Fish Image Segmentation Using Salp Swarm Algorithm

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Abstract. Fish image segmentation can be considered an essential process in developing a system for fish recognition. This task is challenging as different specimens, rotations, positions, illuminations, and backgrounds exist in fish images. In this research, a segmentation model is proposed for fish images using Salp Swarm Algorithm (SSA). The segmentation is formulated using Simple Linear Iterative Clustering (SLIC) method with initial parameters optimized by the SSA. The SLIC method is used to cluster image pixels to generate compact and nearly uniform superpixels. Finally, a thresholding using Otsu's method helped to produce satisfactory results of extracted fishes from the original images under different conditions. A fish dataset consisting of real-world images was tested. In experiments, the proposed model shows robustness for different cases compared to conventional work.

Keywords: Image segmentation · Fish database
Salp Swarm Algorithm · Superpixels · Optimization

1 Introduction

Meta-heuristics, in computer science and optimization, are procedures intended to generate, find or select heuristic partial search algorithms. That may provide a satisfactory solution to a problem with imperfect or incomplete information. Meta-heuristic can make a few assumptions about the optimization problem that needs to be solved. Therefore, it can be used for a diversity of problems compared to iterative methods and optimization algorithms. However, it does not assure that a globally optimal solution can be found on some problems. Many meta-heuristics apply a form of stochastic optimization. So, the solution found depends on a set of generated random variables in combinatorial optimization. By searching a large set of possible solutions, meta-heuristics can often find satisfactory solutions with less computational effort and optimization algorithms than simple heuristics or iterative methods.

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Swarm algorithm is a category of meta-heuristic algorithms that simulate the collective behavior of decentralized self-organized natural or artificial systems. Many algorithms that belong to such category were found to be promising in solving challenging applications in a broad spectrum of fields. Those algorithms include Particle Swarm Optimization (PSO), Ant Colony Algorithm (ACO), Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO) and Salp Swarm Algorithm (SSA). However, recent literature that compared a number of those algorithms demonstrated the superiority of SSA in single-objective optimization problems [1].

The research done by Ren et al. [2] proposed a new color image segmentation algorithm based on GrabCut. Their technique combined Bayes classification and Simple Linear Iterative Clustering (SLIC) followed by using the GrabCut method to obtain the segmentation. Clustering the features of a color image was done using the SLIC algorithm and the GrabCut framework to overcome the problem of the image segmentation deterioration problem. Another research by Wu et al. [3] presented an algorithm for applying cartoon image segmentation based on adaptive region propagation merging and SLIC superpixels. They proposed a method that improved the quality of the superpixels generation based on the connectivity constraint. Authors in [4] proposed a superpixel based model for thermal IR human face images. In [5], the segmentation algorithm based on SLIC superpixels had been used to eliminate the constructed defect and noise influence using the feature similarity in the preprocessing stage.

In [6], the authors proposed a new modeling method to model local session variations. They tested the efficiency of this approach using databases for fishes underwater that provide more session variations. In [7], the authors investigated the selected features subset for the binary classification problem using logistic regression model. They proposed a modified discrete PSO algorithm for feature selection problem. Their approach integrated an adaptive feature selection method that dynamically relied on the dependence and relevance of the features. The work in [8] proposed a new feature for fish age classification based on an ensemble of wrappers. The effectiveness of their approach using an Atlantic cod database was tested for various statistical learning classifiers.

The work presented in [9] proposed a new approach for feature selection based on the Fish School Search (FSS) optimization algorithm, which aimed to take into account premature convergence. The authors proposed binary encoding procedure for the internal mechanisms of fish school search. In [10] the authors combined K-means algorithm with mathematical morphology for fish images segmentation. Authors in [11] introduced a fish detection method using Bat optimization algorithm to reduce the time of classification within the fish detection process.

The authors in [12] developed a classifier for fish images recognition system that depended on color texture measurements extracted from gray level co-occurrence matrix. Their system started by acquiring an image containing fish pattern; then they segmented the image relying on color texture measurements. Authors in [13] proposed an automatic classification approach for the Nile Tilapia fish based on Support Vector Machines (SVMs) with feature extraction using Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) algorithms. In [14] the centroid-contour distance method was used to classify fish species with two dorsal fins. Various image processing methods were applied on images to extract centroid contour distances. These distances were used as features, and the nearest neighbor algorithm was used for classification.

In this paper, a segmentation model was proposed for fish images using SSA. The segmentation was formulated using SLIC method whose parameters were optimized by SSA. The SLIC method clustered pixels for generating compact and nearly uniform superpixels. In experiments, the proposed model showed robustness for different cases.

2 Preliminaries

2.1 Salp Swarm Algorithm (SSA)

Salps tissues and movement are highly similar to jellyfishes. One of the most noticeable behaviors of salps is their swarming behavior. Salps form a swarm named salp chain. The main reason for this behavior for some researchers is done for achieving better locomotion using rapid, coordinated changes and foraging [1].

The work done by Mirjalili et al. [1] proposed a model of salp to solve optimization problems. They modeled the salp chains, by dividing the population into two categories: leader and followers. The leader is the salp at the front of the chain, whereas the rest of salps are considered as followers. The swarm is guided by the leader, while the followers follow each other. The positions of salps are defined in an n-dimensional search space where n is the number of variables of a given problem. Therefore, the positions of all salps are stored in a two-dimensional matrix called x. It is assumed that there is a food source called F in the search space as a target for the swarm. To update the leader's position, the following equation was applied

$$x_j^i = \begin{cases} F_j + c_l((ub_j - lb_j)c_2 + lb_j) & c_3 \geqslant 0 \\ F_j - c_l((ub_j - lb_j)c_2 + lb_j) & c_3 < 0 \end{cases} \tag{1}$$

where x_j^i shows the position of the leading salp in the j^{th} dimension, F_j represents the food source position in the j^{th} dimension, $(ub)_j$ indicates the upper bound of j^{th} dimension, $(lb)_j$ indicates the lower bound of j^{th} dimension, and the parameters c_2 and c_3 are randomly generated in the interval of $[0, 1]$. Equation (1) indicates that the leader updates its position according to the food source. The coefficient c_1 is a critical parameter in SSA because it balances exploration and exploitation defined as follows:

$$c_1 = 2e^{-(\frac{4l}{L})^2} \tag{2}$$

where l is the current iteration and L is the maximum number of iterations. The followers' positions are updated by the following equation:

$$x_j^i = \frac{1}{2}at^2 + v_0 t \tag{3}$$

where $i \geqslant 2$ and x_j^i shows the position of i^{th} follower salp in j^{th} dimension, t is time, v_0 is the initial speed, and $a = \frac{v_{final}}{v_0}$ where $v = \frac{x - x_0}{t}$. The discrepancy among iterations is equal to 1, and by considering $v_0 = 0$, this equation can be expressed as follows:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{4}$$

where $i \geqslant 2$ and x_j^i shows the position of i^{th} follower salp in j^{th} dimension. With Eqs. (1) and (4), the salp chains can be simulated.

The SSA algorithm starts with initiating random positions for multiple salps. Then, the fitness of each salp is calculated to find the salp with the best fitness and assigned the position of the best salp to the variable F as the source food to be chased by the salp chain. In the meantime, the coefficient c_1 is updated using Eq. (2). For each dimension, the position of leading salp is updated using Eq. (1). Moreover, the position of follower salps is updated utilizing Eq. (4). If any of the salps goes outside the search space, it will be brought back on the boundaries. All the above steps except initialization need to be executed iteratively until the satisfaction of predefined criteria. Notice that, during optimization, the food source will be updated because the salp chain finds a better solution by exploiting and exploring the around space. The salp chain has the potential to move towards the global optimum that changes over the course of iterations. The SSA algorithm has the following features:

– SSA algorithm saves the best solution obtained so far and assigned it to the food source variable, so it never gets lost even if the whole population deteriorates.
– SSA algorithm updates the position of the leading salp concerning the food source which is the best solution obtained, so the leader always exploits and explores the around space.
– SSA algorithm updates the follower position of salps concerning each other. Thus they move gradually towards the leading salp.
– Gradual movements of follower slaps preserve the SSA algorithm from stagnating in the local optima.
– Parameter c_1 is the main controlling parameter, and it adaptively decreased during iterations. Thus, the SSA algorithm first explores the search space and then exploits it.

These features make the SSA algorithm theoretically and potentially able to solve single-objective optimization problems with unknown search spaces. The SSA algorithm computational complexity is of $O(t(d \times n + Cof \times n))$ where t represents the iterations number, d is the variables (dimension) number, n is the solutions number, and Cof indicates the objective function cost.

2.2 SLIC Method

Simple Linear Iterative Clustering (SLIC) is one of the most important superpixels segmentation algorithms that requires low computational power. To accurately generate compact and uniform superpixels, the algorithm combines 5-D colors and image plan space. SLIC algorithm performs local clustering in 5-D space which is the CIELAB colorspace of l, a, b values and the pixels coordinates of x, y [15]. Euclidean distances in CIELAB color space are useful for small distances. Measure of distance D_s is defined as

$$d_{lab} = \sqrt{((l_i - l_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2)}, \tag{5}$$

$$d_{xy} = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2)}, \tag{6}$$

$$D_s = d_{lab} + \frac{m}{S} d_{xy} \tag{7}$$

The algorithm starts with sampling cluster centers that are regularly spaced. Then, moves the centers to initialize locations according to the lowest gradient position in a 3×3 grid. Image gradients $G(x, y)$ are computed using

$$G(x, y) = \|I(x+1, y) - I(x-1, y)\|^2 + \|I(x, y+1) - I(x, y-1)\|^2 \tag{8}$$

where $I(x, y)$ is the lab vector of the pixel at position (x, y), and $\|.\|$ represents the $L2$ norm. Intensity information and color are taken into consideration. Finally, pixels in the larger segment neighborhood will have the same label. The algorithm then enforces relations by relabeling disjoint segments with the labels of the largest adjacent cluster.

3 Proposed Fish Segmentation Model

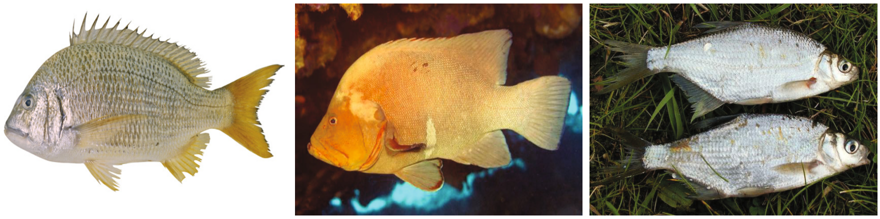
In this section, a model was proposed to extract fish from fish images under different conditions. This method uses the SLIC segmentation algorithm to produce superpixels based on the SSA optimization and then apply the method of Otsu to threshold the output superpixel image. Algorithm (1) presents the proposed fish segmentation method steps.

Algorithm 1. Fish Segmentation Proposed Model

1: Input the fish images $\{I\}_{i=1}^{N}$, where number of images is represented by N and the i^{th} input image is represented by I_i.
2: Calculate superpixels $S_i(I_i)$ using SLIC segmentation with initial values optimized by SSA.
3: Use the method of Otsu to separate the pixels in the foreground or background for superpixels image $S_i(I_i)$ of SLIC.
4: Convert superpixels' image to a binary image $B_i(S_i)$ using the optimum threshold.
5: Determine the fish pixels from the original image I_i to get $I_i(fish)$ using the binary image $B_i(S_i)$.

4 Experimental Results and Discussion

In this paper, a dataset of 3,960 real-world fish images collected from 468 species was used [6]. These images were captured in different conditions, namely, "controlled", "out-of-the-water" and "in-situ". The "controlled" images were taken under a constant background and illumination is controlled consist. The "out-of-the-water" images were natural underwater images of fish. The "in-situ" ones were out of the water images, and the background is varying with limited control over the illumination. Figure 1 shows a sample for each condition.



(a) (b) (c)

Fig. 1. Samples of fish images. (a) controlled (b) out-of-the-water (c) in-situ

The effectiveness of the proposed model was investigated by two types of analysis based on the applied conditions for the fish images in the dataset. In the first scenario, the proposed method was applied to the "controlled" images. Three different fish specimens with different colors, namely Acanthopagrus Latus, Alectis Ciliaris, and Aesopia Cornuta, captured under a constant background with controlled illumination were used in this scenario. Figure 2 shows the proposed segmentation results for different images. The results showed the robustness of this research method compared to a direct threshold using the Otsu's method and the active counters [16,17] method.

The second scenario used fish images under "out-of-the-water" and "in-situ" conditions. These types of images were more complicated than the controlled ones since the background was not constant and the illumination might vary from one image to another. Figure 3 shows the results for Aethaloperca Rogaa and Acanthopagrus Australis fish specimens. In addition, a segmentation method based on active counters was implemented and its relevant results were compared with the proposed model. The same database was used for this comparison.

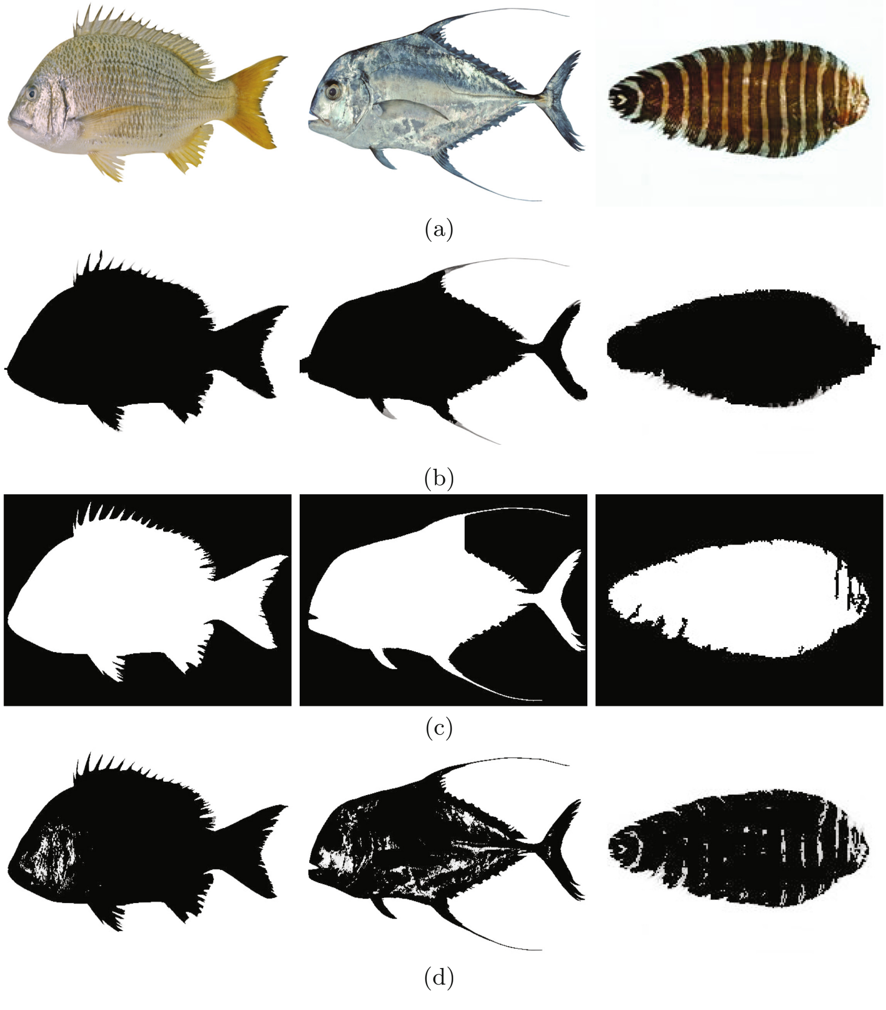
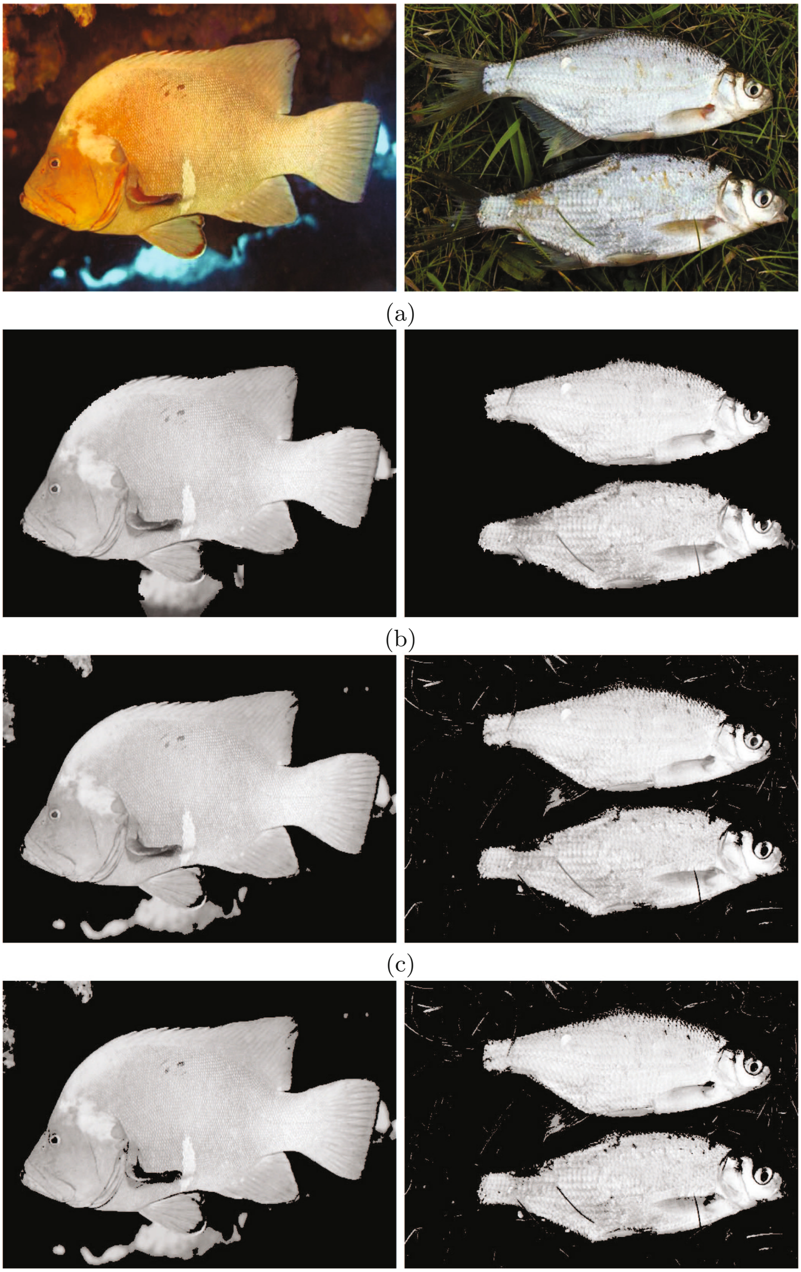


Fig. 2. Fish segmentation of the proposed method under "controlled" conditions. (a) Original images (b) Proposed segmentation (c) Active contours [16,17] (d) Otsu's segmentation



(a)

(b)

(c)

(d)

Fig. 3. Fish segmentation of the proposed method under "out-of-the-water" and "in-situ" conditions. (a) Original images (b) Proposed segmentation (c) Active contours [16,17] (d) Otsu's segmentation

5 Conclusion

In this paper, a segmentation method for real-world fish images was proposed based on the SSA. The SLIC method was used with initial parameters optimized by the SSA to generate compact and uniform superpixels. A thresholding with a simple Otsu's method was then used for the superpixel image to segment fishes and excluded the background from the original images under different conditions. A fish dataset consisting of real-world images with more than 400 species was tested. Results showed that the proposed model showed a robustness for different cases compared to conventional work.

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