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An Algorithm for Selecting the Head and Tail of an Intact Fish in the Overlapping Multi-fish Image for Freshness Detection

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***Abstract*—The fish freshness detection application assists the public in determining the freshness of fish purchased at the market. The application operates two principal tasks: detecting body parts' regions of interest (ROI) and classifying freshness. For ROI detection, the You Only Look Once (Yolo) method detects intact fish and their parts, such as heads and tails. Then, a Convolutional Neural Network classifies them for freshness. However, the input image for Yolo may contain fish with arbitrary placement resulting in overlapped and redundant detected parts. Hence, an algorithm to select the appropriate head and tail of an intact fish from the detected parts is required to correctly aggregate the freshness classes of all fish in the image. This study proposes a head and tail selection algorithm using two principal components: the head-tail distance and the intersection over the fish part. The experimental results on 20 overlapping fish images show that the algorithm selects heads and tails with an accuracy of 84.21%. The best weights for both components are 0.6-0.4 to 0.8-0.2.**

Keywords*—head and tail selection, fish freshness, intersection over fish part, intact fish, distance

I. Introduction

Fish has become a high-value commercial commodity due to a community demand as a daily dish. Therefore, the need for fish by the community is high, and continued. As an essential daily necessity, selecting fresh fish in the market by consumers is an important issue that should be addressed [1], because fish is a perishable food [2]. In traditional markets, the seller sells fresh until not-fresh fish. Hence, consumers should have the sense to distinguish between fresh and non-fresh fish. The non-destructive visual freshness inspection can be assisted with an automatic system to detect freshness [3], [4], both with and without touching. Determining fish freshness requires input as a region of interest (ROI) of body parts, such as eyes [5], skin, and even head and tail. Then, the system classifies the ROI into freshness classes, as conducted by [6] [7]. This result is what the community needs as a reference for the freshness level of fish purchased in traditional markets.

An automatic system for detecting fish freshness based on digital images operates two principal tasks: detecting the ROI of body parts and classifying freshness. The detection of body parts is addressed by object detection modules such as You Only Look Once (Yolo) [8] or its modifications, Region-based Convolutional Neural Network (RCNN) [9] or its enhancements, RetinaNet [10], and others. The ROI required in the application is the head, tail, and intact fish. Each ROI is classified into a freshness class; therefore, each body part obtains its freshness label. This module uses Convolutional Neural Networks (CNN) such as MobileNet [11], Multi-level Residual VGGNet [12], and VGG16 [13].

However, the freshness classification provides a label of the freshness class for each object detected in the image input. Consequently, each intact fish with a head and tail detected obtains its freshness class. This issue raises a redundancy of freshness class in intact fish. Images with many fish and arbitrary placement also cause confusing heads and tails that are part of the intact fish. Therefore, the application should aggregate the freshness class of intact fish along with detected tails and tails. This aggregation is accomplished if the application can discover the correct head and tail as part of an intact fish. The issue is that some heads or tails might overlap with intact fish, leading to false aggregation of heads and tails with intact fish. The overlapping of several heads and tails with intact fish is addressed by an algorithm that selects the proper head and tail. Some methods for solving this issue are partial selection by encoding with intra-parietal sulcus [14] and diversity on fairness [15]. However, these methods select objects randomly and are not case-specific. Selecting the head and tail as part of the intact fish requires them to be in a straight line with highly overlapped intact fish.

This study proposes an algorithm for selecting heads and tails as part of intact fish by regarding specific requirements: the head-tail distance and the intersection over the fish part. The inputs are the objects detected by the Yolo module. The outcome is the head and tail as part of intact fish. The algorithm experimented with 20 images from Fish and Fish Part Detection (FFPD)[13] with a simple and complicated overlapping fish position. The experimental results show that the algorithm discovers heads and tails correctly, with an accuracy of 84.21%.

The rest of this paper is the research methodology that discusses problem analysis, algorithms, datasets, and evaluation metrics, followed by a discussion of results and analysis, and this paper closes with conclusions.

II. Research Methodology

A. Problem Analysis

Fish freshness detection application uses ROI input of heads, tails, and intact fish where each object obtains its freshness class label. For intact fish, heads and tails would also be detected in the ROI of intact fish. When the image contains many fish with complicated overlapping, the system should choose which heads and tails are part of the intact fish. The body parts discovered would be aggregated for freshness class with intact fish. Another issue is the geometric variation where the position of the intact fish in the image might be landscape or portrait.

As presented in Fig. 1, the analysis of the geometric problem provides an example of an intact fish in a landscape position where the width is greater than the object's height. In the figure, another fish head overlaps the intact fish. The detection results of the head are indicated by a blue dashed bounding box (BBha) and yellow (BBhb), while the blue indicates the tail dashed bounding box (BBt). Intact fish objects are indicated by a black bounding box (BBf). This image shows one intact fish detected with two heads and one tail. The tail object detected can be confirmed as part of the intact fish because there is one tail. Geometric changes strongly influence this problem according to what is described in the image. In general, the position of the head and tail of the fish is a straight line according to the fish's direction. However, the geometrical problems are affected by the overlapping head, tail, and intact fish and the distance between the head and tail. The following geometric parameters are needed to solve the problem of selecting the correct head and tail:

1. Intersection Over Fish Part (IOF)
   Intersection Over Fish Part (IOF) is a metric to measure the degree of overlap between body parts (head and tail) with intact fish, *IOFh* and *IOFt* for head and tail, respectively. *IOFh* is calculated from the intersection between the head bounding box area (*BBh*) and fish bounding box divided by the head bounding box area, the same way for *IOFt*. The range of *IOF* values is [0,1], where the higher the *IOF* of a body part indicates greater the possibility as part of intact fish.
2. Width and height of intact fish
   Other geometric parameters influencing the selection of heads and tails are the width and height of the bounding box of intact fish (*BBf*), *w0* and *h0*. The *w0* is calculated from the geometric width of *BBf*, while *h0* is calculated from the geometric height of *BBf*. Fish with landscape position meets the *w0* > *h0* constrain, while portrait position meets the *h0* > *w0* constrain.
3. The farthest distance of the bounding box between the head and tail pairs
   The farthest distance between the pairs of heads and tails (*w1*) represents the distance between the heads and tails in a straight line, as in common fish. Geometrically, this distance is calculated from the outermost (farthest) bounding box distance between the head bounding box (*IOFh*) and the tail bounding box (*IOFt*). This study assumes that the farther out *w1* is, the more possible the head and tail pair are part of an intact fish.

Searching for head and tail as part of intact fish was conducted by calculating the distance between the head and tail pair (*Dist*), which was influenced by the geometric distance *w1* and the head and tail *IOF*. The two components are combined with a certain weight as described in the next subsection.

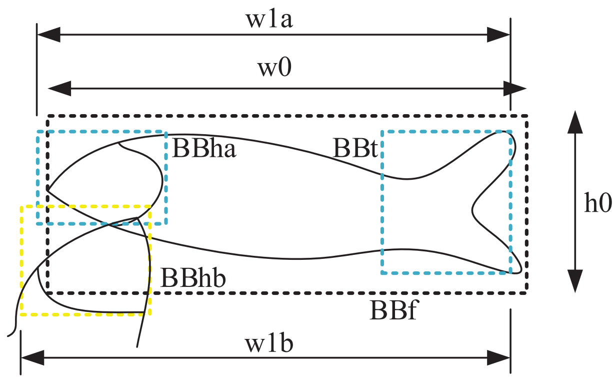

Fig. 1. Geometric analysis.

B. Proposed Method

This research is part of a fish freshness detection system divided into several modules: object detection using Yolo, fish freshness classification, head-tail selection for intact fish, and freshness class aggregation, as presented in Fig. 2. The third module, discussed in this paper, proposes an algorithm to discover the head and tail as part of an intact fish. It received the intact fish, head, and tail from Yolo object detection and then generated an intact fish with the correct head and tail. Details of the algorithm are as follows:

1. Let *dh* and *dt* as list of head and tail
2. Calculate *IOF* of each head and tail
3. Let *H* as list of *dh* ≥ 0.5, *T* as list of *dt* ≥ 0.5
4. If *n*(*H*)>1 or *n*(*T*)>1 do 5-14 else do 15
5. Calculate *w0* and *h0*
6. On each pair of heads and tails, do steps 8-13
7. If *w0* > *h0* do 8-10 else do 11-13
8. Calculate *w1a*, *w1b*
9. Get *w1* as minimal of *w1a* and *w1b*
10. $Dist = 0.6 * w1/w0 + 0.4 * IOF_h * IOF_t$
11. Calculate *h1a*, *h1b*
12. Get *h1* as minimal of *h1a* and *h1b*
13. $Dist = 0.6 * h1/h0 + 0.4 * IOF_h * IOF_t$
14. Select *J* as min(*Dist*)
15. If *n*(*H*) atau *n*(*T*) = 0: *J* = max(*IOF* of head or tail)
16. Select head and/or tail associated with *J*

The algorithm handles variations in landscape and portrait positions of intact fish. The algorithm attempts to calculate the distance between the head and tail based on the outermost distance of the bounding box, combined with the intersection of the head and tail to the intact fish. The two components are combined with some weights, respectively. Having obtained *Dist* for each head and tail pair, we calculate *J* by selecting the smallest *Dist*. The heads and tails associated with *J* represent the head and tail selected as part of the intact fish.

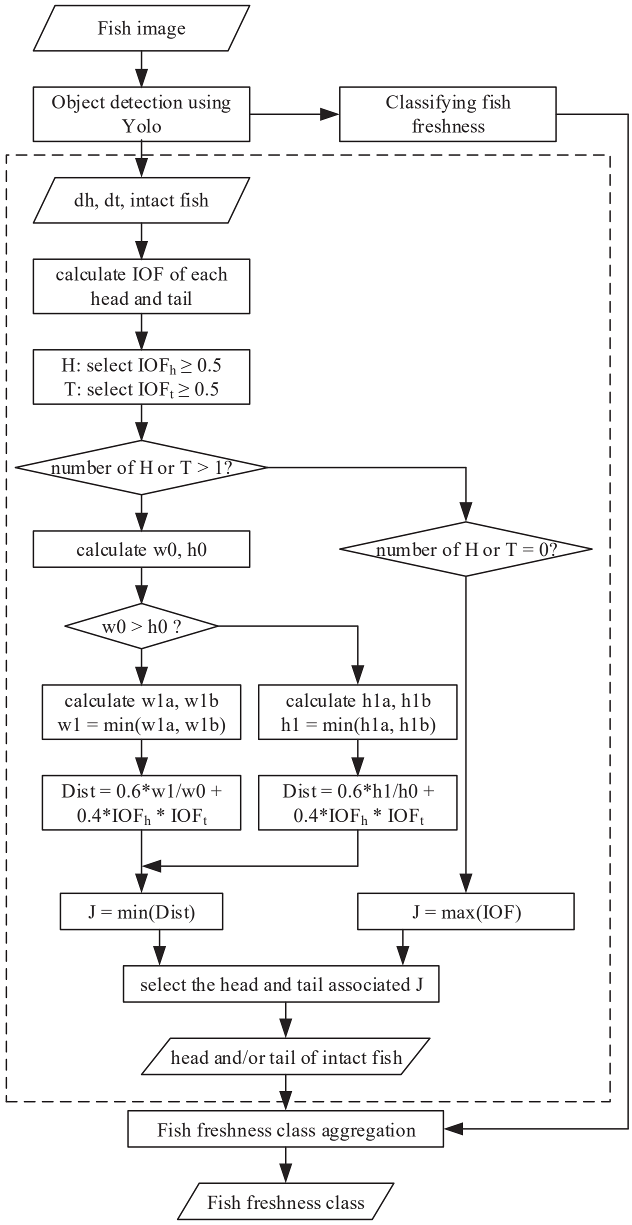

Fig. 2. Selecting head and tail of intact fish algorithm.

C. Dataset

We used 20 image samples from Fish and Fish Part Detection (FFPD) [16], as presented in Fig. 3, randomly selected from simple and complicated overlapping fish cases. The cases of intact fish that we experimented with included: intact fish with two heads and one tail or one head and two tails, intact fish with only two or more heads/tails, and one image containing one or more intact fish. There are also fish positional variations consisting of diagonal, portrait, and landscape represented by 3, 8, and 9 images, respectively. The number of fish in images varies between two to six, where all fish overlap. The image size is 624×832 pixels. Experimenting with such variations of the image complexity is to test the robustness of the proposed algorithms to solve similar conditions in real applications.

D. Evaluation Metric

The Head and tail selection algorithm is used to reconcile body parts with intact fish. The selected body part might be false or true. The experimental results on 20 images are mapped to the confusion matrix. Subsequently, we evaluate the performance of the algorithm using accuracy. Accuracy is calculated using the following equation.

$$Accuracy = \frac{TSR}{N} \tag{1}$$

where *TSR* is the true selection result of the heads and tails found, *N* is the number of intact fish in the tests conducted.

III. Results and Discussions

A. Experimental scenario

We experimented with 20 images by running a fish freshness detection application, then evaluated the performance of the head and tail selection algorithm on intact fish. The algorithm parameters, head-tail distance weights, and head-tail IOF were tested with the following variations: 0.5-0.5, 0.6-0.4, 0.7-0.3, 0.8-0.2, and 0.9-0.1. The weight selection is based on the head-tail distance being more dominant than the IOF. We start with the same weight to the weight's dominance of the head-tail distance. Then, we analyze how much influence the right weights should be utilized.

B. Results and Analysis

The experiment was conducted on 20 images consisting of 5 simple images and 15 complicated overlapping fish images. The images tested are diverse, such as the number of intact fish in one image and the number of heads and tails overlapping with intact fish. Includes horizontal and vertical intact fish directions to test the geometric reliability of the algorithm. The object detection results in all images are presented in Fig. 3.

The summary of information on the detection of body parts that overlap with whole fish is as follows: 2 heads ((a), (g), (m), (q), (t)), 1 head and 2 tails ((b), (h)), (n), (o)), (e), (l), (m), (s)), 2 heads and 2 tails ((c), (i)), 2 tails ((d)) , 4 heads ((d)), 1 head and 1 tail ((e), (g), (o), (t)), 3 heads and 2 tails ((f)), 2 heads and 1 tail ((f), (g), (h), (i), (j), (k), (l), (r)), 1 head ((g), (n), (s)), 1 tail ((j)), 2 heads and 3 tails ((p)). Therefore, we used a large variety of intact fish and selected heads and tails. The algorithm's input is the image of the object detection result from the system module. The output is the head and tail part of the intact fish.

TABLE I. HEAD AND TAIL DETECTION RESULT

No.	Image	Num. of intact fish	Num. of true selection				
			0.5 – 0.5	*0.6 – 0.4*	*0.7 – 0.3*	*0.8 – 0.2*	*0.9 – 0.1*
1	(a)	2	2	2	2	2	2
2	(b)	1	0	0	1	1	1
3	(c)	1	1	1	1	1	0
4	(d)	2	1	1	1	1	1
5	(e)	2	2	2	2	2	2
6	(f)	2	1	1	1	1	1
7	(g)	4	4	4	4	4	4
8	(h)	2	2	2	1	1	1
9	(i)	2	0	1	1	1	1
10	(j)	2	2	2	2	2	2
11	(k)	1	1	1	1	1	1
12	(l)	2	1	1	2	2	1
13	(m)	3	2	2	2	2	2
14	(n)	2	2	2	2	2	2
15	(o)	3	3	3	3	3	3
16	(p)	1	1	1	1	1	0
17	(q)	1	1	1	1	1	1
18	(r)	1	1	1	1	1	1

19	(s)	2	2	2	2	2	2
20	(t)	2	1	2	1	1	2
Total		38	30	32	32	32	30
Accuracy			78.95	84.21	84.21	84.21	78.95

Fig. 3. Object detection results.

The results of the head and tail selection by the algorithm are presented in Table 1. The number of fish objects that should find their body parts is 38 whole fish from the image with various problems. The test is carried out with head-tail distance weights and IOF ranging from 0.5-0.5 to 0.9- 0.1. The results showed that there were intact fish got their body parts correctly in all weight variations, such as images (a), (e), (g), and (k). These images discover the body parts even though we used different weights; this problem is easy to solve. Some images are successfully detected by balanced weights (0.5-0.5) but fail when using dominant weights (0.9-0.1), such as images (c) and (p); there are also vice versa, such as images (b) and (i). These results indicate that the selection of weights also affects the results achieved. We do this test to get the best weight composition in the algorithm. In addition, there are also intact fish objects that the algorithm fails to resolve with any weight, such as image (m), were out of 3 detected intact fish, only two fish found the head and tail correctly.

Among all images, this algorithm resolves ten images in which the heads and tails have been correctly selected, although all of them were tested with different component weights. The images are (a), (e), (g), (j), (k), (n), (o), (q), (r), (s). These images were completed perfectly because the correct head and tail have large IOF and appropriate head-tail distance. However, image (i) becomes the image with the worst detection results because the algorithm is stuck with choosing the wrong pair of head and tail. This image's problem is caused by a correct non-detected tail covered by other fish and the overlap of the other tail with a large IOF.

The overall analysis showed that of the 38 intact fish found, the algorithm operated to resolve 30 to 32 intact fish. The algorithm achieves 30 images with an accuracy of 78.95% at weights of 0.5-0.5 and 0.9-0.1. The best accuracy achieved was 84.21%, with 32 completed intact fish; the weights were 0.6-0.4, 0.7-0.3, and 0.8-0.2. Accordingly, the algorithm achieves the best performance with an accuracy of 84.21%.

IV. Conclusions

This study proposed an algorithm for selecting the head and tail of an intact fish based on the result of Yolo objects detection. The proposed algorithm was tested on 20 images consisting of multi-fish with arbitrary overlapping placements, variation in position, and the number of fish. The experiment result showed that the algorithm discovered 38 intact fish with an accuracy of 84.21%. The head and tail selection algorithm used two principal components: head-tail distance and intersection over the fish part (IOF). The experimental results show that the best weight for the two components is 0.6-0.4 to 0.8-0.2. The proposed algorithm performed satisfactorily for almost any case except to discover an intact fish's proper head and tail in a diagonal position. Therefore, subsequent research to handle multi-fish with overlapping diagonal placement is required.

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