# COMPUTER VISION BASED SORTING OF ATLANTIC SALMON (*SALMO SALAR*) ACCORDING TO SIZE AND SHAPE

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Abstract: Intensive use of manual labour is necessary in the majority of operations in today's fish processing plants, incurring high labour costs, and human mistakes in processing, evaluation and assessment. Automatization of processing line operations is therefore a necessity for faster, low-cost processing. In this paper, we present a computer vision system for sorting Atlantic salmon according to size and shape. Sorting is done into two grading classes of salmon: "Production Grade" and "Superior/Ordinary Grade". Images of salmon were segmented into binary images, and then feature extraction was performed on the geometrical parameters to ensure separability between the two grading classes. The classification algorithm was a threshold type classifier. We show that our computer vision system can be used to evaluate and sort salmon by shape and deformities in a fast and non-destructive manner. Today, the low-cost of implementing advanced computer vision solutions makes this a real possibility for replacing manual labour in fish processing plants.

## 1 INTRODUCTION

During the last few decades, the number of whitefish processing plants in Norway has diminished considerably for several reasons. In aquaculture, although the production volume of salmonids has increased tremendously over the same period of time, most of the fish are currently exported as raw material, i.e. gutted fresh or frozen. In both sectors, particularly due to the high labour costs, fish processing is often unprofitable. For instance, for slaughtering of farmed salmonids, the needed manpower is typically 25-40 persons per shift to process 40-100 tons of bled, gutted fish packed in ice. Therefore, greater automatization of various unit operations, preferably at low investment costs, represents a common strategy within the fish processing industry today. A fish processing line consists of several separate unit operations. Arnarson et al. (1988) reviewed and outlined a number of possibilities for implementing computer vision for automation and improving product quality in the fish processing sector. However, several unit operations in a fish processing line still rely on, at least in part, repetitive manual labour. Manual processing and grading has several drawbacks. It is influenced by human factors such as mistakes, occasional omissions in processing and fatigue. These factors may result in imperfections that decrease product quality and thereby reduce profit (Pau and Olafsson, 1991). Therefore, there is a need for automation of basic processing operations to obtain faster processing and a more objective and consistent quality determination (Strachan and Murray, 1991; Gunnlaugsson, 1997; Brosnan and Sun, 2002). Here computer vision can contribute to further improving the quality of fish products. With the latest developments in camera technology and the continuous increases in CPU speed, computer vision technology has become increasingly more relevant.



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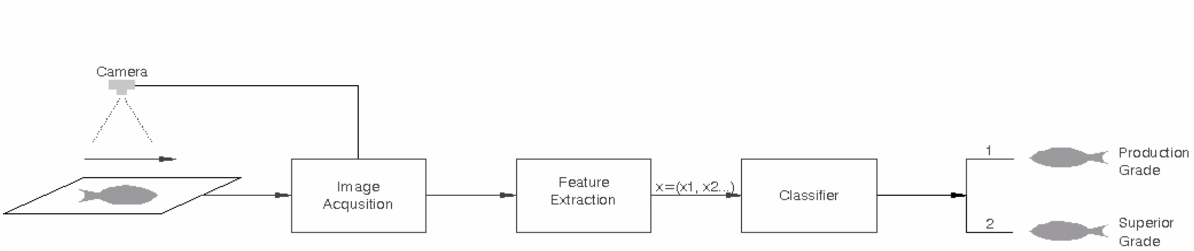


Figure 1: Stages of classifier design.

Today computer vision solutions are easy to implement with high flexibility and low cost. Until recently, the cost of high-resolution, high-speed cameras has been comparatively high. These factors imply that computer vision can be used effectively for online processing of fish (Arnason et al., 1988). The non-destructive nature and the sheer speed at which the quality of fish can be evaluated and sorted are other important factors that encourage the use of computer vision based solutions.

Computer vision has proven successful for online process control and inspection of food and agricultural products with applications ranging from simple automatic visual inspection to more complex vision control (Gunasekaran, 2001). Strachan and Murray (1991) describe how they developed a machine, based on image analysis, for discriminating mature herring by sex using infrared light.

Computer vision algorithms for automated processing of channel catfish (*Ictalurus punctatus)* have been developed to detect fish orientation, identify the head, tail and fins, and to determine cutting lines for deheading, detailing, and defining (Jia et al., 1996). Moreover, automated separation has been developed for several marine fish species (Wagner et al., 1987; Strachan and Murray, 1991; Strachan, 1993) and for freshwater species such as carp *(Cyprinus carpio),* St. Peter's fish (*Oreochromis sp.)* and grey mullet *(Mugil cephalus)* (Zion et al., 1999). Walkott (1996) gives examples on how shape region features can be used for object recognition.

When farmed salmonids are slaughtered, the fish size distribution approximately follows a Gaussian distribution curve. From a processing point of view, a uniform fish size is much favored. This has to do with production planning including issues such as the correct adjustment of gutting machines, possible further processing to a certain uniform product (e.g. fillet) and delivery of chilled gutted fish of a given weight class to a specific costumer. Another factor is that a certain fraction of the fish carries different kinds of blemishes that originate from the farming period. Sexually mature fish, fish with different body deformities ('short tails' and 'humpbacks')

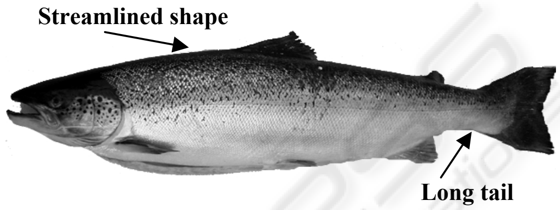


Figure 2: Superior class salmon.

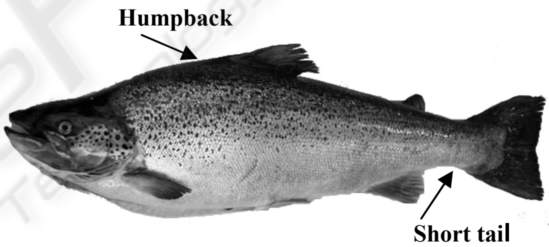


Figure 3: Production class salmon.

(fig. 3) and skin defects (excessive loss of scales, wounds, etc) all occur. Accordingly, our goals were to develop computer vision based methods able to (fig. 1):

(i) reject sexually mature fish and sort/grade fish with deformities in shape. Such a sensor system should be placed prior to fish processing since such fish are not worth processing.

(ii) grade fish according to these shape parameters.

Today, salmonids in Norway are graded according to external quality as follows: 'Superior' (no blemishes), 'Ordinary' (minor degree of blemishes), (fig. 2), 'Production' (part of the fish may be used for human consumption) (fig. 3) and 'Rejected' (not for human consumption, see (i)).

# 2 MATERIALS AND METHODS

## 2.1 Fish and fish sampling

Atlantic salmon (*Salmo salar*) from one fish processing plant were used. *Group I*: Nine 'Production Grade' (weight: 3.58 ± 0.23 kg; length: 50 ± 2 cm; were selected from the slaughter line on 12 Oct 2003. The fish were bled and gutted at the plant.

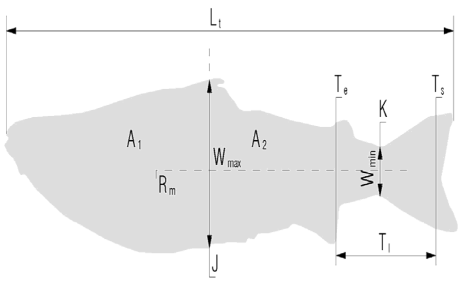


Figure 4: Shape parameters for feature extraction.

*Group II:* Fourteen "Superior/Ordinary Grade" fish were collected from the same commercial processing line on 12 Oct 2003. Thus, the fish ('Superior Grade') had been bled and gutted at the plant. The mean fish weight and length were 4.60 ± 0.4 kg and 59 ± 3 cm, respectively.

## 2.2 Image Acquisition

The images, intended for feature extraction, were captured using an image acquisition system for a digital colour camera (Nikon Coolpix 5000, Japan) at a resolution of 1600 x 1200 pixels and acquired in the JPEG format. These were still images. However, ccommercial industrial full frame digital cameras with comparable resolution are available at near real-time speeds (HVDUO-5M, HanVision Co, Korea). The use of line-scan colour cameras is most likely preferable in an industrial setting, due to their high-speed and the fact that fish in most cases are transported on conveyor belts. The white balance of the camera was set using the camera's automatic white balance. The fish were illuminated using only one illumination setup. This setup used two parallel halogen lamps under a white glass board to provide the necessary illumination, with colour temperature 2900 K. The lamps were placed 30 cm below the fillet. The images were acquired with a camera mounted in a stand on a 90˚ angle, 100 cm above the fillet. Images were processed with Adobe Photoshop prior to processing with Matlab Development Environment 7.01 (Mathworks, Natick, Massachusetts, USA). Images were filtered, scaled and rotated appropriately in the Matlab Image Processing toolbox. Images originally had random orientation, with a different angle to the horizontal axis. Some images were in the flipped orientation. By using and writing Matlab functions, all these images were oriented in the same direction prior to the feature extraction procedure in Matlab.

## 2.3 Feature Extraction

The features are derived from the geometry of the salmon's shape. Standards that the fish processing industry uses for classification of "Production Grade" and "Superior/Ordinary Grade" are also based on the geometrical parameters of salmon shape. An inspector at the processing line usually looks after parameters such as 'humpback', 'short tail' and 'sexual maturity' when he wants to detect and grade a "Production Grade" salmon. "Superior/Ordinary Grade" salmon has a 'streamlined' shape and with a 'long tail' and reduced 'roundness' compared to "Production Grade" salmon.

Based on the industrial standards and the geometrical parameters defining the shape of salmon (fig. 4), four features were chosen for extraction, which would allow us to classify the salmon. The first parameter was the ratio ($R_{lw}$):

$$R_{lw} = \frac{L_t}{W_{\max}} \tag{1}$$

where $L_t$ is the total length of fish from its nose to the end of the tail, and $W_{\max}$ is the maximum width of fish.
The second parameter was the area ratio ($A_r$):

$$A_r = \frac{A_1}{A_2} \tag{2}$$

where $A_1$ is the area on the front half of the fish and $A_2$ is the area on the back.

The third parameter was the ratio ($W_r$):

$$W_r = \frac{W_{\max}}{W_{\min}} \tag{3}$$

where $W_{max}$ is the maximum width of fish and $W_{min}$ is the minimum length of the fish.
The final parameter was the ratio ( $R_{tl}$ ):

$$R_{tl} = \frac{T_l}{L_t} \qquad (4)$$

where $T_l$ is the tail length, and $L_t$ is the total length of the fish.

In this way we used a total of four features $x_i$, $i = 1,2,3,4$ :

$$x_1 = R_{lw} \qquad (5)$$

$$x_2 = A_r \qquad (6)$$

$$x_3 = W_r \qquad (7)$$

$$x_4 = R_{tl} \qquad (8)$$

creating the (1x4) feature vector:

$$x = [x_1, x_2, x_3, x_4] \qquad (9)$$

Figure 5: Segmented binary image.

The geometrical parameters in figure 4, which are used in the feature's definition, were derived in Matlab from the segmented binary image of the salmon (fig. 5). The size of the image was defined with the pair $(r,c)$, where $r$ is the total number of rows, and $c$ is the total number of columns. The images were cropped and scaled in Matlab in such a manner that the first column is the start point of the nose of the fish, and the last column corresponds to the end of the tail. Consequently the total length $L_t$, which is the length from the nose to the end of the tail, was defined as equal to the total number of columns in the image:

$$L_t = c \qquad (10)$$

The width $W$ of fish is the width of the fish at any point. In Matlab it was calculated as the number of pixels equal to one (=1) in the row direction at the given column position. The maximum width of fish, and the appropriate column position, where the maximum width occurred, was defined as:

$$[W_{max}, J] = \arg\max_j [W] \qquad (11)$$

The maximum width occurred at the column position located between the dorsal fin (fig. 4) and the belly. The minimum width of the fish was defined in the same fashion, where we ensured that the searching was done on the back side of the fish, from column $J$ to the end of the tail. The minimum width of a fish, together with the position where it occurred, was:

$$[W_{max}, K] = \arg\min_j [W] \qquad (12)$$

In the $x_2 = A_r$ feature, $A_1$ in figure 4 was defined as the area of the front half of the fish, from the head of the fish until the midpoint $J$ at the dorsal fin, where the maximum width occurred. $A_2$, on the other hand, is the area portion of the back half of the fish from the midpoint position $J$ from the dorsal fin to the end of the tail. The reason why the area ratio was recorded as a feature was that the ratio aspect analysis indicated that the "Production Grade" fish was rounder than the "Superior/Ordinary Grade". The mean area ratio for "Production Grade" fish was 1.3 ± 0.183, while for "Superior/Ordinary" fish the mean area ratio was 0.9 ± 0.15.

Tail length $T_l$ (fig. 4), was defined as the difference:

$$T_l = T_s - T_e \qquad (13)$$

where, $T_s$ was the position calculated as the beginning of the tail, seen from the tail side of the fish, and which was calculated as the difference between the total length of the fish $L_t$ and the value which was 10% of the $L_t$.

$$T_s = L_t - \frac{L_t}{10} \qquad (14)$$

The point position $T_e$ was designated as the end of the tail and was located at the ventral fin. Calculating this involved using more parameters. The ventral fin of salmon served as the boundary for the tail length. After localizing the point $K$, where the minimum width occurred, the middle position $R_m$ was found, which was the row point at half of the $W_{min}$ . By scanning the binary image from the midpoint $J$ to the point $K$ we found the point $T_e$ where the width of the fish was 50% bigger than $W_{half} = \frac{W_{min}}{2}$ :

$$T_e = \arg_j \left[ W; W \geq \frac{3}{2} W_{half}, J \leq j \leq K \right] \quad (15)$$

## 2.4 Training of the Classifier

A dataset consisting of 23 labeled binary images of salmon was used to train the classifier. Nine images of “Production Grade” label salmon and fourteen “Superior/Ordinary Grade” label salmon were used for this purpose. Prior to training we had to decide what type of classifier was most suitable for this case. By analyzing the adopted criteria for feature extractions one by one, we determined how good these criteria were if used as a single classification criterion.

Using only a single criterion for classification was ineffective. We could not reliably separate the “Production Grade” from the “Superior Grade” salmon. By combining two or more criteria, the separability between classes was more reliable. By applying aspect ratio $R_{lw}$ in combination with the area ratio $A_r$, the separability of classes improved (fig. 6). Similar results were obtained with the other combinations of features.

The decision boundary in figure 6 implied that a linear classifier might perform the classification quite well. Therefore, we applied Linear Discriminant Analysis – LDA to train the classifier and took into consideration all four features. The function written in Matlab was based on the Fisher’s linear discriminant (Theodoridis and Koutroumbas, 2003):

$$FDF = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} \quad (16)$$

Testing of the classifier’s performance was done with the Leave One Out (LOO) method (Theodoridis and Koutroumbas, 2003). Training of the algorithm was done with N-1 samples and the test was carried out using the excluded sample. If $X_1$ and $X_2$ were the respective data for classes 1-“Production Grade” and 2-“Superior Grade”, then the training was done using $[X_1 - X(j)]$ and $[X_2 - X(j)]$ samples respectively and the test was carried out with the excluded sample $X(j)$.

$$\begin{bmatrix} X_{1,1} \\ X_{1,2} \\ \cdots\cdots \\ X_{1,j} \\ \cdots\cdots \\ X_{1,N} \end{bmatrix} \xrightarrow[\text{Train with (N-1)}]{} \begin{bmatrix} X_{1,1} \\ X_{1,2} \\ \cdots\cdots \\ X_{1,j+1} \\ \cdots\cdots \\ X_{1,N} \end{bmatrix} \xrightarrow[\text{Test}]{} \left[ X_{1,j} \right]$$

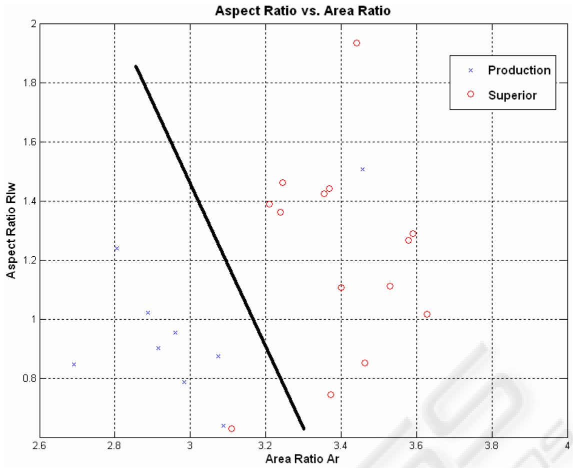


Figure 6: Features of aspect ratio $R_{lw}$ and area ratio $A_r$. The dark line could serve as a decision boundary for our classifier. Classification error was lower than when we used only one feature.

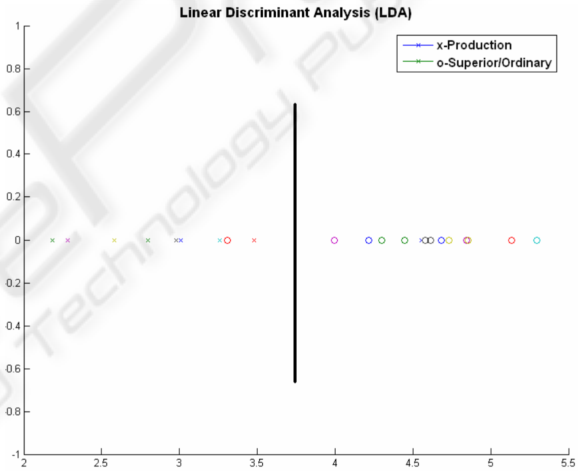


Figure 7: Linear discriminant analysis for training the algorithm with all four features used.

# 3 RESULTS AND DISCUSSION

Twenty three salmon of “Production Grade” and “Superior/Ordinary Grade” were sorted according to four features. The classification error was three, two from “Production Grade” and one from “Superior/Ordinary Grade”. In percent this classifier has an 87% (20 out of 23) sorting reliability as estimated using the Leave One Out method.

One of the two “Production Grade” salmons which are not correctly classified lies further to the right (fig. 7). From the data log we have from the day we picked the fish at the processing plant, the existing ‘outlier’ has neither ‘humpback’ nor ‘short tail’. It was classified as “Production Grade” salmon from the production chief because it had a 'black head'. The work presented, carried out in laboratory conditions, with this classification reliability has to be repeated with a bigger dataset and repeated in the working conditions in the fish processing plant. The work shows a feasibility of sorting one type of fish into different grading classes based on the standards specified by the fish processing industry. There are several problems on which one must focus attention when doing image acquisition of salmon and labelling them into grading classes:

1. The illumination/backlighting system has to be carefully set in order to provide easy thresholding and segmentation of fish images.
2. Labelling of salmon, for the training phase, into grading classes has to be carried out by experts; otherwise one might end up with fish having, for instance, a wrong class label without satisfying any of the parameters defining that class.

# 4 CONCLUSION

A computer vision system and algorithm for sorting Atlantic salmon into two grading classes is described. This classification algorithm works with an estimated sorting reliability of 87%. An improved version of this system can potentially be used to substitute manual inspectors in the fish processing line. Further work is required in acquiring a bigger dataset and expert help on the correct, unmistakable labelling of grading classes, before building a prototype.

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