Automatic searching of fish from underwater images via shape matching

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***Abstract*—To conserve and manage fish in fisheries, people monitor the growth and quantities of fish by underwater videos and images. However, the efficiency of finding fish from videos and images is limited by manual operation. In this paper, to improve the efficiency, we propose an automatic method for searching of fish from underwater images via shape matching. A segmentation method, Segmentation by Aggregating Superpixels (SAS), is used to partition all objects from an underwater image. To search for fish from these partitioned objects, Inner-Distance Shape Context (IDSC) is applied as a shape matching method to measure the shape similarity. The proposed method can overcome the disturbing of specific underwater environment, such as blurring and fish's deformation in underwater images. Experimental result shows that the method is effective to search for fish by computer automatically and it can be widely applied to fish surveillance in fisheries.**

I. Introduction

In fisheries, people search for fish from underwater videos and images to monitor the growth and quantities of fish. But the workload of artificial searching of fish from videos and images is huge. Replacing human manually with computer automatically is an important part to cut the workload and raise efficiency. Some methods have been proposed, for example, Spampinato[1] presented a machine vision system that automatically determines and annotates characteristics of underwater video images. Chuang[2] proposed a systematic hierarchical partial classification algorithm for underwater fish species recognition. Ravanbakhsh[3] proposed an automated approach for fish detection using a shape-based level sets framework. However, these methods above didn't consider the effects of specific underwater environment, when searching of fish.

While there is a clear advantage to using computer automatically, there still exist practical challenges that are particular in aspects of specific underwater environment:

- The underwater images are blurring due to strong scattering of light by the water.
- There are many objects except fish in the complex underwater environment.
- Fish may deform while swimming in underwater images.

These challenges above add the difficulties of automatic finding fish from underwater images.

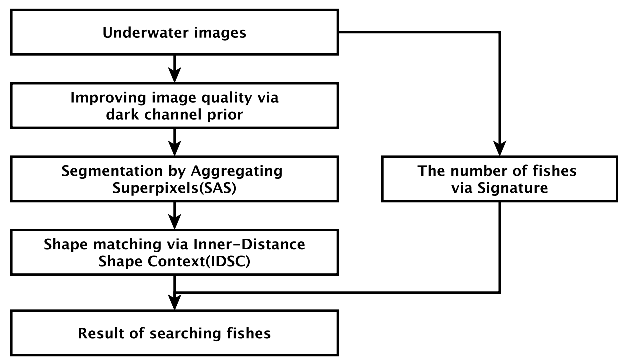

Fig. 1: The flow chart of automatic searching of fish from underwater images via shape matching.

In this paper, an automatic method for searching of fish from underwater images via shape matching is proposed to overcome the challenges described above. Fig. 1 shows the method we use. Firstly, we apply the dark channel prior to eliminate blurring in images. Next, all objects in every underwater image are partitioned via Segmentation by Aggregating Superpixels (SAS)[4]. Then, to find fish from partitioned objects, Inner-Distance Shape Context (IDSC)[5], a shape feature descriptor, is applied as shape matching method. It is based on Shape Context (SC)[6], which isn't good to deal with the situation that the fish may deform while swimming when IDSC could. Finally, combining the number of fish that is obtained by Signature[7] and shape matching result, the fish can be searched from underwater images. In this paper, we will describe our method for automatic searching of fish in detail.

II. METHOD

A. Dark Channel Prior Algorithm

The blurring and low-contrast is the characteristic of underwater images, which is similar to haze image. It is the main challenge in searching of fish from underwater images. To overcome the effects of blurring and low-contrast, we apply the dark channel prior[8], which was proposed to remove haze from a single input image. Since the underwater images are similar with the haze images, this method mentioned can be also applied to underwater images.

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The dark channel prior is based on that most local patches in haze-free outdoor images contain some pixels, which have low intensities in at least one color channel. Using this prior with the haze-imaging model, a high quality haze-free image can be recover. When the dark channel prior is applied to an underwater image, a clear image is generated. Fig. 2 shows a result of the dark channel prior experiment. From Fig. 2, we can see that the underwater image becomes clearer without the “haze”.

(a) (b)

Fig. 2: “Haze” removal result. (a) input underwater image. (b) image after “haze” removal by dark channel prior.

B. *Segmentation by Aggregating Superpixels*

To search for fish from an underwater image, all objects must be partitioned from the image first by image segmentation that is the process of partition a digital image into multiple segments. A variety of segmentation methods have been proposed, and the methods can behave quite differently in different situations. For example, Normalized Cuts[9] criterion measures both the total dissimilarity between the different the different group as well as the total similarity within the groups. Mean Shift[10] is a non-parametric feature-space analysis technique for locating the maxima of a density function.

In our experiment, we use Segmentation by Aggregating Superpixels (SAS)[4] to partition complete object from underwater images. SAS is based on bipartite graph partitioning, which is able to aggregate multi-layer superpixels in a principled. It can effectively encode complex image structures for segmentation with superpixels as grouping cues.

The segmentation result of Fig. 2(b) is shown in Fig. 3 via SAS. From Fig. 3, we can see that Fig. 2(b) is partitioned into twelve objects, and fish are completely partitioned from the image.

Fig. 3: The segmentation result.

C. *Inner-Distance Shape Context*

After image segmentation, fish needed to be found from these objects, which are the result of segmentation. Human usually use shape features based on biological morphology to find fish from many objects. And computer vision can simulate human to automatically search for fish by shape matching from these objects in underwater images. In the process of shape matching, a shape of real fish (Fig. 4) is needed as a template image. After all objects matching with the template image via shape matching method, the similarity of them can be obtained.

Fig. 4: Fish template.

Shape Context[6] is a feature descriptor used in shape matching. It is intended to be a way of describing shapes that allows for measuring shape similarity and the recovering of point correspondences. Shape Context is more robust against noise, outlier and clutter than other descriptors.

Shape contexts consists of the following steps:

1) Finding a list of points on shape edges: Edge pixels of objects can be obtained by an edge detector, such as Canny edge detector[11]. Then, pick a random set of points from the edges, $P = \{p_1, \dots, p_n\}$, $p_i \in R^2$, of n points.

2) Computing the shape context: For each point p_i on the shape, consider the $n-1$ vectors obtained by connecting p_j to all other points. The set of all these vectors is a rich description of the shape localized at that point.

$$h_i(k) = \#\{q \neq p_i : (q - p_i) \in bin(k)\} \tag{1}$$

is defined to be the shape context of p_i.

3) Computing the cost matrix: The cost of matching two points is computed by $C_{ij} = C(p_i, q_j)$,

$$C_{ij} \equiv C(p_i, q_j) = \frac{1}{2} \sum_{k=1}^{K} \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}. \tag{2}$$

4) Finding the matching that minimizes total cost: A one-to-one matching p_i that matches each point p_i on shape 1 and q_j on shape 2 that minimizes the total cost of matching,

$$H(\pi) = \sum_i C(p_i, q_{\pi(i)}). \tag{3}$$

5) Modeling transformation: Given the set of correspondences between a finite set of points on the two shape, a transformation can be estimated to map any points from one shape to the other.

6) Computing the shape distance: The shape distance which represent the dissimilarity between two shapes. It is a weighted sum of three potential terms,

$$D = aD_{ac} + D_{sc} + bD_{be} \quad (4)$$

where D_{ac}, D_{sc} and D_{be} denote appearance cost, shape context distance and transformation cost.

However, Shape Context used Euclidean distance that is sensitive to articulation. The deformation of fish while swimming will easily affect the result of Shape Context. To overcome the effect of fish' deformation, we apply Inner-Distance Shape Context (IDSC)[5], which used inner-distance to replaced Euclidean distance, as shape matching method to find fish from many objects in underwater images. Inner-distance is defined as the length of the shortest path within the shape boundary. It is insensitive to articulation and sensitive to part structures. Therefore, IDSC can overcome the problem that fish may deform while swimming.

IDSC is a shape matching method, which is based on shape context, and it uses inner-distance and inner-angle to replace the Euclidean distance and relative orientation in Shape Context. It is not only robust against noise, outlier and clutter but also not affected by the deformation of fish.

In our experiment, the shape distances between fish template and objects, which are computed by IDSC, are shown in TABLE I. A small value for shape distance implies that the object is more similar to fish template.

Object	object1	object2	object3	object4	object5	object6
Distance	106.01	79.90	66.66	88.71	61.58	72.29
Object	object7	object8	object9	object10	object11	object12
Distance	104.30	80.23	74.48	105.63	103.26	74.84

TABLE I: The shape distance between every objects and fish template.

D. Determining the Number of fish

After shape matching, the shape distances between template and objects are obtained. Shape distances indicate the dissimilarity between objects and fish template. But the number and position of fish can't be determined. Therefore, we can't determine which are fish. If we differentiate between fish and other animals by setting a fixed shape distance threshold, it will be difficult to find a threshold that can be applied to all underwater images.

Therefore, to determine the number of fish in every underwater image, we use Signature[7], which is defined as the sign function of the Discrete Cosine Transform of an image, to generate saliency map and salient objects. By setting a threshold value in saliency map, the most salient objects and its quantity can be obtained. In the underwater images, fish are the most salient objects. So the number of most salient objects is the quantity of fish. According to the number of most salient objects, we can find a few of the most similar objects that are fish.

The saliency map of Fig. 2(a) is generated by Signature. However, there are many salient objects in this saliency map. To find the most salient objects, we set a threshold value. The most salient objects are shown in Fig. 5. From this image, we could see that the number of the most salient objects is two. So there are two fish in Fig. 2(a).

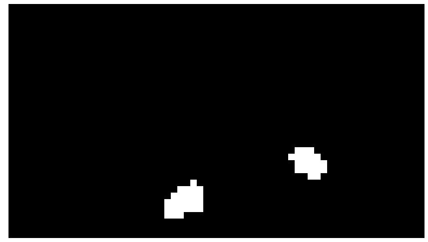
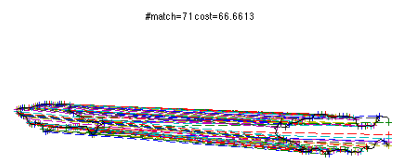
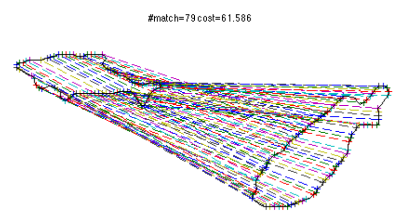


Fig. 5: The number of fish.

According to the number of fish and the shape distance between fish template and objects in Fig. 2(a), the two objects with the shortest distance are fish. From TABLE I, we can see that the $object3$ and $object5$, which have the shortest distance, are fish. The shape matching results of them are shown in Fig. 6. In Fig. 7, the bounding box is the searching of fish result.



(a)



(b)

Fig. 6: The shape matching results of two best matching objects. (a) object3. (b) object5.

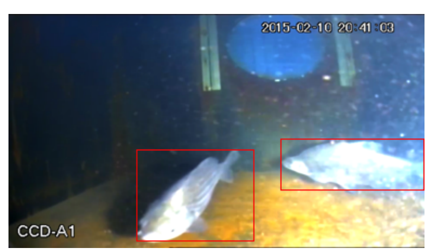


Fig. 7: The searching result of fish.

III. Conclusion

In this paper, we propose an automatic method to search for fish from underwater images using shape matching. The experimental result shows that the dark channel prior can reduce the influence of blurring in images. And IDSC can overcome the effects of fish's deformation when searching for fish from objects, which are the segmentation results. The proposed method not only can cut workload by automatic searching of fish from underwater images, but also can overcome these challenges of specific underwater environment, such as blurring of images, deformation of fish. It contributes to accurately search for fish from underwater image and can be widely applied to fish surveillance in fisheries.

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