Towards Automated Sorting of Atlantic Cod (*Gadus morhua*) Roe, Milt, and Liver – Spectral characterization and classification using visible and near-infrared hyperspectral imaging

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ABSTRACT

Technological solutions regarding automated sorting of food according to their quality parameters are of great interest to food industry. In this regard, automated sorting of fish rest raw materials remains as one of the key challenges for the whitefish industry. Currently, the sorting of roe, milt, and liver in whitefish fisheries is done manually. Automated sorting could enable higher profitability, flexibility in production and increase the potential for high value products from roe, milt and liver that can be used for human consumption. In this study, we investigate and present a solution for classification of Atlantic cod (*gadus morhua*) roe, milt and liver using visible and near-infrared hyperspectral imaging. Recognition and classification of roe, milt and liver from fractions is a prerequisite to enabling automated sorting. Hyperspectral images of cod roe, milt and liver samples were acquired in the 400 – 2500 nm range and specific absorption peaks were characterized. Inter- and intra-variation of the materials were calculated using spectral similarity measure. Classification models operating on one and two optimal spectral bands were developed and compared to the classification model operating on the full VIS/NIR (400 – 1000 nm) range. Classification sensitivity of 70% and specificity of 94% for one-band model, and 96% and 98% for two-band model (sensitivity and specificity respectively) were achieved. Generated classification maps showed that sufficient discrimination between cod liver, roe and milt can be achieved using two optimal wavelengths. Classification between roe, milt and liver is the first step towards automated sorting.

Keywords: Automation, Atlantic cod, roe, milt, liver, raw material, industrial, sorting.

1. Introduction

The whitefish industry in Norway is a growing industry with small profit margins. The total quantity of whitefish catch in 2013 was 0.775 million metric tons measured in live round weight (Olafsen et al., 2014). From this amount, there were generated 0.34 million metric tons (44% of the total catch) of rest raw material (by-products). Rest raw material is the raw material that is generated after the fish are gutted and processed. The most known rest raw materials are heads, tongues, liver, roe and milt. The amount of rest raw material that is utilized is only 113 800 tons, meaning that 226 000 tons of rest raw material are not utilized at all. Thus, there is a large potential in increased utilization of rest raw material, which may enable a more sustainable and profitable whitefish industry.

One of the main reasons for the absence of the higher utilization of rest raw material from white fish are the lack of technological solutions regarding automated sorting and handling on-board the vessels. After gutting, the rest raw materials from white fish are piled randomly in fractions and there is a need to physically separate them before they can be utilized or stored. The separation of fractions or sorting of whitefish roe, milt, and liver, is done manually due to the lack of technology solutions for automated sorting. The manual sorting is a laborious and costly process. Annually, the total available quantum of roe, milt, and liver combined is ca 95000 tons (Richardsen et al., 2014, Norwegian Directorate of Fisheries 2015). From a technical point of view, it is very challenging to handle such large amount of roe, milt, and liver manually, to sort these fractions and to preserve them in a cost-efficient manner without automated solutions. Currently, a small amount of roe, milt, and liver are used for human consumption and majority goes to flour and oil products that are used as feed for fish and domestic animals. Automated sorting could make possible for a general increase in utilization of these rest raw materials and contribute in a higher bio-resource efficiency of the whitefish catch and reduction of waste. Specifically, it would enable higher flexibility for production and increase the potential for high value products that can be used for human consumption instead for feed. For example, liver is used for oil production, while roe and milt can be sold as whole fractions, preserved, salted or used for extraction of omega-3 (Rustad et al., 2011). Because roe, milt, and liver have different chemical composition, enzymatic activity and behave differently during storage and in order to keep the best quality they need to be sorted and treated accordingly to the intended use. Therefore, the effect of automated sorting is not only economical; i.e. higher profitability and capacity compared to manual labour; but also environmental as more by-products would be used for human consumption and less would go to waste.

In order to enable physical automated sorting of roe, milt and liver, one should be able to recognize and classify these fractions in separate classes (Falch et al., 2006). Classification of roe, milt, and liver, due to the similarities in the appearance manifested in colour and texture, is a challenging research task. Firstly, it is necessary to be able to discriminate between liver, roe and milt effectively by use of a non-destructive on-line sensor technology. Recently, image based sensor technologies (Mathiassen, 2009; Balaban et al., 2012; Mathiassen et al., 2011; Jackman et al., 2011; Misimi et al., 2014) as well as visible and near infrared (VIS–NIR) spectroscopy have been successfully proved to be efficient and advanced tools for non-destructive analysis and control for food quality for both external and internal parameters and features (Wu & Sun, 2013; Kamruzamman et al., 2015; Cheng & Sun, 2014; ElMasry & Sun, 2010; Heia et al., 2007; Sivertsen et al, 2011; Måge et al., 2013; Iqbal et al., 2013, Huan et al., 2014).

In particular, Iqbal et al., 2013 developed a hyperspectral imaging system in the near infrared (NIR) region (900–1700 nm) to predict the class category in cooked, pre-sliced turkey hams based on spectral characterization of colour. Spectral data were extracted and analyzed using partial least-squares (PLSs) regression, and nine wavelengths were identified for colour (a – redness) prediction with a correlation coefficient R^2=0.74. Xiong et al. 2015 investigated the potential of hyperspectral imaging (HSI) for quantitative determination of total pigments in red meats, including beef, goose, and duck. The models they developed yielded good results with the coefficient of determination (R^2) of 0.953, indicating that hyperspectral system had the capability for predicting total pigments in red meats.

Balaban et al. (2012a) developed a method for weights prediction of Pollock roes based on 2D images. Balaban et al. (2012b) reported that evaluation and quantification of colour of Pollock roe based on digital images is a difficult and complicated operation due to colour variations on the surface area of the roe. They developed methods based on image analysis to quantify colour defects on Pollock roe such as green spots, dark strips, dark colour, and uneven, colouring due to “freezer burn”. These defects were identified in the CIELab colour space (L-lightness, a-redness, b-yellowness).

Bekhit et al. (2009) characterized colour parameters (Lightness L, redness a, yellowness b, hue H, and chroma C) and spectral surface reflectance of raw and processed roes from six commercial New Zealand fish species such as chinook salmon, hoki, southern blue whiting, hake, blue warehou, and barracouta. The spectral reflectance of the roe surfaces reflected the differences found among the raw roes and the impact of the processing. From all colour parameters, the redness (a-channel in CIELab colour space) was the major contributor in the separation of the different roe products.

Kurnianto et al. 1999 used a machine vision system for grading of herrings roes according to weight and colour. The weight prediction was based on shape and contour analysis of the herring roes. They also showed a subsystem for ultrasonic imaging for firmness measurement. The colour of the roes was analyzed in R-red channel of the RGB images acquired with the JVC CCD camera of 512x512 resolution. The total grading of 82-88% accuracy was acquired with the validation tests in the developed system. Beatty et al. (1993) used shape descriptors for automated herring roe grading. Croft et al. 1996 report an "intelligent" decision system based on shape, firmness/texture and colour to determine the final grade of the roe product using fuzzy-logic and model-matching procedures reaching a classifier accuracy of 95%.

Mathiassen (2009) used machine vision and a 5-DOF (Degree-Of-Freedom) robot arm to sort cod viscera based on stereo camera platform with digital images in the visual range by combination of colour and image texture. The main challenge was to identify the respective fraction in the digital image and it was concluded that detection and identification of fractions is a very challenging problem to solve based on only digital images (visual spectrum) without any prior spectral characterization.

Therefore, based on the literature review, the operation of automated classification of roe, milt and liver appears to be challenging and complicated due to similarities of these fractions in colour and uneven distribution of colour over the surface area. The objective of our research in this study was enable the first step towards automated sorting of roe, milt and liver by accomplishing these research subtasks: a) completely characterize roe, milt and liver from Atlantic cod by collecting reflectance spectra in the VIS/NIR (400-1000 nm) and SWIR (960 – 2500 nm) wavelength range; b) establish a classification model for the most optimal wavelengths or combination of wavelengths across the VIS/NIR range (400-1000 nm); c) identify the most optimal wavelengths for the VIS/NIR range for particular wavelengths for which there are commercially available lasers; and finally d) test and develop classification/prediction maps.

2. Materials and methods

2.1. Sample preparation

In this study, sixty samples of three different raw materials (liver, roe and milt) originated from Atlantic cod (gadus morhua) were prepared. The raw material was shipped from Nergård AS whitefish company (Nergård AS, Tromsø, Norway). Samples were cut to nearly the size 3 cm x 2 cm x 1.5 cm (length x width x thickness). The samples were divided into 3 groups consisting of 20 samples of roe, 20 samples of liver and 20 samples of milt, group A, B and C respectively. Each sample was placed on a separate petri dish and labeled with corresponding group letter and sample number. The samples were used to extract spectral characteristics, establish and verify the classification models.

2.2. Hyperspectral imaging system

Hyperspectral images were acquired using two push-broom line scanning hyperspectral cameras HySpex VNIR-1600 and HySpex SWIR-320m-e (Norsk Elektro Optikk AS, Skedsmokorset, Norway). The working spectral range for the VNIR-1600 system is 400-

1000nm with a spectral resolution of 3.7 nm, thus producing the total of 160 spectral bands. The size of instantaneous field of view (iFOV) is approximately 10cm, with a spatial resolution of 1600 pixels. The SWIR-320m-e system acquires hyperspectral images in the wavelength range of 960-2500 nm, producing the total of 256 spectral bands. The size of iFOV is approximately 9 cm, with a spatial resolution of 320 pixels. The working distance for both cameras was 30 cm. Constant broad band illumination across the iFOV was provided by two 150 W halogen lamps (Norsk Elektro Optikk AS, Skedsmokorset, Norway). Polarizers (VLR-100 NIR, Meadowlark Optics, Frederick, Colorado, USA) were mounted on the camera lens and on the light sources in order to avoid specular reflection from the samples. Translation stage (Motorized Linear Stage 8MT175, Standa Ltd, Vilnius, Lithuania) and stepper motor (8SMC1-RS232, Standa Ltd, Vilnius, Lithuania) were used to perform translation motion of the samples under iFOV of the cameras.

Calibration parameters of each camera were acquired during calibration procedure performed prior to the experiment and stored in a form of calibration files. The calibration files contain information about sensor responsivity, pixel-to-pixel non-uniformities, band numbers and bad pixels.

2.3. Hyperspectral imaging and image preprocessing

Each sample was imaged individually. A petri dish with the sample was placed on the translation stage together with a standard teflon calibration tile (Spectralon, Labsphere Inc., North Sutton, USA) and then conveyed across the field of view of the camera. The frame period (22000 μs and 10101 μs for HySpex VNIR-1600 and HySpex SWIR-320m-e, respectively) and integration time (21000 μs and 4500 μs for HySpex VNIR-1600 and HySpex SWIR-320m-e, respectively) were set in the image acquisition software (HySpex Ground, Norsk Elektro Optikk AS, Skedsmokorset, Norway) and remained the same for all the samples. The dark current effect of the camera was corrected by subtracting the background signal in real time during image acquisition process. The calibration files were used to convert all images to “at sensor radiance” data followed by denoising procedure using the Minimum Noise Fraction (MNF) transformation (Green et al., 1988). Denoised radiance data were then converted to reflectance according to the following equation:

$$I_i = \frac{R_i * Iref_i}{W_i} \quad (1)$$

where *I* is reflectance image, *R* is noise-reduced hyperspectral image, *Iref* is known reflectance of the Spectralon calibration tile, *W* is white reference image, *i* is the band number *i* = 1, 2, 3,...,*n* and *n* is the total number of bands.

2.4. Extraction and characterization of spectra

After image acquisition and reflectance calibration, the ENVI software (Exelis Visual Information Solutions, Inc., Boulder, Colorado, USA) was used to extract reflectance spectra from the samples. For each sample, five random locations were selected and spectra were extracted by averaging over a 10 x 10 pixel window. In total, 200 spectra were extracted for material A (roe) and B (liver), and 95 spectra were extracted for material C (milt) (one image was corrupted during acquisition). Mean reflectance spectra of each tested raw material were calculated from the extracted spectra and transformed into an absorbance profile according to

$$A = -\log_{10} R \quad (2)$$

where *A* is absorbance and *R* is mean reflectance spectra of the given raw material.

The absorbance profile of each raw material was analyzed and the spectral features were characterized. Inter- and intra-variation of each raw material were calculated using spectral similarity measure (Spectral Angle Mapper - SAM) (Schowengerdt, 1997).

The SAM method is a spectral classification algorithm that operates in n-dimensional space. The method determines spectral similarity measure as an angle between two spectra, treating them as vectors in space with dimensionality equal to the number of spectral bands. This method is insensitive to illumination since the SAM algorithm uses only the vector direction and not the vector length (Kruse et al., 1993). SAM can be also used as image classification algorithm. Most common approach is pixel-wise classification, where spectra of each pixel are matched with reference spectra of the known material (Bac et al, 2013). The performance of SAM and other widely used supervised classification methods for food applications has been investigated by Park et al. (2003, 2007).

2.5. Wavelengths selection

Image classification is a decision process where each pixel of the image is assigned to a known cluster/class. Since hyperspectral imaging provides information of a very high spectral resolution, it is possible to construct the classifier that takes advantage of a nearly continuous spectrum. Such a classifier can provide detailed classification maps based on the full spectral profile. However this approach is not a practical solution in industrial applications, due to high complexity of the system. Moreover, a system operating in the wavelength range above 1000 nm would significantly increase the overall costs of the system.

In our case, the classification algorithm should be able to distinguish three different raw materials liver, roe and milt, using a limited number of spectral bands, preferably in visible range of the spectrum.

The extracted reflectance spectra were used in wavelength selection procedure. Two models were investigated, Model I operating on a single spectral band and Model II that involves operation on two spectral bands. The optimal bands were selected using leave-one-out cross-validation method (LOOCV). Cross validation methods are commonly used to compare the performance of two or more different algorithms and find the best algorithm for the available data, or alternatively to compare the performance of two or more variants of a parameterized model. In leave-one-out cross-validation, each iteration uses nearly all the data except for a single sample for training and the model is validated on that single sample. An accuracy estimate obtained using LOOCV is known to be almost unbiased, however it has high variance (Refaeilzadeh et al., 2011; Efron, 1983).

2.5.1. Single band model

To provide the reader with better understanding of the selection procedure we present the evaluation of a model on a one band. In total, 295 reflectance spectra were extracted from 59 samples for material A – roe (100 spectra), B – liver (100 spectra), and material C – milt (95 spectra) Spectral reflectance values for given band are split into a training group and a validation group. The training group consists of the 290 reflectance values from 58 samples and the validation group consists of 5 reflectance values from 1 sample. Mean reflectance μ and standard deviation σ for three raw materials are calculated using the values from the training group. Classification criteria are then calculated using $\mu_m \pm \sigma_m$ as a cut-off, where m is the index corresponding to raw material A, B, or C. Reflectance values from validation group are compared to classification criteria and the number of correctly classified values is recorded. The process is cross-over in successive rounds such that each sample is held-out for validation. The total number of correctly classified values is used as an estimate of model performance on the particular band. After each band is evaluated, the band with the highest performance is selected as the optimal band.

2.5.2. Two bands model

For two band model (Model II), the spectra were first processed according to the following equation:

$$Y = \frac{(I_{b1}+I_{b2})}{(I_{b1}-I_{b2})} \quad (3)$$

where *I* is reflectance image and *b1*,*b2* are two selected spectral bands.

LOO cross-validation was performed on all possible two-band combinations. Classification criteria were calculated using $\mu \pm 2\sigma$ as a cut-off. The total number of correctly classified values is used as an estimate of model performance on the particular band combination. After all possible combinations are evaluated, the band with the highest performance is selected as the optimal combination. Performance of 1 band model and 2 bands model was compared to SAM classification of the spectra based on the full visible spectrum (160 spectral bands). The performance was tested by sensitivity (Se) and specificity (Sp) which are measures of the performance of a diagnostic test and are intimately connected with probability calculations and are calculated as

$Se = \frac{TP}{TP+FN}\, and\, Sp = \frac{TN}{FP+TN}$, where TP-True Positives, TN-True Negatives, FP-False Positives, FN-False negatives (Vidakovic, 2011).

2.6. Image classification

For the purpose if image classification additional 4 images were acquired. Each image consisted of three samples (one sample of each raw material A – roe, B – liver, and material C – milt) None of the samples were previously used for spectra extraction and evaluation of the models. The images were classified using established classification models (Model I and Model II). The obtained classification maps were compared to the classification maps generated by pixel-wise SAM algorithm operation on the full spectral profiles from VIS/NIR range (160 spectral bands).

3. Results and discussion

Flexible automation, i.e. automation that is able to handle biological variation of raw material in shape, colour, texture, mechanical and optical properties is one of the most immediate needs of fisheries in Norway (Tveterås 2014, Balaban, Misimi & Alcicek 2015). Currently, the physical sorting of white fish roe, milt and liver remains a manual operation due to the lack of technological solutions for automated sorting. The first step towards automation of this operation is development of a method for robust discrimination and classification of roe, milt and liver from randomly piled fractions on-board vessels after manual handling.

Due to the similarities in colour between roe, milt and liver, there has been difficult to recognize and classify these fractions by digital images in visible range (Mathiassen 2009) when they are piled up randomly. Spectral characterization was therefore performed in order to select the optimal wavelengths that maximize the class separability between roe, milt, and liver. It is known that reflectance spectra can reveal information about the differences in colour of roe (Bekhit et al., 2009). We performed a complete characterization by measuring spectral reflectance in visible (VIS), near-infrared (NIR) and short-wave infrared (SWIR) band. To the best of our knowledge, this is the first study to have performed complete spectral characterization of roe, milt and liver over such a broad spectral band.

3.1. Spectral characteristics

The average absorbance profiles of the tested raw materials in the whole spectral range of 400-2500 nm were calculated from the extracted spectra. The spectral characteristics are presented in Fig.3. The absorption bands around 540-580 nm are related to hemoglobin absorption (Sivertsen et al., 2011; Prahl 2010). Absorption peaks appearing at 760, 980 and 1450 nm (O-H stretching third, second and first overtone) and 1938 nm (O-H bending second overtone) are due to water content in the materials (Wu, et al. 2013). Around 930 nm, absorption bands are related to the CH_2 bond (Ortiz-Somovilla et al., 2007), which is characteristic of fat. Other bands corresponding to fat content are located around 1210 nm (C-H stretching second overtone) (Fernandez-Cabanas et al., 2011), 1717 and 1760 nm (C-H stretching first overtone) (Ozaki, Morita, & Du 2007). Peaks at around 2304 and 2340 nm are associated with the C-H combination (Burns & Ciurczak, 2008).

3.2. Intra- and inter- similarity

Spectral similarity measure (Spectral Angle Mapper – SAM) was used to calculate intra- and inter-similarity of the raw materials in 400-1000 nm range. Intra- similarity was calculated between all extracted reflectance spectra and corresponding mean spectrum of the material. Obtained results are presented in Fig. 4. It can be clearly seen that all calculated SAM values are smaller than 0.20. The highest variation of the spectra has been observed for material A – roe, ranging from 0.03 to 0.19. Values obtained for material B – liver and C – milt didn't exceed 0.15 and 0.10 respectively. Presented results indicate high intra-similarity of all three materials with material C being the most homogenous one.

Inter- similarity of tested raw materials was calculated using mean reflectance spectra of the materials. Obtained results are presented in Table 1. The highest spectral difference (SAM = 0.25) have been found between materials A and C, roe and milt, respectively. It can be also seen that material B is more similar to material A (SAM = 0.16) than to material C (SAM = 0.19).

3.3. Wavelength selection

By analyzing the LOO cross validation results the optimal spectral bands were selected for Model I and Model II. Statistical measures of the performance of the classification models are presented in Table 2. Five wavelengths were selected as optimal for Model I and twenty band combinations for Model II. The inspection of the obtained results reveals that for classification performed with wavelength 444 nm (Model I) the classification sensitivity would reach 74%, 71% and 65% for material A, B and C, respectively. The specificity for the selected wavelength would reach 91%, 92% and 98% for material A, B and C, respectively. The obtained values, especially sensitivity, are low as compared to the results obtained using full 400 – 1000 nm wavelength range (SAM). This is explained by a significant reduction of the number of bands from 160 to 1 for Model I.

Classification statistics corresponding to Model II were superior to Model I. The mathematical pre-treatment of two spectral bands according to eq. 3 increased the sensitivity and specificity of the classification. Moreover, the performance of Model II using optimal wavelengths was similar to that of SAM utilizing full wavelength range (160 bands).

3.4. Image classification

Performance of the classification models (Model I and Model II) were compared using images of mixed raw materials. Obtained classification maps of three raw materials are presented in Fig. 5. The best performance was observed for pixel-wise SAM classification using the full wavelength range (Fig. 5b). The difference in performance between the Model I (Fig. 5c) and the Model II (Fig. 5d) is clearly visible. Classification map provided by Model II is more accurate, consists of less misclassified pixels, and is more similar to the one obtained using pixel-wise SAM for full 400 – 1000 nm wavelength range. Miss-classified pixels have their origin in high spectral similarity between raw materials, as shown in table 1. Similar problem was highlighted by Park et al. (2007). The overall performance of image classification can be improved by optimizing the classification algorithm, e.g. by taking spatial content into account. Optimization of the image classification was out of the scope of this study and it will be subject to future work.

3.5. Industrial relevance of results, economic and environmental advantages of automated sorting

The method we have presented in this study has an immediate industrial relevance and there are several reasons why the method has potential for industrial application. Firstly, for most of the identified optimal wavelengths in classification Model I and II there are commercially available lasers or diffuse tube lights at precisely the identified wavelengths or adjacent to those. Given the smoothness of the absorbance spectra (Figure 3), following wavelengths from Table 2 can be substituted with commercially available lasers (Table 3). Secondly, the trade-off between cost and practicality of the imaging system on one hand vs specific wavelengths identified in Table 2 highlights that the hyperspectral system, which is costly for industrial use, in the current study can be easily downscaled to a practical image acquisition system with the identified commercially available lasers (Table 3) and a low cost camera that has a solid spectral response on the range highlighted in Table 2. Combination of two different wavelengths from Model II can also be solved by triggering two lasers (with respective wavelengths from Model II) alternately every second frame of the camera in order to generate almost simultaneously two images that can be used for analysis and image classification.

The key economic advantage of automated sorting of roe, milt and liver for the whitefish fisheries is higher profitability. Since whitefish fisheries operate with very low margins, introducing a higher degree of automation is a question of their survival (Tveterås et al., 2014). In Table 4 is shown an estimate to illustrate the economic advantage of automated versus manual sorting based on the provided data from Richardsen et al. (2014) and Statistics Norway (SSB, 2015). We assume that by introducing automated sorting of roe, milt and liver one has to consider: 1) investment costs in new technology consisting of machine vision systems and robots to perform automated sorting; 2) operation costs for the new machinery; maintenance cost for the new machinery; and 4) salaries for personnel involved in operation and maintenance. The cost involving all these steps would still be lower than 1/3 of the totally estimated cost of 155 mil USD needed for manual labour (Table 4). Therefore, it is estimated that a direct implication of introducing automated sorting of roe, milt, and liver in whitefish fisheries would be annual savings up to 100 mil USD. On the societal aspect, introduction of new ICT and automation technology would attract labour force with high education level to serve and maintain the new machinery. This is crucial for a sector that is struggling with recruitment of trained workforce. The environmental impact of introducing automated sorting is that the capacity is increased and larger quantities of roe, milt and liver will go to products for human consumption and the waste from these fractions would be considerably reduced. All of these aspects are crucial for a sector that is trying to become sustainable and bio economically efficient.

4. Conclusions

In this study, hyperspectral images of cod liver, roe and milt samples were acquired in the 400 – 2500 nm range and specific absorption peaks were characterized. Inter- and intra-variation of the materials were calculated using spectral similarity measure. One-band and two-band classification models were developed to differentiate between the three raw materials in VIS/NIR (400 – 1000 nm) range. Important wavelengths were identified using cross-validation method, leading to the classification sensitivity of 70% and specificity of 94% for one-band model, and 96% and 98% for two-band model (sensitivity and specificity respectively). Classification maps were generated using optimal wavelengths and compared to the classification maps generated from the full spectral profiles from VIS/NIR range. The results showed that discrimination of cod liver, roe and milt is possible using combination of two optimal bands and that hyperspectral system, which is costly for industrial use, can be easily downscaled to a practical image acquisition system with a camera having a solid spectral response and by triggering two lasers (at two optimal wavelengths) alternately every other camera frame.

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TABLES

Table 1 Inter- similarity of tested raw materials

	A - roe	B - liver	C - milt
A - roe	0		
B - liver	0.16	0	
C - milt	0.25	0.19	0

Table 2 Performance of the classification models

Model	Spectral band (nm)		A - roe		B - liver		C - milt	
			Sensitivity [%]	Specificity [%]	Sensitivity [%]	Specificity [%]	Sensitivity [%]	Specificity [%]
Model I	444		74	91	71	92	65	98
	448		71	95	72	94	64	98
	441		74	90	72	91	64	98
	451		70	96	73	96	62	98
	480		69	100	73	95	63	97
Model II	462	604	97	96	94	94	96	98
	466	604	97	96	95	96	95	98
	470	604	97	98	94	97	96	98
	473	604	97	99	93	99	96	98
	477	604	96	100	93	98	97	98
	477	829	97	94	95	94	97	98
	481	600	97	100	94	97	97	98
	481	847	97	95	94	95	97	98
	484	604	97	100	95	97	96	98
	484	843	97	95	94	96	97	98
	488	600	97	100	95	96	95	96
	488	836	97	96	94	96	97	98
	491	600	97	100	95	96	95	94
	491	843	98	96	94	97	97	96
	495	600	97	100	95	96	95	94
	495	850	97	97	94	97	97	95
	499	600	97	100	94	97	95	94
	499	847	96	97	94	98	97	94
	502	854	97	97	94	98	97	94
	506	847	97	97	94	98	97	94

SAM*	415 - 992	96	100	97	98	100	100

*Classification performed using spectral angle mapper (SAM), classification thresholds: 0.125, 0.125 and 0.100 for material A, B and C, respectively.

Table 3. Available lasers and diffuse light tubes to for optimal wavelengths identified in Table 2 or for wavelengths adjacent to these

Spectral band (nm)	Commercially available laser/diffuse light (nm)
415	405
441,444, 448, 451	450
462, 466, 473, 477, 481, 484, 488	470
491,495,499, 502, 506	514
600, 604	635
829, 836	830
843, 847, 850	850
990	980

Table 4. Estimate of economic and profitability advantage of introducing automated sorting of roe, liver and milt. One operator is expected to sort 25 kg of fractions per hour, which for 95000 tons a year there is a need for 3,8 mil working hours to sort all fractions.

Operation/Cost	Measurement Unit	Cost (NOK)/USD
Sorting capacity one operator	25 kg/hour	
Amount of by-products to sort	95 000 000 kg/year	
Total hours for manual sorting	3 800 000 hours	
Man-Year	1950 hours	
Total Man-Years for sorting	1949 Man-Years	
Salary for one Man-Year	-	659 660/79605*
Total cost for manual sorting	-	1 285 374 359/155 114 807*

*Rate exchange from 29.09.2015