Computer Vision-Based Sorting of Atlantic Salmon (*Salmo salar*) Fillets According to Their Color Level

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ABSTRACT: Computer vision method was used to evaluate the color of Atlantic salmon (*Salmo salar*) fillets. Computer vision-based sorting of fillets according to their color was studied on 2 separate groups of salmon fillets. The images of fillets were captured using a digital camera of high resolution. Images of salmon fillets were then segmented in the regions of interest and analyzed in red, green, and blue (RGB) and CIE Lightness, redness, and yellowness (Lab) color spaces, and classified according to the Roche color card industrial standard. Comparisons of fillet color between visual evaluations were made by a panel of human inspectors, according to the Roche *Salmo*Fan™ lineal standard, and the color scores generated from computer vision algorithm showed that there were no significant differences between the methods. Overall, computer vision can be used as a powerful tool to sort fillets by color in a fast and nondestructive manner. The low cost of implementing computer vision solutions creates the potential to replace manual labor in fish processing plants with automation.

Keywords: Atlantic salmon, color,computer vision, processing line, quality control

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 fish are exported as raw material, that is, gutted fresh or frozen fish. In both sectors, fish processing is often unprofitable due to the high labor costs. For instance, where salmonids are filleted, the manpower needed on the filleting line alone is typically 20 to 40 persons per shift to process 35 tons of bled, gutted fish from the slaughter line. Ostvik and Jansson (2004) reported that Norway with the present technological level has the highest production cost in fisheries compared to Poland and China. Labor costs represent the bulk of the production costs in Norway. They estimate that the automation of fish processing plants employing computer vision and other robotic machinery in substituting human inspectors would bring savings in labor costs of approximately $1 per produced kilogram of fish.

One of the operations along the fish processing line is color grading of salmon fillets. It is generally accepted that color of salmon products is one of the most important quality parameters in fish processing. Consumers associate redder salmon with being fresher, having better flavor, higher quality, and higher price (Anderson 2000). In addition, different markets tend to have special preferences concerning fillet color. According to market analysis from SalmoBreed (Osland 2001), the Japanese market, for instance, prefers fillets with a deeply red color.

According to the Norwegian Standard NS 9402 (1994), the color measurement of salmon fillets is done using the Roche color cards. Human inspectors are trained to grade fillets by color according to these cards. This manual grading has several drawbacks. First, it greatly increases the production costs. Second, the color grading is not fast, and it is not consistent because human inspectors are subjected to factors such as eye fatigue, lack of color memory, and variations in color discrimination (Irudayaraj and Gunasekaran 2001), resulting in mistakes and occasional omissions in processing. These factors may decrease the product quality and thereby reduce profit (Pau and Olafsson 1991).

Automation of fish processing with computer vision, apart from savings in labor costs, can bring also an overall improvement in the product quality (Arnarson and others 1988). In food industry, there has been a rapid growth over the past decade in development and use of noninvasive methods to evaluate quality (Lin and others 2003). Although a huge variety of examples of using computer vision in food industry have been reported (Panigrahi and Gunasekaran 2001), the use of computer vision in automation of fish processing industry is still limited.

A typical computer vision system (Figure 1) consists of the illumination setup for the acquisition of scene images, a camera for image capturing, and a PC. After the images are captured, they are sent to the computer for further processing. The computer is used for designing the algorithm that enables feature extraction, segmentation, quantification and classification of images, and the objects of interest contained in these images. Feature extraction consists of the choice of distinguishing features that can be used for discriminating patterns in different categories (Duda and others 2001). Segmentation is used to subdivide the image into its constituent regions of interest (Gonzales and others 2004). Two steps are important in the computer vision algorithm design stage: image processing and image analysis. Image processing involves a series of image operations that enhance the quality of image in order to remove defects such as geometric distortion, noise, and nonuniform lighting. Image analysis is the process of distinguishing the objects (regions of interest) from the background and giving quantitative information used for decision making (Brosnan and Sun 2004). Computer vision has

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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 (Panigrahi and Gunasekaran 2001). Mery and Pedreschi (2004) used computer vision for segmentation of color fruit images. Abdullah and others (2000) examine the color of muffins with a computer vision system for separating dark from light samples using pregraded and nongraded muffins. Davidson and others (2001) showed how digital images could be used to estimate physical features such as the color of baked dough. Brosnan and Sun (2004) presented a review on how computer vision can be used to estimate the quality in certain foods such as bakery products, meat, fish, vegetables, grains, fruits, and so on. In fish processing, Strachan and Murray (1991) present a machine, which is based on computer vision, for sex discrimination of mature herring. Misimi and others (2006) have used the computer vision to classify Atlantic salmon in 2 grading classes. Here, a computer vision algorithm was designed to extract the geometrical features of salmon: length, width, area, and ratios among these. Having generated this set of features, a classifier was designed and trained to be able to grade salmon into 2 grading classes: "production grade" with many external deformities and "superior grade" without visible external flaws.

The idea of using color for in-cannery sorting of raw salmon was tested by Schmidt and Cuthbert (1969). They reported that reflectometer measurements using the ratio 650:570 nm correlated well with visual assessment and Hunter *a* and *b* value assessments of flesh color. Color in computer vision has also been used as sorting criteria for classification of fish species (Strachan 1993).

Our goal was to show that, by using computer vision, color of fillets could be quickly assessed from a single image. As a rule of thumb, any method should be able to perform such assessments at about 1 s or less per fillet to cope with the speed of the production line. This restriction alone as well as the contact free feature of computer vision in ¨evaluating quality excludes a number of other sensors that may otherwise be suitable. In the present study, we wanted to compare our computer vision results with the values determined manually using the Roche *Salmo*Fan™ lineal ruler and Roche color card, which according to standard NS 9402 (1994) are used for evaluation of color of salmonids by the fish processing industry.

Materials and Methods

Fish and fish sampling

Atlantic salmon (*Salmo salar*) from 2 different fish processing plants (Marine Harvest and Salmar AS, Hitra, Norway) was used.

Group I: Four "Superior Grade" (weight: 3.7 ± 0.4 kg, length: 60 ± 3 cm, condition factor range: 1.50 to 1.84) and 1 sexually mature fish (weight: 4.3 kg, length: 71 cm, condition factor: 1.19) were selected from the slaughter line on November 12, 2004, at the Marine Harvest salmon processing plant. According to the Norwegian Industry Standard for Fish NBS 10-01 (1999), a "Superior Grade" salmon is a first class product without substantial faults, damage, or defects, and provides a positive overall impression. Condition factor (K) is a number that is used to quantify the condition of fish. Fulton (1902) proposed to use a mathematical formula for this quantification:

$$K = \frac{10^5 W}{L^3} \tag{1}$$

where W is the weight of the fish in grams (g), L is the length of fish in millimeters (mm).

Fish with the condition factor $K = 1$ are considered as poor fish (Barnham and Baxter 1998) because they are long and thin. Fish with $K = 1.4$ are considered to be good fish, being well proportioned, while fish with condition factor $K = 1.6$ are fish in excellent condition.

The fish, except the sexually mature fish, were bled and gutted at the plant. All fish were transported to our laboratory in styrofoam boxes containing ice. The fish were subjected to postrigor analysis 3 d postmortem. The core temperature was 1.4 ± 0.4 °C. At this point, the sexually mature fish was filleted. Fillet color ($n = 8$) was determined using sensory evaluation, a Minolta chromameter, and a computer vision system.

Group II: "Superior Grade" fish (weight: 5.6 kg ± 1.0 kg, length: 74 cm ± 5 cm, mean condition factor: 1.4, $n = 18$) were sampled individually (January 5, 2005) from a commercial processing line (Salmar AS) prior to killing and further processing (that is, the fish were not bled). Our fish were rapidly killed by a blow to the head, placed in styrofoam boxes containing ice, and transported to our laboratory. Fish were stored on ice in a cold room at 5 °C. The fish had been fasted for 30 d before slaughter and the content of astaxanthin in the muscle of fish from the same batch (cage) was 7.3 mg/kg. After 4 d of ice storage, the fish were filleted (postrigor) before being subjected to the various analyses the same day. The ultimate fillet pH was 6.46 ± 0.06 ($n = 18$). The fillets were of very good quality, with a firm, elastic texture with practically no visual signs of gaping. The following fillet quality-related parameter was assessed: color ($n = 33$). The assessment was done using the sensory evaluation method, the Minolta chromameter, and the computer vision system.

Sensory evaluation of color

The color of the fillets (both groups) was descriptively evaluated by 3 panelists according to the Norwegian Standard NS 9402 (1994) for measuring color of Atlantic salmon. This evaluation was performed visually in the daylight using Roche color cards (Figure 3.)

Instrumental evaluation of color

L^*, a^*, and b^* values (CIE 1976) were measured using a Minolta Chromameter CR-200/CR231 (Minolta, Osaka, Japan). Color readings for all fillets were taken at the same day when the sensory

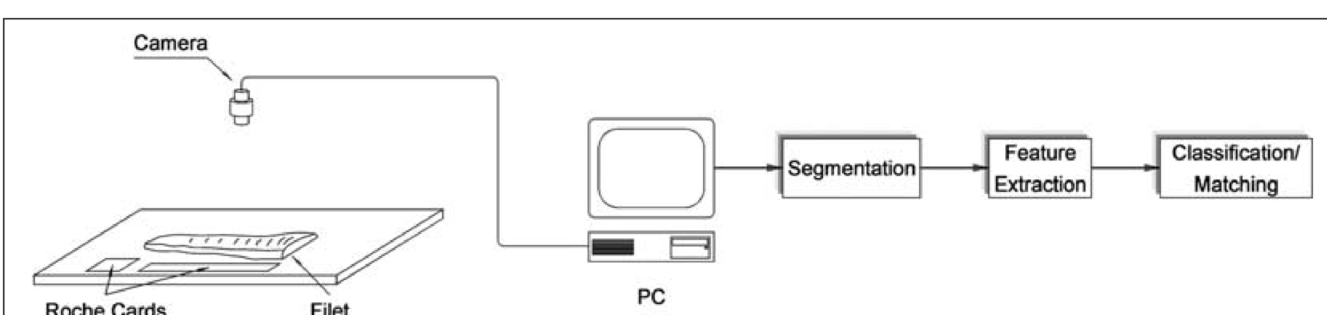

Figure 1 — The computer vision system for color evaluation

evaluation of color of fillets was performed and prior to taking the image with digital camera. The chromameter consists of a pulsed xenon lamp that illuminates the surface of the fillet and collects the reflected light for color analysis. For all fillets of both groups, the color-related assessments were carried out in white muscle (locations 1 to 3) and in the belly flap (locations 4 to 5) (Figure 2). Here, L^* denotes lightness in the scale of 0 to 100 from black to white, a^* is redness (+) values are red whereas (–) values denote green and b^* denotes yellowness (+)–yellow or (–)–blue. The chromameter instrument was calibrated using a standard white plate and was positioned perpendicular to the fillet surface when the measurements were taken. The chromameter measurements were collected over the 8 mm dia of the probe area.

Computer vision evaluation of color

Each fillet from both groups was photographed (Figure 2) along the Roche *Salmo*Fan ruler (range: 20 [pink] to 34 [dark red]) and Roche color card (range: 11 [light orange] to 18 [dark red]) (Hoffmann-La Roche, Basel, Switzerland) (Figure 3). Images of fillets were captured on the same day the sensory and the instrumental evaluation of color were performed, but they were processed later.

Image acquisition

The images of fillets for color assessments were captured using a computer vision system (Figure 1) for a digital color camera (Nikon Coolpix5000, Nikon, Tokyo, Japan) at the resolution of 1600 × 1200 pixels. Images were acquired in the JPEG format and processing was carried out in the captured images (still). However, commercial industrial full frame digital cameras with comparable resolution are available at near real-time speeds (Pacer Components PLC, Berkshire, England). The use of a line-scan color camera is most likely preferable in an industrial setting, due to their high speed and the fact the fish in most cases are transported on conveyor belts. The white balance of the camera was set using the camera automatic white balance based on a white plate covering the entire field of view of the camera. Two different illumination setups were used during the image acquisition. The first setup, for color evaluation of fillet Group I, used 2 parallel halogen lamps with color temperature 2900 K and 300 W each (Figure 4). The lamps were placed 30 cm below the fillet, whereas the reflecting white cardboard plates were set at an angle of 45°. Reflection plates were used to provide with diffuse illumination in order to avoid specular reflections from the fillet and to improve the quality of the captured images. The images were acquired freehand in a 90° angle, 60 cm above the fillet. The 2nd setup, for evaluation of fillet Group II, used 4 lamps (2900K, 15W, 135 mA) as suggested by Papadakis and Abdul-Malek (2000) (Figure 5). In this setup, the lamps were positioned in a 45° angle and 40 cm above the fillet, whereas the camera was fixed to a bar, perpendicular to the plane where the fillets were located.

Image segmentation and enhancement

Color analysis and classification of fillets according to Roche cards by computer vision were performed in red, green, and blue (RGB)

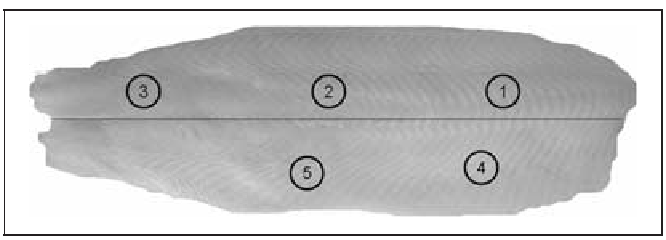

Figure 2 — The computer vision color data were compared with Roche *Salmo*Fan™ and Roche Color Card readings and L^*, a^*, and b^* values in locations 1 to 5. Numbers on the fish are the locations where the measurements were made.

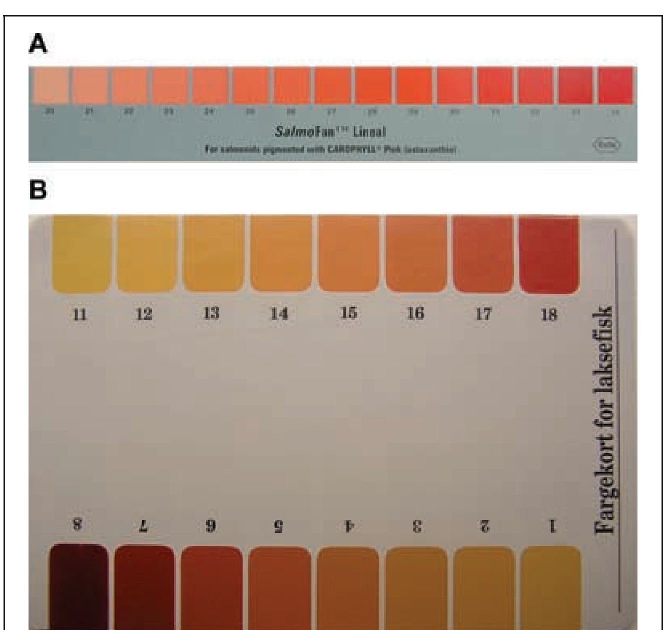

Figure 3 — Roche cards used for evaluation and classification: (a) Roche *Salmo*Fan ruler, (b) Roche color card

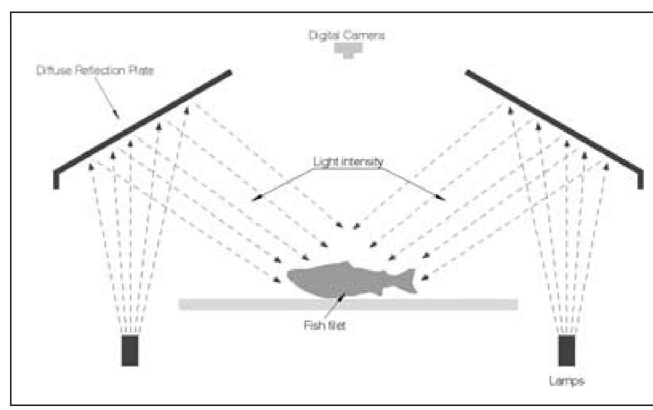

Figure 4 — Experimental setup for the illumination of fillet Group I

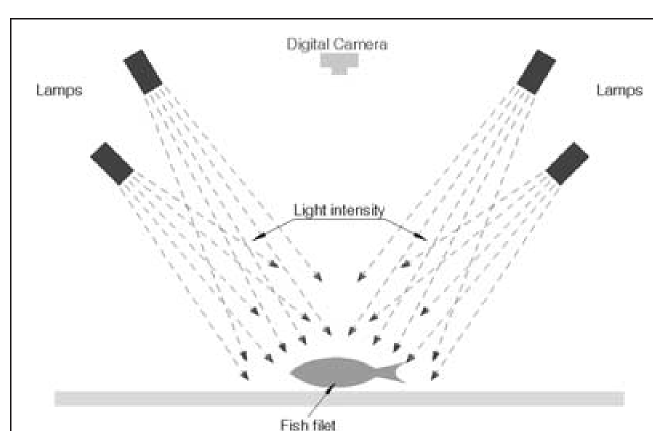

Figure 5 — Experimental setup for the illumination of fillet Group II

and CIE $L^*a^*b^*$ color space. The algorithm for classification of the fillets was developed within the Matlab 6.5 Development Environment (Mathworks, Mass., U.S.A.) using the Image Processing Toolbox 3.2. The sequence of the classification algorithm is depicted in Figure 6. After image acquisition, the fillet could be isolated from background either in Matlab or even simpler in Adobe Photoshop(Adobe, San Jose, Calif., U.S.A.), in order to be viewed as a single region of interest for further analysis. For the purpose of this work, the segmentation was optional, but in an online application the segmentation of fillets from the background would be necessary for the purpose of color matching. Then, the segmented image was converted to a true color RGB image, isolating the fillet from the image background (not of interest for further analysis). The image enhancement consisted of filtering the fillet images from high frequent components and noise. From the color scores of the Roche *Salmo*Fan™ ruler and Roche color card, we generated a look-up table by integrating the color of every color rectangle and finding its mean value. For the color evaluation of the fillets according to the Roche *Salmo*Fan ruler, we used all color scores (20 to 34), while for the evaluation according to the Roche color card, we used the color scores designated with numbers from 11 to 18 (Skrede and others 1990).

Normalized RGB and look-up table generation

In the look-up table, the information for each color score of the Roche ruler was memorized in form of means of normalized red (R), green (G), and blue (B) values. The normalization of RGB values was done to remove the device dependency toward the RGB color space and to remove the brightness. The normalized values were calculated from these expressions:

$$r = \frac{R}{R+G+B} \tag{2}$$

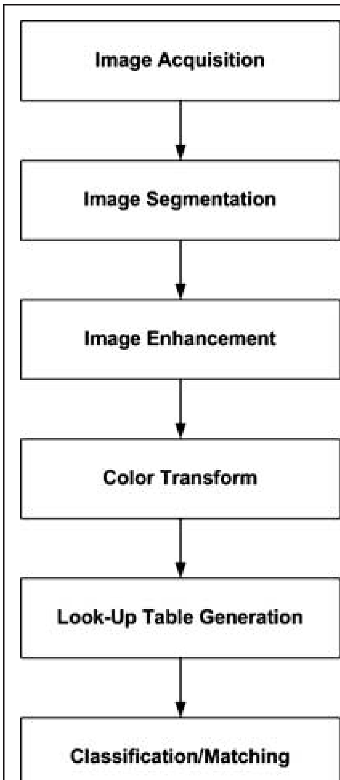

Figure 6—The sequence of the classification/ matching algorithm

$$g = \frac{G}{R+G+B} \tag{3}$$

$$b = \frac{B}{R+G+B} \tag{4}$$

Color feature extraction and classification

From the mean r_{li}, g_{li}, r_{ci}, and g_{ci} values, the algorithm created 15 color pairs (r_{li}, g_{li}), one for each value of the Roche *Salmo*Fan ruler, and 8 color pairs (r_{ci}, g_{ci}) for the Roche color card. For a normalized values of red, green, and blue (RGB), the relationship $r + g + b = 1$ holds (Panigrahi and Gunasekaran 2001), and hence the value b is not taken into consideration, because it can always be calculated by simply taking $b = 1 - (r + g)$. After the retrieval of mean values for R and G for each Roche color score, the algorithm proceeded with the calculation of the mean red and green values for the regions of interest in the fillet (Figure 2). There were 5 regions of interest the algorithm dealt with. Each region of interest was chosen simply by clicking with a mouse on the region of interest in the fillet image for classification according to Roche ruler. For each fillet, the algorithm calculated 5 pairs of mean values for red and green, each pair corresponding to the chosen region of interest, and compared these with the matching pairs

$$m_j = (r_j, g_j),\ j = 1, \ldots 15 \tag{5}$$

from the Roche *Salmo*Fan ruler. Geometrically, pairs r_{li},g_{li} lie in the plane $r_l O g_l$, whereas pairs r_{ci}, g_{ci} lie in the plane $r_c O g_c$. Determination of the matching Roche scores of the selected regions of interest was done according to the nearest neighbor principle (Theodoridis and Koutroumbas 2003). This means that the region of interest was assigned the color of its nearest neighbor. Calculation of distances for the nearest neighbor rule was done by calculating the Euclidian distance between the fillet point $\overline{p_i}$ in red, green, and blue (RGB) space and Roche color vector m_j (Gonzales and others 2004) which is given by

$$D_E(\bar{p}, m) = \|p - m\| = \left[(p_R - m_R)^2 + (p_G - m_G)^2\right]^{1/2} \tag{6}$$

The estimated Roche score of the fillet point $\bar{p}_i$ is computed by

$$R(\bar{p}_i) = 19 + \arg \min_{j=1,\ldots 15} D_E(\bar{p}_i, m_j) \tag{7}$$

Statistics

Mean, standard deviation was calculated and analysis of variance (ANOVA) was performed using Minitab 14.1 (Minitab Inc., Pine Hall, U.S.A.) statistical software. A significance level of $P < 0.05$ was chosen.

Results and Discussion

A major finding regarding the fillet color (Figure 2) was that, for both groups, no significant differences ($P > 0.05$; Table 2) in the color values according to Roche card were found between the computer vision method and the traditional method of sensory evaluation of color by human inspectors. From Table 1, it is seen that the color discrimination did not differ much from the sensory evaluation method and the computer vision method. By looking at the means and the standard deviations (Table 1) between sensory evaluation and computer vision method of color measurement according to the Roche cards, it was noted that there was no significant difference between them. This was evident for both groups. As is seen in Table 1, computer vision evaluation gave higher values in Roche scores for 1 unit than the sensory evaluation method for 2 of overall 5 fillet locations. Statistical analysis (Table 2) for both groups of

Table 1—Comparison of color values in different 5 locations (Figure 2) on Atlantic salmon fillets as determined by computer vision and the Roche *Salmo*Fan ruler

	Fillet color values				
Method	**1**	**2**	**3**	**4**	**5**
Group I*					
Roche SalmoFan-visual	23[a]	23[a]	20[a]	22[a]	21[a]
Computer vision	22[a]	20[a]	21[a]	21[a]	20[a]
Group I					
L^* (Minolta-M)	40 ± 1	39 ± 2	38 ± 1	45 ± 3	45 ± 2.5
a^* (M)	11 ± 1	11 ± 0.5	12 ± 1	12 ± 2	12 ± 1
b^* (M)	11 ± 1	11 ± 1	12 ± 1.5	13 ± 3	15 ± 2
L^*(computer vision-CV)	62 ± 1	63 ± 0.5	62 ± 2	64 ± 0.5	64 ± 1
a^* (CV)	34 ± 3	33 ± 3	38 ± 2	27 ± 3	28 ± 2
b^* (CV)	58 ± 3	59 ± 3	61 ± 2	54 ± 3	54 ± 3
Roche SalmoFan-visual	28 ± 1	28.5 ± 1	29 ± 1	22 ± 1	23 ± 1
Computer vision	29 ± 1	29 ± 1	30 ± 1	23 ± 1	23 ± 1
Group II†					
L^* (Minolta-M)	40.25 ± 2.4	40 ± 2	38 ± 1.3	51 ± 3	51 ± 6
a^* (M)	11.8 ± 1	12 ± 1	11.5 ± 1	15 ± 1.5	13 ± 1.3
b^* (M)	12 ± 2	12.8 ± 1	11.5 ± 1.7	17.5 ± 2.5	15 ± 2
L^* (CV)	64.3 ± 0.5	64 ± 0.5	64 ± 1	65.5 ± 0.5	66 ± 0.5
a^* (CV)	26 ± 3	28 ± 2.5	28 ± 5	18 ± 3	17 ± 1.5
b^* (CV)	59 ± 6	63 ± 3	55 ± 7	50 ± 7	50 ± 4.5
Roche SalmoFan-visual	27 ± 1	28 ± 1	27 ± 2	24 ± 2	23 ± 2
Computer vision	28 ± 1	28 ± 1	28 ± 2	23 ± 2	23 ± 2

[a]Sexually mature fish (n = 1).

fillets included all fillets and their color scores (consequently all the means of color values in Table 1) measured by the sensory evaluation method and the computer vision method. This analysis showed that there was no significant difference between the sensory evaluation method and computer vision method.

An immediate implication of these results is that the computer vision method is not different from the traditional sensory evaluation of fillet color. The advantages of using computer vision in automating the operation of color sorting of salmon fillets, as reported in (Irudayaraj and Gunasekaran 2001), are the long-term consistency and objectivity in color assessment. This is because in computer vision, there is no eye fatigue or lack of color memory, and illumination conditions are uniform (Irudayaraj and Gunasekaran 2001). In addition, automation of this operation can bring a reduction in labor costs and production costs. Automation can remove the need for operator facilities, lighting, heating, clothing, and washing facilities (Purnell 1998). An important ability of computer vision method is that once the image of fillet is captured, one can measure the color of the entire fillet (the mean color value) or one can measure the color of a specific region of interest, as in locations (1 to 5) in Figure 2.

The color scores were significantly different from 1 point to another point of assessment ($P = 0.000$) on the fillet for both groups of fillets no matter which method for color evaluation was used (color of location 1 is different from the color of location 5). This was because locations in the white muscle (1 to 3), where we measured the color, were redder than locations (4 to 5) in the belly flap. In Table 1, it is shown that L^* values for the white muscle locations (1 to 3) were lower from those of belly flap locations (4 to 5), which means that the belly flap locations are brighter. The same conclusion is drawn by looking at the values generated by the computer vision method and sensory evaluation according to the Roche card standard. Both of these methods gave higher (redder) Roche color card scores for the white muscle locations (1 to 3) than for those of belly flap (4 to 5).

The significance level ($0.997 > 0.119$) for method comparison was higher for the 1st group (Method*Point in Table 2) than for the 2nd. In this table are shown the difference between sensory evaluation method and computer vision method (Method in Table 2), the difference between locations of assessment for both methods (Point in Table 2), and the difference between the methods taking all points into the account (Method∗Point in Table 2). The higher significance level for the 1st group may be due to different illumination setups used for the image acquisition but also due to the different group sizes. By analyzing L^* values for both groups, it was noted that the 1st group was slightly darker in the muscle flesh (Table 1). By looking at the L^* values generated by both the chromameter and the computer vision algorithm, it is seen that the 1st group appeared slightly darker than the 2nd one. This was also confirmed by the Roche color card scores obtained from the sensory evaluation and the computer vision algorithm. The means of color assessments according to the Roche color card for both of these methods were higher for the 1st group.

Computer vision values for the color scores of fillets generated by the algorithm were consistent, because the algorithm gave the same values under the given illumination conditions, and was invariant to illumination, provided that the illumination was the same for all fillets, which were used in the classification. On the other hand, human ability to distinguish color tends to be subjective. This can make the same Roche scores be interpreted differently, depending on light conditions, that is, whether human inspectors were performing classification in the daylight conditions or in the artificial illumination conditions. Provided that illumination is controlled, for example, in a light box, the assessment of fillet color with computer vision algorithm would be consistent and stable.

Table 2—Analysis of variance (ANOVA) for the computer vision method of evaluation and the method used by human inspectors

	***P* value**
Group I	
Method	0.715
Point	0.000
Method∗ Point	0.997
Group II	
Method	0.189
Point	0.000
Method∗ Point	0.119

When it comes to the Minolta chromameter measurements, the CIELab values generated by the Minolta chromameter and those generated by the computer vision algorithm showed large deviations in mean value (Table 1). For instance, the mean of the computer generated L^* value for a certain location of color assessment was on average 23 units higher than the value measured with chromameter. This deviation is within the standard range reported earlier in the Kim and others (2005), and it is due to the brighter illumination used by the computer vision setup. The Minolta chromameter uses a pulse of xenon light to illuminate the examination area, which is 8 mm in diameter and measures the reflected light from the flesh.

This made CIELab values generated by the Minolta chromameter not comparable with the CIELab values generated from the computer vision algorithm, as reported in Kim and others (2005). The CIELab values by algorithm were obtained by converting the normalized RGB values into the CIELab color space. However, the converted color values may differ considerably from the standard CIELab values taken with chromameter and, therefore, would not allow the comparison of values between those generated by algorithm and those generated by chromameter (Kim and others 2005).

Conclusions

The results have demonstrated the ability of the method based on computer vision to classify fillets according to color. This method was a fast, nondestructive, and contact-free evaluation and was not significantly different from the traditional method of evaluating the color by human vision. The results have demonstrated that the computer vision-based method of evaluating color was just as good as the traditional one. The better side of the computer vision method is that this method is faster, robust, and consistent. Since human operators are a factor in product contamination, the costs of preserving hygiene with the large numbers of staff present in a fish processing plant increase the overall production cost. The use of computer vision would result in a decrease of product contamination. With the automation of fish processing, there would also be less need for lighting and heating of the production premises and automation would allow processing in environments beneficial to quality of fish products, for example, sustained low temperatures. Time savings would also be considerable. A computer vision system is designed to process a minimum of 1 fillet per second, while human inspectors use longer time when using either a sensory or instrumental method because they are susceptible to fatigue and because of the involved labor. And finally, the fish processing plants would save $1 per kilogram in labor costs. These are the estimated labor cost savings for the Norwegian fish processing industry. When it comes to implementation of the computer vision system in the future, it is preferred to use controlled illumination conditions for the purpose of classification of fillets, for example, by using a light box with a uniform illumination. Results showed that computer vision-based classification can be successfully used to replace human inspectors in the color assessment of salmon fillets.

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