge-based decision system will be saved into different files. A single file is then opened to save the names of all the images and the important data from various modules of the software so that these can be easily called in from the off-line graphical demonstration program for detailed analysis.

Individual modules of the system have been extensively tested and validated as they were developed. Also, a number of tests have been conducted on the integrated on-line system. A sample of the performance data collected is shown in Table 1. Data included is for several batches containing various grade combinations of roe skeins.

Table 1. Samples of Performance Data

Grd 1	W_{est}	W_{real}	CI	FI	SI	Grd
	30.9	31.1	69.7	98	75.4	79.7
	29.8	28.5	62.1	95.6	83.8	78.1
	28.6	26.7	98	88.4	76.2	79.2
	25.5	27.5	79.1	91	91	79.9
Grd 2	30.3	29.9	97	34.6	16.7	20.3
	18.9	19	75.7	98.1	33.5	24.5
	27.1	26.8	31	90	30.5	20.4

In the table, Grd, W_{est}, W_{real}, SI, CI, and FI represent grade, estimated weight (in grams), real weight (in grams), shape index, color index, and firmness index, respectively.

At present, a new industrial prototype system has been developed in collaboration with our industrial partner. A picture of the prototype system is shown in Figure 5. Performance of the system is being tested at the plant of our industrial collaborator.

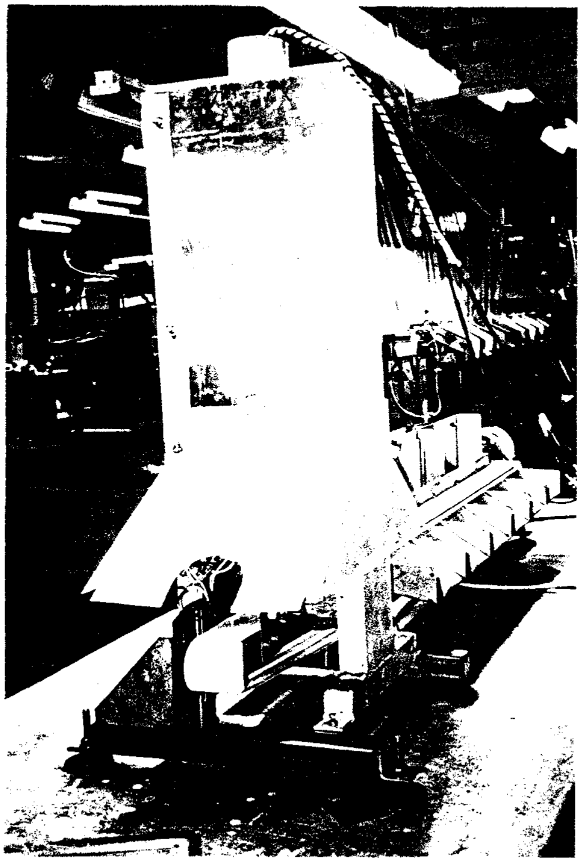

Figure 5: A Picture of the Industrial Prototype System.

5 Conclusions

The experiments conducted in laboratory and at an industrial plant show that the methodology described in this paper for automated herring roe grading is very promising. Typically, a grading accuracy of approximately 85% to 90% can be achieved, and it is believed that even better accuracy is achievable once the system is fully tuned and operational.

Acknowledgements

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