CHUTE BASED AUTOMATED FISH LENGTH MEASUREMENT AND WATER DROP DETECTION

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ABSTRACT

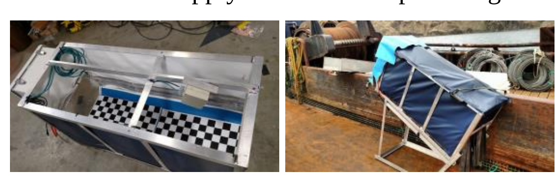
Image processing and analysis techniques have drawn increasing attention since they enable a non-extractive and non-lethal approach to fisheries survey, such as fish size measurement, abundance prediction, catch estimation and compliance, species recognition and population counting. In this work, we present an innovative and effective method for measuring the chute-based fish length based on the morphological midline of the fish. The midline is generated through recursive morphological operations on the segmented fish mask. To conduct reliable measurement, even under harsh environment, we also propose a systematic method for detecting water drop on camera lens. The robust detection, which can be performed either in real-time or in offline processing, is based on a blur measure derived from the gradient of the image and the contour of fish.

Index Terms— Morphological midline, fish length, blur measure, water drop detection

1. INTRODUCTION

Recently, the potential of using automatic image processing system in fishery draws attention from both industry and aquaculture science [1-3]. Counting and isolation of fish after captured are normally carried out directly on fishing vessels. The conventional laborious manual process increases the required labor and limits the efficiency of fisheries for either commercial or research purposes. An automated chute-based fish monitoring system can systematically perform fish body segmentation and length measurement. Therefore, a successful development of these algorithms will be beneficial to significantly speed up this indispensable process on fishing vessels. Compared to traditional manual sorting and measuring, the automatic image processing system is faster, less error-prone and more scalable. While there are many advantages to use automatic image processing system in fishery or aquaculture, challenges from the inspected subjects and operation environment remain [1]. For example, the live fish, when passing through the chute, may move and deform freely, making it difficult to segment them or to measure their lengths. The environment may have dynamic lighting changes with restricted visibility, or moreover, the cameras may be occasionally splashed by water, etc. In this work, the fish images are automatically captured from chute on board by a static camera as shown in Fig. 1. The images are only taken when fish is sliding through the chute and trigger the infrared sensor attached on the chute. With a set of background images of the chute without fish, we can build a Gaussian mixture model (GMM) for each image pixel [4], so that the fish foreground can be segmented based on background subtraction. However, because the fish slide freely on the chute surface, the fish body might not be straight, making it difficult to estimate the fish length. Furthermore, sometimes water is accidentally sprayed on the camera lens by fish or fishermen, resulting in blurs on fish images, and causing problems in subsequent segmentation, length measurement, and further applications, such as species recognition. Therefore, we propose two algorithms to deal with the above problems. One is the midline point algorithm for measuring the curved fish body. The other is the water drop detection algorithm for water drop detection. The midline is generated through recursive morphological operation on the fish mask. While the algorithm is similar to the skeletonization algorithm which are based on digital morphological erosion or distance transform [5-7], it improves the measurement performance by guaranteeing to robustly generate a list of midline points and two endpoints (head and tail) to effectively represent the fish body morphology. On the other hand, our proposed water drop detection algorithm is inspired by [8] for water drop detection. A blur measure is derived from the gradient of the image and the contour of the segmented fish. We assume that in the areas affected by water drops, the fish contour is relatively blurry and the image gradients are smaller than those of unaffected areas.

The rest of the paper is organized as follows: Section 2 discusses how this paper relates to prior works. Section 3 describes how we apply the midline point algorithm to



(a) (b)

Fig. 1. Chute with a static camera, a) interior view with checkboard for calibration, b) installation with cover on board.

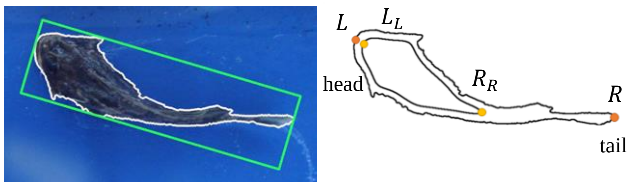


Fig. 2. The new midline points L_L and R_R as the closest points on sub-contour(s) to the previous midline points, with the initial midline points being the left- and right-endpoints.

measure the fish length. Section 4 introduces the blur measure and its application to water drop detection. Section 5 shows the experiment results and discussions, followed by the conclusion in Section 6.

2. RELATED WORKS

One of the challenges in length measurement of fish by computer vision is that the fish body may be not straight. Strachan [9] purposes a method by connecting the midpoints of the vertical lines perpendicular to the orientation of the fish to measure the fish length. White et. al [10] further improve the flexibility of this method by using a moment-invariant method to determine the orientation of the fish. Both of their methods generate a line along the orientations of fish body and tail, and well describes the length of deformed fish. However, when the fish body is greatly curved, the midpoints of the vertical lines could fall on one side of the fish body due to the changing of the width of fish along its orientation.

For the water drops or blur detection problems, there have been some works done, but none of them are suitable for our application settings. Alippi et al. [8] propose a method detecting external disturbances on camera lens by comparing the blur measures of a series of frames which contain the same scene acquired from a static camera, but it is not suitable when the texture and size of the subject keep changing in consecutive images. Kanchev et al. [11] propose an algorithm for detecting blurred regions in images by using wavelet-based histograms and SVM, but since the patches for generating histogram are selected from the whole image, it is more suitable for the images in which edges and features are roughly evenly distributed.

3. MORPHOLOGICAL MIDLINE

The general idea of morphological midline is by connecting the midline points whose distances to both sides of the segmented object (fish) contour are the same. To generate the midline points, we assign left- and right-endpoints on the object contour, and recursively apply morphological erosion on the object mask by a circle structure element. Then, at each recursion, we effectively find the candidates of midline points on the contours of eroded object mask (discussed in the following subsection).

We define the set of sub-contours of an object contour C as $\mathcal{S}(C) = \{C_i | i = 1,2,\dots,n\}$, which consists of several contours of the object mask enclosed by C after a

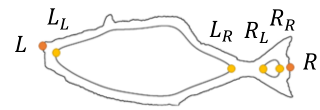


Fig. 3. One contour is split into two sub-contours.

morphological erosion. If C has no sub-contour, we have an empty set $\mathcal{S}(C) = \phi$. To facilitate the description of the morphological midline point algorithm, we denote the Euclidian distance between two points, P_1 and P_2, as $d(P_1, P_2)$. We also define the distance between a point P and the contour C as $d(P, C) = d(C, P) = \min_{P_i \in C} d(P, P_i)$.

3.1. Locating Head and Tail Endpoints

To use the midline point algorithm to generate the midline of the fish, we have to first assign the left- and right-endpoints as the head and tail endpoints. Assume we already have the fish segmented as foreground object, we perform principle component analysis (PCA) on the fish contour points to find the orientation of the fish. Then we can choose the head endpoint as the point whose component along the orientation of the fish is the largest. To choose the tail endpoint, however, especially for the fish with forked tails, we have to choose the middle of the notch between the lobes of the tail fin. In order to find the best choice, we use a scoring function so that the points closer to the center of the fish body and farther from the tips of the tail fin get higher scores, and the point at the tail having highest score is chosen as the tail endpoint.

3.2. Midline Point Algorithm

The pseudo code for our proposed midline point algorithm is given in Algorithm 1. The input is a segmented object contour C, and left- and right-endpoints L and R, which are assumed to be available. The output $M = M(C, L, R)$ is the list of midline points from left-endpoint to right-endpoint. Steps 5 and 6 find the new midline points L_L and R_R as the closest points on sub-contours to the previous midline points, with the initial midline points being the left- and right-endpoints (i.e., either head or tail) of the segmented object contour (see Fig. 2). Because the structure element is a circle, the distances from L_L and R_R to either side of the contour should be very close, satisfying the criteria of midline points. Step 8 recursively finds the midline points of the sub-contour by assigning L_L and R_R as endpoints if they are on the same sub-contour. If L_L and R_R are on different sub-contours due to multiple generated sub-contours in one erosion (see Fig. 3), Steps 10 and 11 recursively find the midline points of these two sub-contours separately, under the constraint that two additional endpoints L_R and R_L (one from each sub-contour) are closest to each other, so that these two sub-contours can be connected with the shortest distance. The midline point search will now be split into two separate tasks and continue from there.

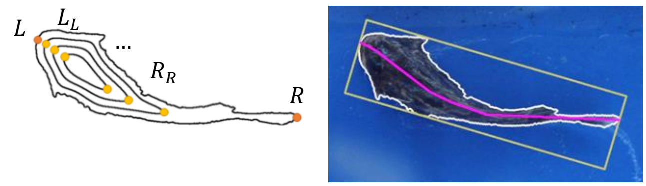


Fig. 4. The midline points are recursively identified, and finally connected to form the midline.

Algorithm 1: Finding midline points by recursive morphological operation

Input: Contour C, and endpoints L and R
Output: List of midline points $M = M(C, L, R)$

initialize M as empty list, $M \leftarrow M + L$
if $\mathcal{S}(C) = \phi$ **then**
    $M \leftarrow M + R$, **return** M
end if
select left sub-contour $C_L \leftarrow \arg\min_{C_i \in \mathcal{S}(C)} d(L, C_i)$
and right sub-contour $C_R \leftarrow \arg\min_{C_i \in \mathcal{S}(C)} d(C_i, R)$
select left midline point $L_L = \arg\min_{P \in C_L} d(L, P)$
and right midline point $R_R = \arg\min_{P \in C_R} d(P, R)$
if $C_L = C_R$ **then**
    $M \leftarrow M + M(C_L, L_L, R_R)$
else
    select midline points
    $(L_R, R_L) = \arg\min_{(P_1,P_2), P_1 \in C_L, P_2 \in C_R} d(P_1, P_2)$
    $M \leftarrow M + M(C_L, L_L, L_R) + M(C_R, R_L, R_R)$
end if
$M \leftarrow M + R$, **return** M

Finally, to generate the midline from the list of midline points, we can either connect the midline points by piecewise straight lines or by splines (see Fig. 4). In practice, we apply a Gaussian blur followed by a thresholding on the fish mask to approximate the morphological erosion to reduce both the computation time and the noise on contour. If the standard deviation of the Gaussian blur is $1/n$ of the widest width of a fish contour, the number of midline points of the fish is about n. To be more specific, the smaller the standard deviation, the more precise but also more noise-sensitive the midline points.

4. BLUR MEASURE AND WATER DROP DETECTION

To detect water drops on camera lens, we can use the blurriness information of the images. However, because most fish images captured from the chute on vessels are textureless, we cannot compare the blurriness with arbitrary regions in the image [11]. Moreover, since the fish in each image could be different in texture and size, we cannot compare the blurriness among consecutive images either [8].

The general idea of our water drop detection is based on the assumption that the edges on the fish contour becomes relatively blurry in the area affected by water drop than in the unaffected area. With the fish segmentation result based on GMM-modeled background subtraction as described in Section 1, we can thus measure the blurriness/sharpness of edge on the fish contour.

4.1. Sharpness on Contour

We define the sharpness of a contour point x in image z as:

$$m(x) = \frac{\|\nabla z(x)\|_2}{\|z(x)\|_2},$$

where the operator $\|.\|_2$ is the ℓ-2 norm. In practice, we first find the sharpness $m_R(x)$, $m_G(x)$ and $m_B(x)$ for each R-G-B channel respectively, and then calculate the total sharpness as $m(x) = m_{RGB}(x) = \left(m_R^2(x) + m_G^2(x) + m_B^2(x)\right)^{0.5}$.

4.2. Blur Measure

The idea of blur measure for water drop detection is that if a contiguous area lacks of sharp points, we assume the blurriness is caused by water drop. First, we use Otsu's threshold to separate all the detected contour points based on their sharpness into two groups: S (sharp points) and B (blurry points). Then we can define the density of sharp points in a contiguous window $h \subset C$ of the contour as:

$$p_h(S) = \frac{|h \cap S|}{|h|}.$$

If the density is much smaller than the average density on the contour, i.e., if $p_h(S) \ll p_C(S)$, we assume there is a potential water drop around h. Finally, we define the blur measure of a contour C as:

$$\text{blur}(C) = \frac{p_C(S)}{\min_{|h|=N} p_h(S)},$$

where N is a fix window size. If $\text{blur}(C)$ is larger than a threshold (we use 1000 in the experiments) or if $\min_{|h|=N} p_h(S) = 0$, we conclude that there is a water drop.

After the water drops are detected, we can either manually remove the water drops if the process is in real-time; or we can use the unaffected image areas to extract useful features for species classification or recover the shape of the fish at the affected area using the results of classification. These are beyond the scope of this paper and left for future works.

5. EXPERIMENT RESULTS

The proposed methods are evaluated by a set of images captured from chute on vessel. The resolution is 1920 × 1080 pixels. Because the camera is not shooting perpendicular to the chute surface, we first de-skew the fish based on a calibration image where chessboard is placed on the chute surface, and then do segmentation. The segmentation result (see Fig. 5) is refined using a histogram backprojection procedure [12] and further processed for the fish length measurement and water drop detection.

5.1. Fish Length Measurement

Fig. 5. Rectification and segmentation of fish image.

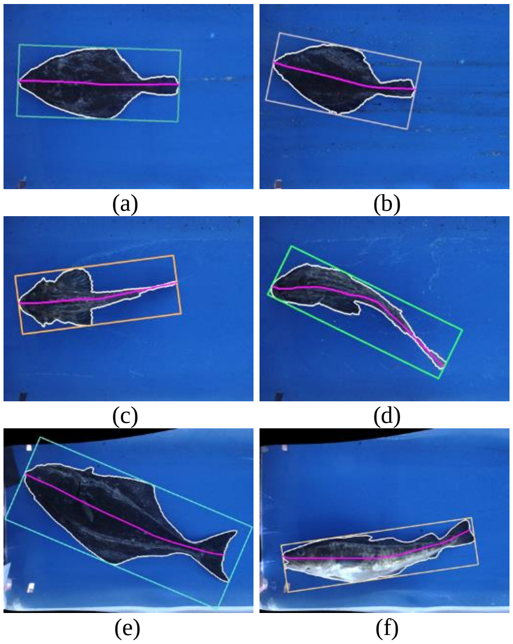


Fig. 6. Midline of fish of different curvatures and shapes of tail fins: a, c) straight, b) body and tail in different orientation, d) greatly curved and e, f) forked tail.

We apply the midline point algorithm to generate the midline of fish. The standard deviation of the Gaussian blur used in the recursive morphological operation is 1/10 of the widest width of the fish contour, resulting in roughly 10 midline points per fish contour. The sample results are shown in Fig. 6. For the straight fish, the midline simply follows the orientation of the fish body. While for the fish whose body and tail have different orientation, the midline is also consistent with the center of the body and tail. It can be seen that even when the fish is greatly curved, the midline is still close to the center of the fish. For the fish having forked tail, the endpoint of the midline is also correct. The experiment is based on 3571 fish samples consisting of 11 species, and a 1.49% of mean of absolute error is achieved. Compared to other methods, such as bounding box or [10], our method performs the best in average (see Table I).

5.2. Water Drop Detection

We use the Scharr operator [13] to get the gradient of images. For the blur measure of the contour, we use window size $N = 0.2 \times |C|$ and set the threshold for $\text{blur}(C)$ as 1000. The sample results are shown in Fig. 7. For the images with water drop, we can see that there are very few sharp points in the affected area; and for the unaffected image, the sharp points are evenly distributed on the contour. The results of a dataset

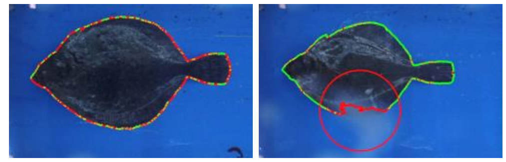


Fig. 7. Water drop detection by sharp/blurry points of fish contour: left) with and right) without water drop. The sharp/blurry points are in green/red. The circle indicates the position of the water drop.

Table I
Mean of absolute error of fish length measurement

Species (number)	Box	[10]	Midline
Arrowtooth Flounder (722)	2.1%	1.6%	1.7%
Flathead Sole (450)	1.1%	1.2%	1.1%
Pacific Cod (282)	1.4%	1.1%	1.1%
Pacific Halibut (213)	3.8%	1.6%	1.3%
Pacific Ocean Perch (156)	5.5%	3.0%	2.7%
Rex Sole (178)	1.4%	1.5%	1.5%
Shortspine Thornyhead (210)	2.7%	1.9%	2.0%
Southern Rock Sole (316)	1.6%	1.7%	1.5%
Walleye Pollock (839)	2.3%	1.9%	1.3%
Yellow Irish Lord (71)	2.1%	1.8%	1.8%
Yellowfin sole (134)	1.5%	1.3%	1.1%
Total (3571)	2.14%	1.68%	1.49%

Table II
TP and FP rates of the water drop detection algorithm

Image	Number	Positive Detection	TP rate	FP rate
Without water drop	184	148	80%	-
With water drop	155	26	-	17%

consisting of 339 fish images are shown in Table II. The water drop detection algorithm achieves a true positive (TP) rate of 80% and false positive (FP) rate of 17%.

6. CONCLUSION

Two novel algorithms aimed to solve on-board fishery problems, i.e., estimating the curved fish length and detecting water drops on camera lens under harsh environment, are proposed. Through recursive morphological operation, the midline point algorithm generates a list of midline points whose distance to both sides of fish body are similar. Experimental results show that we can achieve very reliable midline estimation of fish length measurement with 1.49% of mean of absolute error.

In addition, by defining the blur measure of the fish contour, our water drop detection algorithm can detect the blurred area of the image where the fish contour is affected. Experiment results show that our water drop detection algorithm can achieve a true positive rate of 80% and a false positive rate of 17%.

7. ACKNOWLEDGEMENT

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8. REFERENCES

[1] B. Zion, “The Use of Computer Vision Technologies in Aquaculture – A Review,” *Computers and Electronics in Agriculture*, vol. 88, pp. 125-132, 2012.

[2] J.R. Mathiassen, E. Misimi, M. Bondø, E. Veliyulin, and S.O. Østvik, “Trends in application of imaging technologies to inspection of fish and fish products,” *Trends in Food Science and Technology*, vol. 22, no. 6, pp. 257-275, 2011.

[3] M.-C. Chuang, J.-N. Hwang, K. Williams, and R. Towler, “Tracking Live Fish from Low-Contrast and Low-Frame-Rate Stereo Videos,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 1, pp. 167-179, 2015.

[4] Z. Zivkovic, and F. van der Heijden, “Efficient Adaptive Density Estimation per Image Pixel for the Task of Background Subtraction,” *Pattern Recognition Letters*, vol. 27, no. 7, pp. 773-780, 2006.

[5] P.K. Saha, G. Borgefors, and G.S. di Baja, “A Survey on Skeletonization Algorithms and Their Applications,” *Pattern Recognition Letters*, http://dx.doi.org/10.1016/j.patrec.2015.04.006, 2015.

[6] C. Arcelli, and G.S. di Baja, “A Width-Independent Fast Thinning Algorithm,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 7, no. 4, pp. 463-474, 1985.

[7] C. Arcelli, G.S. di Baja, and L. Serino, “Distance-Driven Skeletonization in Voxel Images, ” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 4, pp. 709-720, 2011.

[8] C. Alippi, G. Boracchi, R. Camplani, and M. Roveri, “Detecting External Disturbances on Camera Lens in Wireless Multimedia Sensor Networks,” *IEEE Transactions on Instrumentation and Measurement*, vol. 59, pp. 2982-2990, 2010.

[9] N.J.C. Strachan, “Length Measurement of Fish by Computer Vision,” *Computers and Electronics in Agriculture*, vol. 8, pp. 93-104, 1993.

[10] D.J. White, C. Svellingen, and N.J.C. Strachan, “Automated Measurement of Species and Length of Fish by Computer Vision,” *Fisheries Research*, vol. 80, pp. 203-210, 2006.

[11] V. Kanchev, K. Tonchev, and O. Boumbarov, “Blurred Image Regions Detection using Wavelet-based Histograms and SVM,” *IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, Prague, Czech Republic, pp. 457-461, 2011.

[12] M.-C. Chuang, J.-N. Hwang, K. Williams, and R. Towler, “Automatic Fish Segmentation via Double Local Thresholding for Trawl-based Underwater Camera Systems,” *IEEE International Conference on Image Processing*, Sept. 2011.

[13] H. Scharr, “Optimal Filters for Extended Optical Flow,” *Lecture Notes in Computer Science*, vol. 3417, pp. 14-29, 2007.