Report 34/2018 • Published November 2018

Automatic quantification of gaping in fish fillets using 3D imaging - Preliminary results for haddock fillets

Final report

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Report

Title: **Automatic quantification of gaping in fish fillets using 3D imaging – preliminary results for haddock fillets – Final report**	ISBN: 978-82-8296-572-9 (pdf) ISSN 1890-579X *Report No.:* 34/2018
Tittel: Automatisk kvantifisering av spalting i fiskefileter ved bruk av 3D-avbildning – innledende tester og resultater for hysefileter - Sluttrapport	*Accessibility:* **Open**
Author(s)/Project manager: Martin H. Skjelvareid (researcher, author), Karsten Heia (project manager)	*Date:* 15.06.2018
Department: Sjømatindustri	*Number of pages and appendixes:* 16+2
Client: Fiskeri- og havbruksnæringens forskningsfond (FHF)	*Client's ref.:* FHF 901507
Keywords: fillet, gaping, 3D imaging	*Project No.:* 12426
Summary/recommendation: See Chapter 1…	
Summary/recommendation in Norwegian: Se kapittel 1…	

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1 Summary

1.1 English version

3D imaging is studied as a potential method for automated quantification of gaping in fish fillets. A total of 153 haddock fillets were included in the study. The fillets were manually evaluated for gaping by three evaluators, each giving scores from 0 (no gaping) to 5 (extreme gaping). The fillets were imaged with a 3D camera, and features from the 3D images were used in a PLS regression model for estimation of gaping score. The model gave an R^2 value of 0.56 and a root mean square error of 0.68, which is considered mediocre in this context. However, the accuracy of the model may be sufficient for classification of fillets into two classes; low-gaping samples and high-gaping samples. A possible improvement to the method is to perform imaging above a small "bump" in the conveyor belt, to better expose the gaping. With this modification, 3D imaging is seen as a promising method for automated, real-time quantification of gaping.

1.2 Norsk versjon

Rapporten beskriver en studie av 3D-avbildning som potensiell metode for automatisert kvantifisering av spalting i fiskefileter. 153 fileter av hyse ble brukt i studien. Filetene ble vurdert for spalting av tre dommere, som brukte en evalueringsskala fra 0 (ingen spalting) til 5 (ekstrem spalting). Filetene ble avbildet med et 3D-kamera, og ulike statistiske beskrivelser av 3D-bildene ble brukt i en PLS regresjonsmodell for estimering av spalting. Modellen ga en R^2-verdi på 0.56 og en RMS-verdi på 0.68, noe som ansees som middelmådig i denne sammenhengen. Modellen kan imidlertid ha en tilstrekkelig nøyaktighet til å dele fileter inn i to klasser; fileter med lav og høy spalting. En mulig forbedring av metoden er å gjøre 3D-avbildningen over en liten «kul» på transportbåndet, for å eksponere spaltingen bedre. Med en slik modifisering anses 3D-avbildning som en lovende metode for automatisert kvantifisering av spalting i sanntid.

2 Introduction

The degree of fillet gaping is one of the most important quality parameters for fish fillets, in addition to color (also dependent on blood content) and the presence of defects such as bones, remains of skin, nematodes, etc. The degree of gaping is influenced by mechanical handling of the fish and degradation of connective tissue, e.g. by enzymatic degradation. At Nofima, the degree of fillet gaping is manually evaluated based on a scale from 0 (no gaping) to 5 (extreme gaping). A set of example pictures is used in the evaluation (Akse *et al.,* 2010) . Several studies have been performed that include gaping as a quality parameter (measured manually), but there is very little literature available on methods for automated quantification of gaping.

The degree of gaping is related to the three-dimensional shape of the fillet, and various methods for 3D shape measurement are available. The most commonly used 3D measurement method for objects on conveyor belts is based on illumination with a laser line and imaging with a monochrome camera. For each pixel in the image, triangulation can be used to calculate the object's height above the conveyor belt. The laser illumination and the camera system can be integrated into a single unit, a "3D camera". 3D imaging has been used to detect wounds and deformities on whole salmon (Sture *et al.,* 2016), but we have not found literature on 3D imaging used for quantification of gaping.

It is possible to measure fillet gaping using other imaging techniques in addition to 3D imaging. Gaping creates "shadows" which are visible in ordinary 2D images of fillets. Using imaging processing techniques, these shadow zones can be identified, and the degree of gaping can be quantified. Particular types and placements of light source(s) can also be used to enhance the shadow effects (Balaban *et al.,* 2011). However, in this type of imaging, an indirect effect of gaping is measured. Various fillet properties can cause "dark" areas in the image similar to those of gaping, for example blood or melanin spots. Also, it is not possible to measure the depth of each gap exactly (which is relevant to consider the severity of the gaping).

X-ray imaging can also be used to estimate the thickness of the fillet. The main advantage of x-ray imaging is its ability to detect bones, but as the absorption of x-rays in muscle tissue is thickness dependent, the thickness can be estimated based on the absorption image (Mery *et al.,* 2011). Note however that this is also an indirect measurement of thickness, with potential for inaccuracies. X-ray equipment is also quite costly and requires special attention regarding radiation safety.

In comparison to the methods described above, a 3D camera is a relatively low-cost device that measures the surface shape of a fillet directly with high accuracy (typically < 0.1 mm resolution). This type of sensor should therefore be well suited for measuring gaping in fish fillets. The main goal of the study described here is to test this concept on a relatively large number of fillets, and evaluate its accuracy relative to manual evaluations of gaping.

If automated measurement of gaping can be achieved with sufficient accuracy, it could easily be implemented in industrial systems such as those produced by Marel, Valka etc. For example, Marel already uses 3D imaging in portioning machines, and algorithms for gaping could probably be implemented directly on these machines using the same data. Another possibility for implementation is to use the camera "stand-alone" together with a grading system for sorting the fish.

3 Methods and materials

3.1 Raw materials and manual gaping evaluation

Haddock was fished by the fishing vessel “Ballstadøy” on May 24. at “Klakken”, approximately 4 km north of Vardø, Finnmark, Norway. The fish were part of another Nofima project concerning live storage of fish between capture and processing on land. Some of the fish were killed, gutted and iced directly after capture, some of the fish died in the storage tanks and were gutted and iced onboard, and some of the fish were processed on land in Båtsfjord on May 25. A total of 62 fish were shipped to Nofima, packed in styrofoam boxes with ice. These fish arrived on May 28. and were hand filleted before subsequent imaging and gaping evaluation. The skin was left on the fillets. Figure 1 shows an overview of all the fillets. For the sake of brevity, further details regarding handling of the fish are not given here, as the only relevant property of the fish in the current work, is the amount of gaping.

Evaluation of gaping was performed by laying the fillets out on a table and visually comparing them to the images shown in Figure 2. Three evaluators, all part of the Seafood industry department at Nofima, gave their individual score for each fillet. The average of these three values was then used as the final score for each fillet. During evaluation, one of the evaluators would run his/her hand under the fillet to better expose gaping.

The evaluation results showed that the fillets had relatively little gaping, with most fillets receiving scores in the 1-2 range. To generate examples of fillets with higher gaping scores, 60 fillets from the original 124 were selected and handled (“stretching”, bending) on May 29. The fillets were then imaged and evaluated in the same way as on May 28.

The distribution of gaping scores for all fillets (124 on May 28. + 60 on May 29.) is shown in Figure 3a). The distribution has distinct peaks at 1, 2 and 3, corresponding to cases where all three evaluators agreed on the same score. Scores with non-integer values (e.g. 1.33, 2.66) are mean values from cases where the evaluators gave slightly different scores (e.g. [1, 1, 2], [2, 3, 3]). Note that for all fillets, the evaluator scores never differed by more than 1. The distribution in Figure 3a) also shows a slight bias towards lower values. To compensate for this bias, a subset of 153 fillets was selected for use in further analysis. The gaping score distribution of this subset is shown in Figure 3b).

Figure 1 Overview of all 124 fillets imaged and evaluated on May 28.

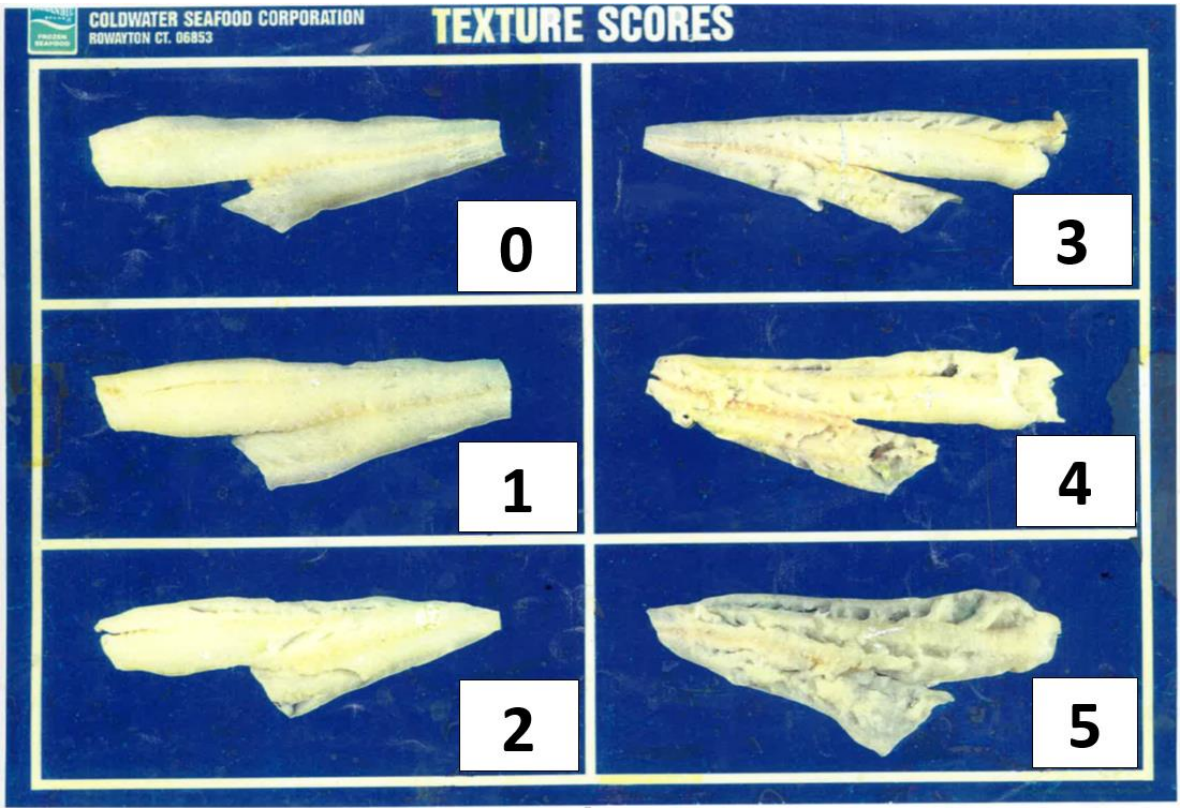
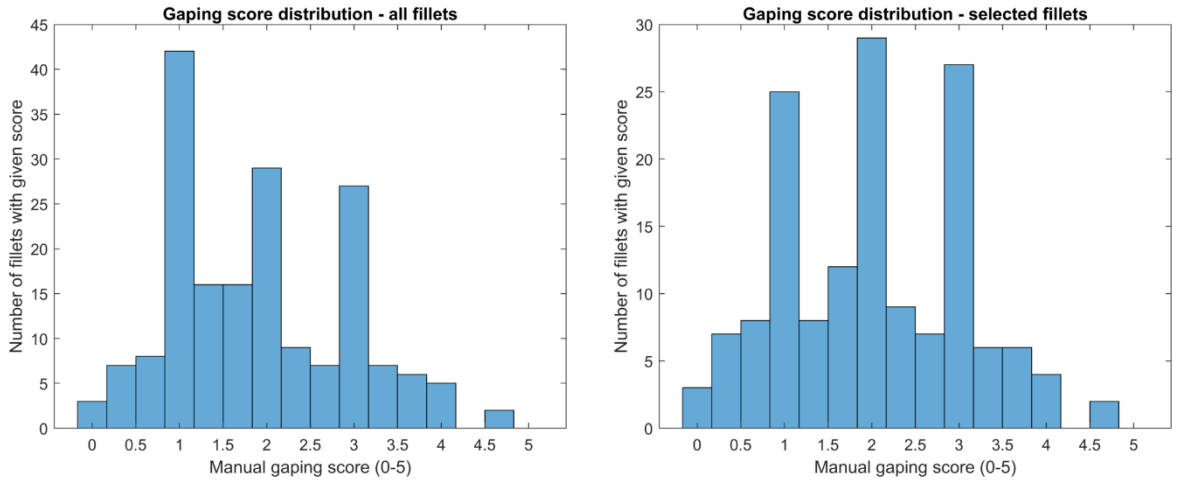


Figure 2 *Example images used in evaluation of gaping. The corresponding gaping scores (0-5) are shown in the lower right part of each image.*



a) b)

Figure 3 *Gaping score distribution. a) All fillets, b) 153 fillets selected for a more uniform distribution.*

3.2 3D camera set-up and specifications

3D imaging was performed with a Gocator 2370 camera from LMI Technologies. The camera was mounted 53 cm above a flat conveyor belt, with the laser line pointing downwards perpendicular to the conveyor belt, and the camera looking down at an angle relative to the laser line. The set-up is shown in Figure 4. The image resolution was 0.3, 0.5 and 0.0022 mm in the x, y, and z directions, respectively.

3.3 Color imaging

A VNIR-640 hyperspectral camera from Norsk Elektro Optikk was used to image the fillets on the same conveyor belt used for 3D imaging. Color images were synthesized from the hyperspectral images using a CIE 1964 10° standard observer model and a CIE D65 daylight illumination model (see Skjelvareid *et al.,* 2017 for further details).

3.4 Image export and import

The 3D images were saved to disk during imaging by a small program written in-house. The program is written in the C programming language and based on the Gocator SDK supplied by LMI Technologies. The files were then read and further processed in Matlab.

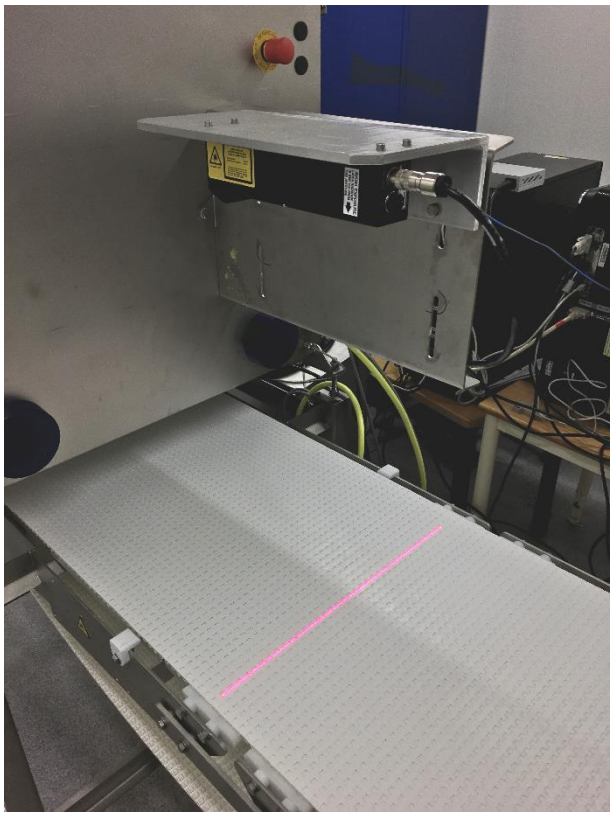


Figure 4 3D camera mounted above conveyor belt.

4 Image examples

Figure 5 shows image examples of one fillet with low gaping (score 1) and two fillets with high gaping (scores 4 and 4.67). Both 3D and color images are included for comparison. In the high-gaping fillets, the gaps can be seen as darker areas in both the 3D and color images. In the 3D images, the darker color corresponds to a lower height above the conveyor belt, and in the color images, the darker areas are caused by the gaps having a shadowing effect.

Figure 6 shows an example of two fillets that, despite having the same gaping score, appear quite different. In the left fillet, gaps in the fillet are overlapping and "smoothed out" while in the right fillet there is a large gap clearly visible in the loin.

During manual evaluation, the gaps in the fillets were made more clearly visible by running a hand underneath the fillet, but with the fillets placed flat onto the conveyor belt, some of the gaps were not clearly visible in the images. To illustrate this, a few fillets were placed on a section of plastic pipe (10 cm radius) and imaged again. An example is given in Figure 7, showing how the shape of the pipe helps to expose the gap in the loin of the fillet.

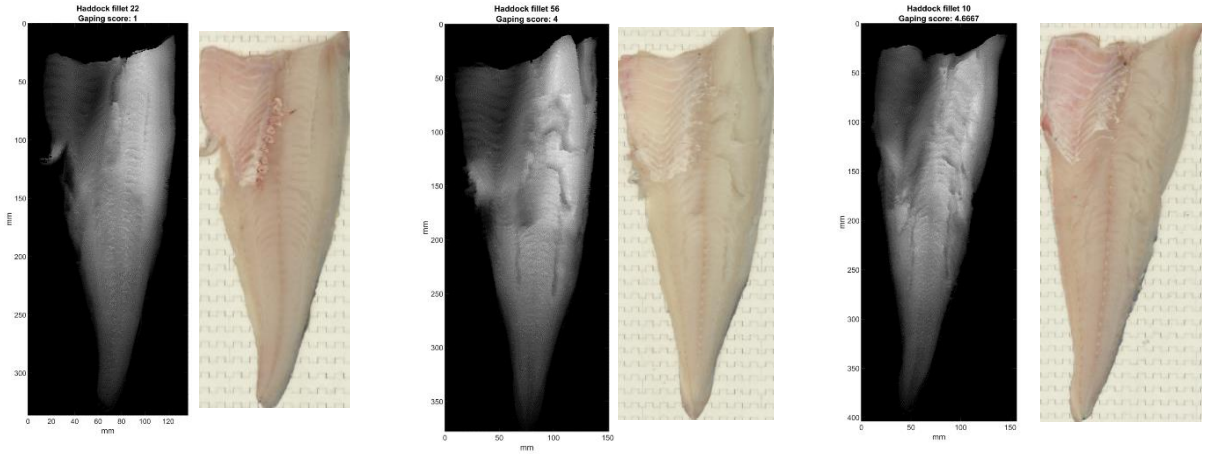


Figure 5 Examples of extremes: Fillets with low and high gaping scores. 3D images (grayscale) and color images are shown for each fillet.

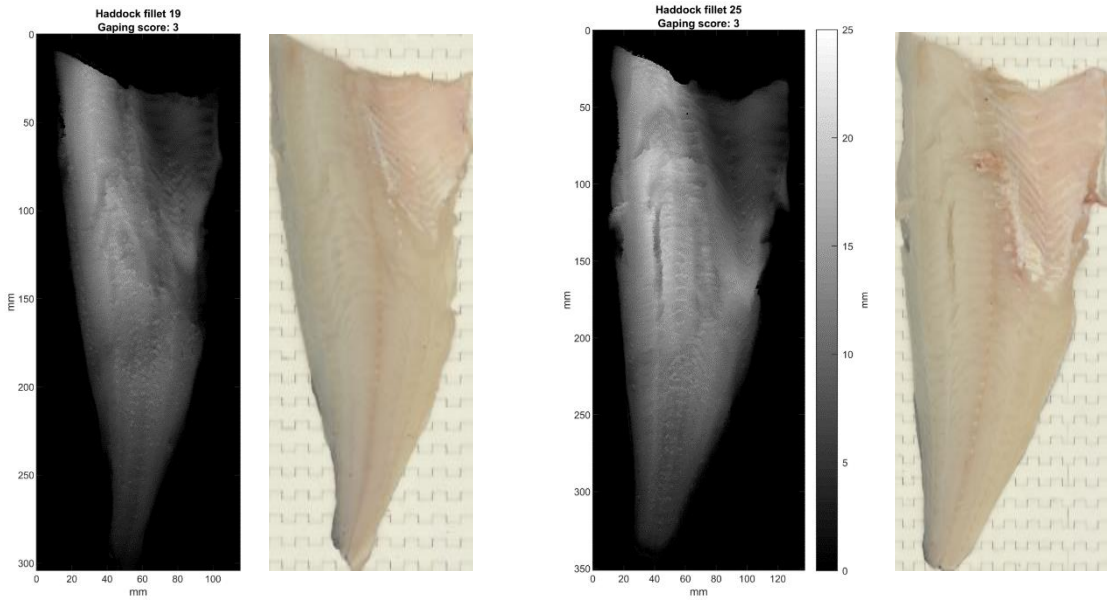


Figure 6 Example of two fillets that have the same gaping score (3) despite appearing quite different.

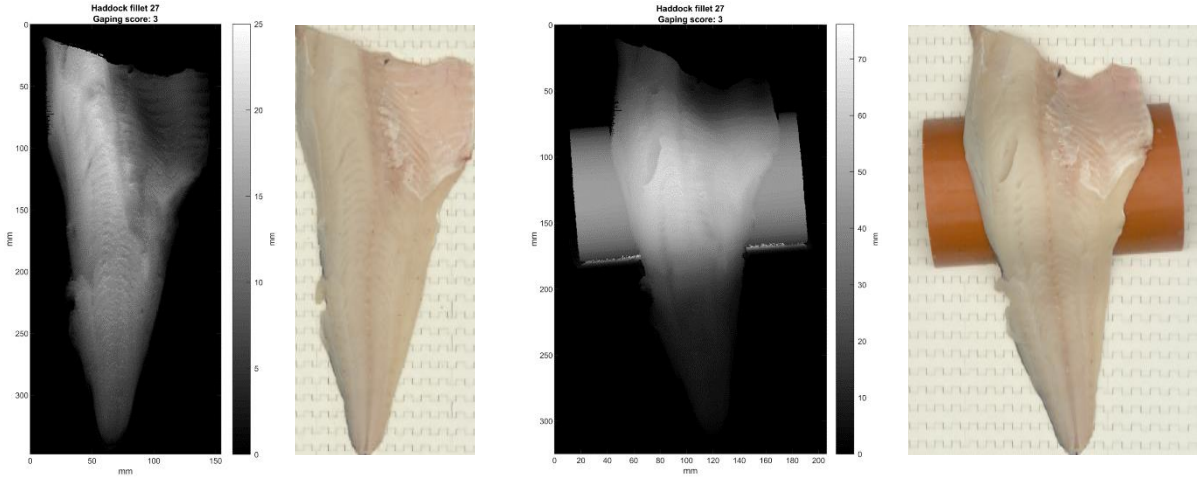


Figure 7 The same fillet imaged flat onto the conveyor belt and placed on a section of plastic pipe. Note how the gap in the loin is clearly more visible in the images to the right.

5 Analysis

5.1 High-pass filtering

In order to study only the shape of the gaps in the fillets, each 3D image was high-pass filtered. Before filtering, the height of each fillet was normalized so that the 99th percentile of height values corresponded to 20 mm. This was done to avoid the size of the fillet affecting the gaping estimation. Filtering was performed by subtracting a low-pass filtered ("smoothed") version of the image from the original image. Low-pass filtering was performed by a Gaussian blur (Matlab function imgaussfilt()), using a filter kernel with sigma = 5 mm. A median filter was also tested (Matlab function medfilt2()), but as this type of filter gave very similar results while requiring more computational resources, the Gaussian blur was preferred.

The effect of high-pass filtering is demonstrated in Figure 8. The upper left image is the original 3D image, with height information encoded as grayscale intensity, as shown by the color bar on the right of the image. The upper middle figure is the corresponding high-pass filtered image. The gaps appear as dark areas in this image. Note that there is also a dark "border" around the fillet. This is a filtering artifact, and the border was removed by first creating a binary segmentation of the fillet, separating fillet and background, and then eroding the fillet segment (Matlab function imerode()) using a disk-shaped element with 4 mm radius. Values outside the eroded fillet segment were set to zero. The high-pass filtered version of the image with the border removed is shown in the upper right part of Figure 8. To further illustrate the effect of low- and high-pass filtering on the image, a "slice" from the images is shown in the bottom part of Figure 8. The position of the slice is indicated with a blue dotted line in the images in the upper part of the figure.

Note that in some images the transition between loin and belly area was so sharp that it appeared similar to gaping in the high-pass filtered image. It should be possible to either a) high-pass filter the image in such a way that this slope is not included or b) to segment the image to exclude the slope. Implementing b) can be done using a priori information about the general shape of a fillet, and some preliminary testing was done along these lines, based on detection of maximum heights and maximum gradients for each horizontal image line. However, the method only worked for some of the fillets, and due to time constraints, it was not developed further. Thus, the results presented later in the report include the loin-belly slope artifact.

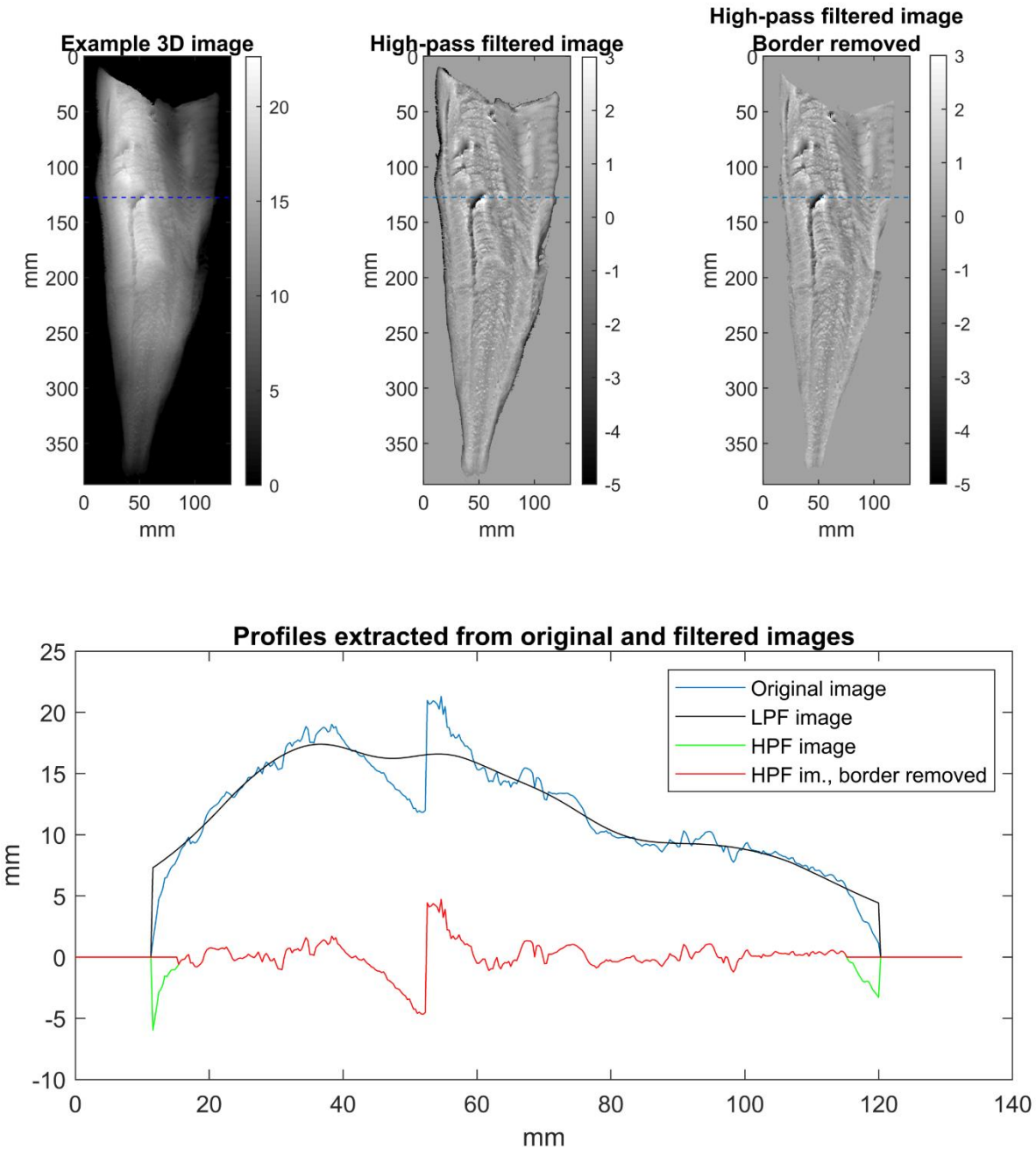


Figure 8 *Demonstration of high-pass filtering of a 3D image. The profiles in the lower plot are taken at the position indicated with a blue dotted line in the images. Note that the red and green lines in the lower plot are mostly overlapping.*

5.2 Segmenting

After a preliminary evaluation of the original and high-pass filtered 3D images, it was decided to only use the loin section of the fillet in the 3D image for estimation of gaping. The loin is both the part of the fillet with the highest commercial value and also the part where gaping occurs most frequently. Excluding belly and tail areas also helps in excluding noise and "false" gaping from the analysis.

The loin area was identified by first detecting all parts of the fillet higher than 75 % of the maximum height. This area was then eroded with a radius of 2 mm and dilated with a radius of 12 mm. Gaping was then identified as areas in the high-pass filtered image with values below -0.7 mm (gap deeper than 0.7 mm).

The segmenting of loin and gaping areas is illustrated in Figure 9. The original image is shown on the left. The middle image shows background as dark gray, fillet as light gray and loin as white. Within the loin area, the depth of the gaping areas is shown, encoded on a gray scale. The right image shows the loin area only (dark gray) with gaping areas indicated as black.

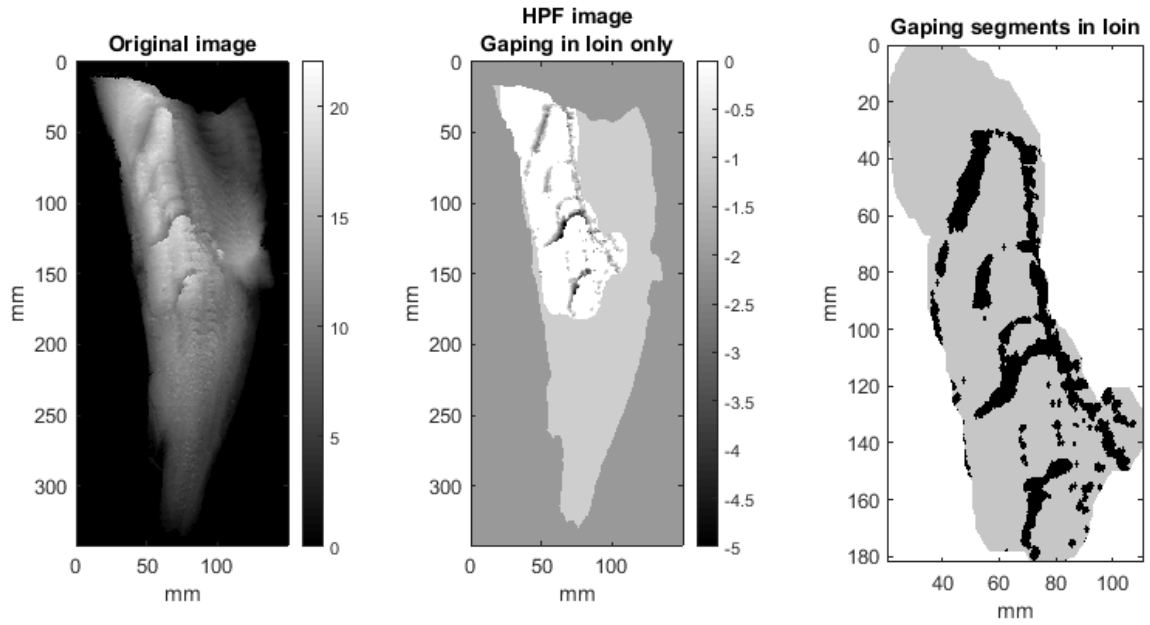


Figure 9 Illustration of segmenting of loin and gaping areas.

5.3 Image features

Several feature "candidates" for gaping estimation were generated based on the 3D image and on the size, shape and depth of the gaping areas. These features were:

- Maximum fillet height before normalization (mm)
- Fillet area (cm^2) and volume (cm^3)
- Fraction of loin classified as gaping area (0-100 %).
- Area of individual gaping segments (mm^2) - 50^{th}, 85^{th} and 100^{th} percentile
- Eccentricity of individual gaping segments (see Matlab function regionprops())
- Depth of gaping in all gaping segments combined (mm) – 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} percentiles.

- Average gaping depth over whole loin area (mm)

Matlab code for gaping feature generation is listed in the appendix in section 10. The features were plotted against the manual gaping score for each fillet, and the Pearson correlation coefficient (R) was calculated for each. The scatter plots for each feature are shown in Figure 10, with the R value given in the title. Based on an evaluation of these, the following five features were chosen as inputs to a regression model for gaping:

- Fraction of loin classified as gaping area
- Gaping segment area, 85th percentile
- Gaping segment eccentricity, 75th percentile
- Gaping depth, 95th percentile
- Gaping depth, average over loin

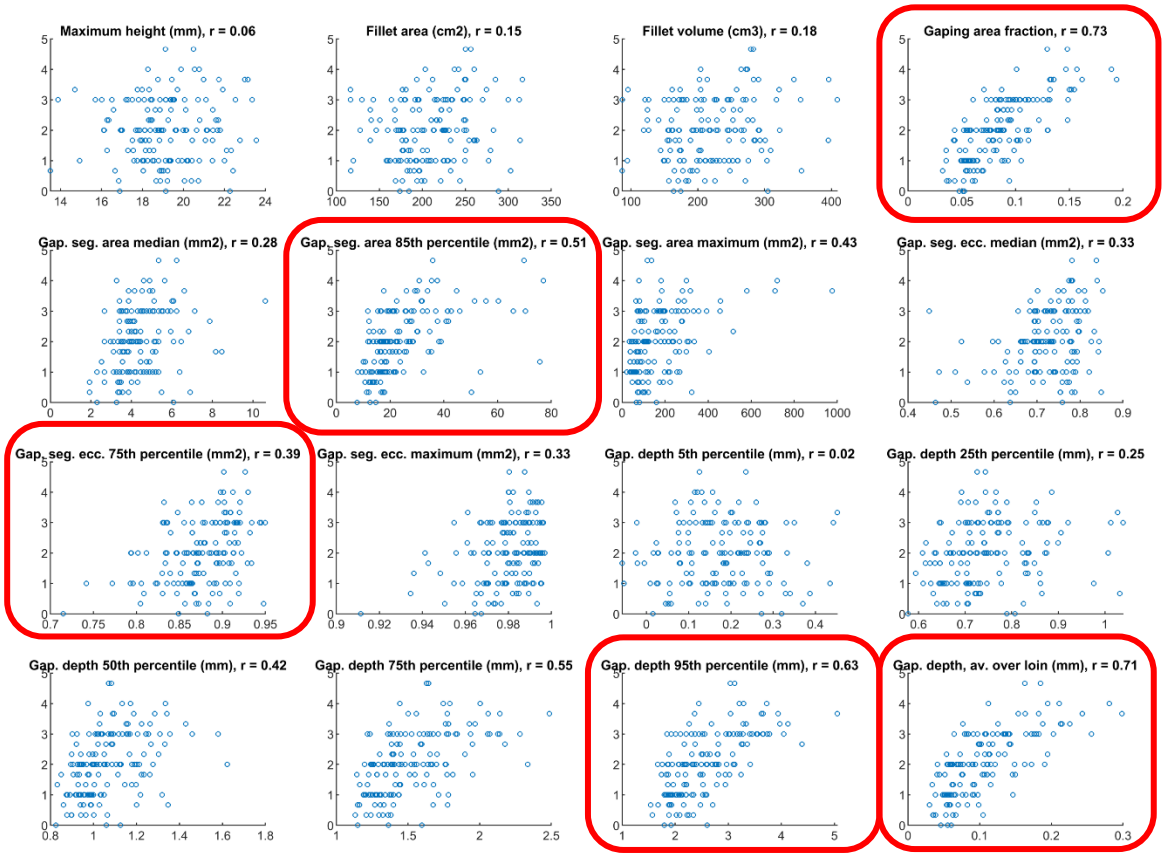


Figure 10 Scatter plots of candidate features versus manual gaping scores. The features chosen for further analysis are indicated with red rounded rectangles.

5.4 PLS regression

Partial least square (PLS) regression was used to estimate the gaping score for each fillet. The five image features listed in section 4.3 were used as inputs (“predictors”) and the average manual gaping score was used as output (“response”). Figure 11 shows mean squared error of prediction and explained variance, plotted against number of PLS components. Based on these, the number of components was set to 2.

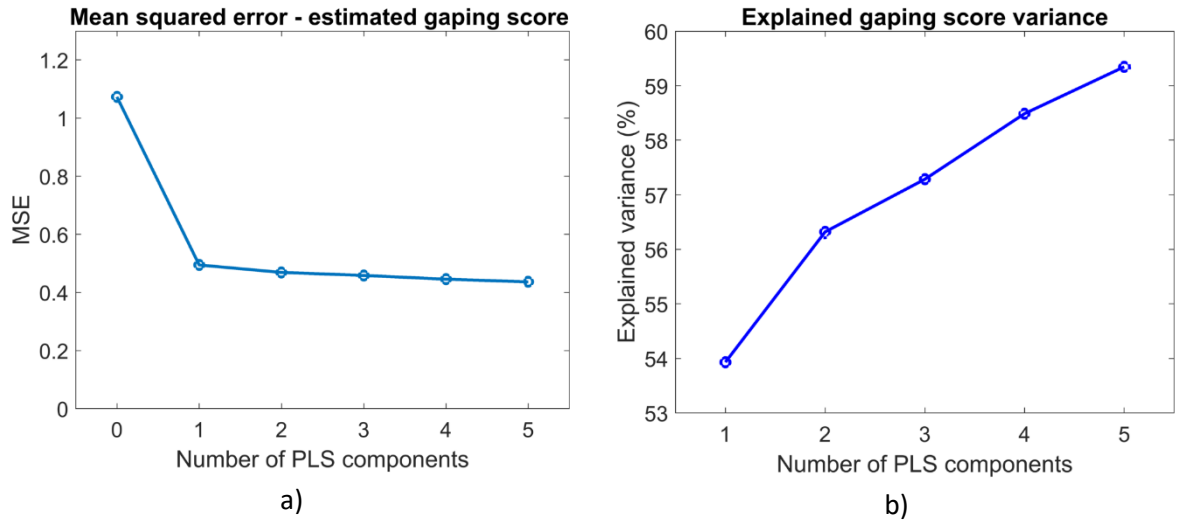


Figure 11 PLS regression statistics plotted against number of components. a) Mean squared error of gaping score, b) explained gaping score variance.

6 Results

The results of PLS regression are shown in Figure 12, as a scatter plot with manual gaping score on the x-axis and gaping score estimated from 3D images on the y-axis. The coefficient of determination (R^2) is 0.56 and the root mean square error of prediction (RMSEP) is 0.68. Clearly, there is a correlation between the manual score and the estimated score, but the accuracy of estimation is mediocre. The model is not seen sufficiently accurate to estimate the individual score values (0,1,2,3,4,5), but it may be accurate enough to separate the fillets into two classes; "low gaping" and "high gaping". For example, if the fillets are separated into classes with gaping scores of either a) equal to 2 or below, or b) above 2, the estimated gaping score gives a 79 % correct classification. This may be sufficient for some applications.

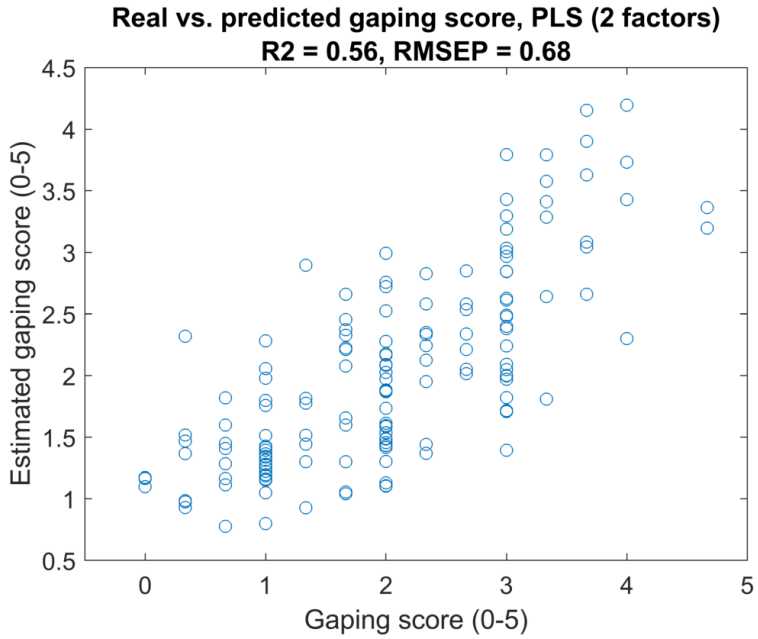


Figure 12 Prediction results from PLS regression.

7 Discussion

The study described in this report was preliminary in nature, performed with limited time, resources and raw materials. The image analysis was done based on the initial ideas about relevant preprocessing, feature generation and regression. However, it is clearly possible to refine the analysis. We hope the methods described in this report can act as a starting point for anyone wanting to implement gaping estimation, and not as a definitive prescription for how this type of analysis should be done.

The gaping estimation results are mediocre at best. However, they show that it is at least possible to calculate an estimate that is reasonably well correlated with the manual gaping score. Note also that the gaping score is subjective, with its own inherent variance, and that this may have contributed to the poor gaping estimation. However, the gaping estimation results may be sufficiently accurate to separate the fillets into two classes with low and high gaping. Similar classification (with a low number of classes) is often used in seafood industry, for example the “superior”, “ordinary” and “production” classes used in salmon aquaculture (Norsk bransjestandard, 1999).

The image examples in Figure 6 and Figure 7 illustrate that the fillet gaping is not always “exposed” and clearly visible to the 3D camera when the fillet is placed flat on a conveyor belt. This is probably also the main reason for the poor performance of the gaping estimation. A possible improvement to the imaging setup could be to image the fillets above a “bump” in the conveyor belt. This is illustrated in Figure 13. The effect of this bump would be similar to that of running a hand beneath the fillet, and will probably improve the gaping estimation significantly. The radius of the bump should be on the order of a few centimeter.

The Gocator 3D camera used in the experiments is a “smart sensor”, meaning that the camera also includes a computer that can process the data in real time. The algorithms for measurement of gaping could possibly be implemented directly on the camera using the Gocator development kit (“GDK”). The camera can also output digital signals for controlling sorting mechanisms directly. Thus, it could be possible to implement a sorting system for gaping based only on the Gocator camera, a conveyor belt and a sorting mechanism.

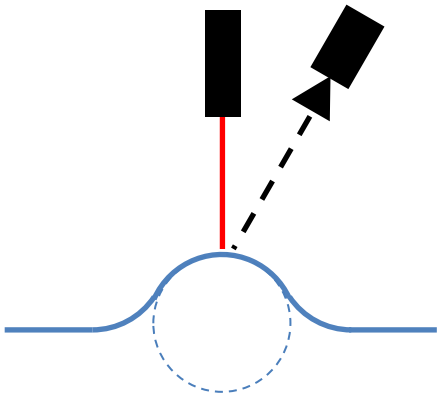


Figure 13 Sketch illustrating a possible concept for better imaging of fillet gaping: Imaging over a conveyor belt "bump".

8 Conclusions

3D imaging of fish fillets can create accurate images of the fillet shape, and by filtering these images, it is possible to separate small gaps in the fillet from the overall shape of the fillet. However, the gaps are not always exposed when the fillet is placed flat on a conveyor belt, and subsequently, they are not always clearly seen in the 3D images. Using images taken on a flat conveyor belt produces mediocre estimates of gaping scores, but the method may be accurate enough to separate fillets into low- and high-gaping classes. A possible improvement to the method is to perform imaging above a small "bump" in the conveyor belt to better expose the gaping. With this improvement, 3D imaging is seen as a promising method for automated, real-time quantification of gaping.

9 Main results

- 3D imaging can reveal detailed information about fillet shape.
- However, fillets on a flat conveyer belt make it difficult to reveal all gapings.
- Introducing a bump on the conveyer belt can help revealing all gapings defects.

10 Deliveries

Minutes from the two referendce group meeting has been prepared and submitted to FHF. The last delivery is this report.

Skjelvareid, M.H. & K. Heia (2018). Automatic quantification of gaping in fish fillets using 3D imaging - Preliminary results for haddock fillets - Final report. Report 34/2018, Nofima, Tromsø.

11 Acknowledgements

Thanks to Torbjørn Tobiassen for supplying the haddock samples used in this project. Thanks to Sjurdur Joensen and Tatiana Ageeva for help with handling and evaluation of the fillets, and to Kate Washburn and Heidi Nilsen for reviewing the report. The project was funded by Fiskeri- og havbruksnæringens forskningsfond (project number 901507).

12 References

Akse, L., S. Joensen, T. Tobiassen, G. Martinsen, K.Ø. Midling & M.S.W Breiland (2010). Torsk kjølt i RSW – råstoffkvalitet til filet og salting. Report 34/2010, Nofima, Tromsø.

Sture, Ø., E.R. Øye, A. Skavhaug & J.R.A. Mathiassen (2016). 3D machine vision system for quality grading of Atlantic salmon. *Comput. Electron. Agric.*, **123**, pp. 142–148, doi:10.1016/J.COMPAG.2016.02.020.

Balaban, M.O., G.F. Ünal Şengör, M.G. Soriano & E.G. Ruiz (2011). Quantification of Gaping, Bruising, and Blood Spots in Salmon Fillets Using Image Analysis. *Journal Food Sci., **76**,* pp. E291–E297, doi:10.1111/j.1750-3841.2011.02060.x.

Mery, D., I. Lillo, H. Loebel, V. Riffo, A. Soto, A. Cipriano & J.M. Aguilera (2011). Automated fish bone detection using X-ray imaging. *Journal Food Eng.,* **105**, pp. 485–492, doi:10.1016/j.jfoodeng.2011.03.007.

Skjelvareid, M. H.; Heia, K.; Olsen, S. H.; Stormo, S. K. Detection of blood in fish muscle by constrained spectral unmixing of hyperspectral images. *Journal Food Eng.*, **212**, pp. 252–261, doi:10.1016/j.jfoodeng.2017.05.029.

Norsk bransjestandard for fisk. Kvalitetsgradering av oppdrettet laks (NBS 10-01) (1999).

Appendix: Matlab code for calculating gaping-related features

```
function [features,featureLabels] =
calcFilletGapingFeatures(im,segIm,hpfIm,meta)
% calcFilletGapingFeatures - calc. gaping features based on 3D image
%
%   Usage:
%   metric = calcFilletGapingFeatures(im,segIm,imhpf,meta,...)
%
%   Input:
%   im          -   original 3D image
%   segIm       -   binary image indicating fillet and background
%   hpfIm       -   high-pass filtered image
%   meta        -   metadata structure for original image
%
%   Output:
%   features        -   vector of features
%   featureLabels   -   cell array of feature labels
%
%   2018-06-06 Martin H. Skjelvareid

%% Parameters
normHeight = 20;            % "Standard" height, used for normalization
maxHeightPercentile = 99;   % Percentile for estimating maximum height
gapingThreshold = -0.7;     % Threshold for detecting gaping in HPF image
loinHeightThreshold = 0.75; % Threshold for original detection of loin area
erodeRadLoinPix = 5;        % Erode radius used in loin segmenting
dilateRadLoinPix = 30;      % Dilate radius used in loin segmenting
erodeRadPixNoise = 1;       % Erode radius for cleaning up detected gaping
dilateRadGapingArea = 2;    % Dilate radius for gaping areas

%% Segment loin area
maxHeight = prctile(im(segIm),maxHeightPercentile);
loinRaw = im > loinHeightThreshold*maxHeight;
loinArea = imerode(loinRaw,strel('disk',erodeRadLoinPix));
loinArea = imdilate(loinArea,strel('disk',dilateRadLoinPix));
loinArea = bwareafilt(loinArea,1);      % Keep only largest area
loinArea = imfill(loinArea,'holes');    % Fill possible holes

%% Identify gaping areas
gapingAreaRaw = hpfIm < gapingThreshold;
gapingAreaRaw = imerode(gapingAreaRaw,strel('disk',erodeRadPixNoise));
gapingAreaRaw = imdilate(gapingAreaRaw,strel('disk',dilateRadGapingArea));
gapingArea = gapingAreaRaw & loinArea & segIm;

%% Limit non-zero pixels in HPF image to gaping areas in loin only
imGaping = hpfIm;
imGaping(~gapingArea) = 0;

%% Normalize to standard height
imGaping = imGaping*(normHeight/maxHeight);

%% Calculate features
% Features relating to fillet dimensions
areaPerPixel = meta.xRes*meta.yRes;
filletAreaCm2 = nnz(segIm)*areaPerPixel/100;
filletVolumeCm3 = sum(im(segIm))*areaPerPixel/1000;

% Features relating to gaping area
```

```
gapingAreaFraction = nnz(gapingArea)/nnz(loinArea);
s = regionprops(gapingArea,'Area','Eccentricity');
gapingSegmentArea = cat(1,s.Area);
gapingSegmentAreaPctl = prctile(gapingSegmentArea,[50 85
100])*areaPerPixel;
gapingSegmentEcc = cat(1,s.Eccentricity);
gapingSegmentEccPctl = prctile(gapingSegmentEcc,[50 75 100]);

% Features relating to gaping depth
gapingDepthPctl = prctile(-imGaping(gapingArea),[5 25 50 75 95]);
avGapingDepthLoin = sum(-imGaping(gapingArea))/nnz(loinArea);

%% Collect features in output vector and write labels
featureLabels = {...
                 'Maximum height (mm)'...,
                 'Fillet area (cm2)'...,
                 'Fillet volume (cm3)'...,
                 'Gaping area fraction'...,
                 'Gap. seg. area median (mm2)'...,
                 'Gap. seg. area 85th percentile (mm2)'...,
                 'Gap. seg. area maximum (mm2)'...,
                 'Gap. seg. ecc. median (mm2)'...,
                 'Gap. seg. ecc. 75th percentile (mm2)'...,
                 'Gap. seg. ecc. maximum (mm2)'...,
                 'Gap. depth 5th percentile (mm)'...,
                 'Gap. depth 25th percentile (mm)'...,
                 'Gap. depth 50th percentile (mm)'...,
                 'Gap. depth 75th percentile (mm)'...,
                 'Gap. depth 95th percentile (mm)'...,
                 'Gap. depth, av. over loin (mm)'...,
                 };

features = [...
             maxHeight;...
             filletAreaCm2;...
             filletVolumeCm3;...
             gapingAreaFraction;...
             gapingSegmentAreaPctl(:);...
             gapingSegmentEccPctl(:);...
             gapingDepthPctl(:);...
             avGapingDepthLoin;...
            ];
```

ISBN 978-82-8296-572-9 (pdf)
ISSN 1890-579X