SHAPE-BASED FISH RECOGNITION VIA SHAPE SPACE

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ABSTRACT

Automatic fish recognition is a recent research work which is needed to assist marine scientists. Among most discriminative features, the fish outline is very efficient for fish recognition. In a previous work, we proposed a method for pattern recognition (classification and retrieval) based on signal registration and shape geodesics. In this paper, we introduce a preliminary step of pose estimation for accelerating the processing time. We then show that shape geodesics may also be used for outline-based fish recognition. Experiments conducted on the SQUID database which is used as a benchmark to evaluate fish shape recognition, show (1) a reduction in computation time of a factor of ten in average, and (2) the outperformance of the proposed scheme compared to previous methods.

***Index Terms*—** Fish recognition, outline, shape, geodesics

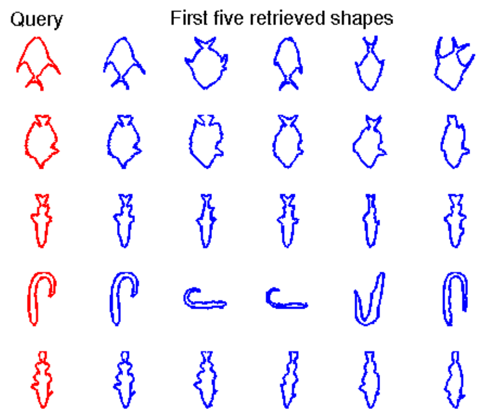

Fig. 1. Retrieval examples of some queries of the marine (SQUID) database. Our approach is able to retrieve well relevant fish shapes of the same species as queries.

1. INTRODUCTION

In order to carry out their work, marine scientists are often required to use underwater video images. Currently, when they need to analyze the images to extract information such as the number, the species, or the behavior of the fish in the video, these scientists mostly use manual processing. However, this work is time consuming, moreover, a relatively off-putting task. Automatic recognition of fish is a research topic that finds its interest in the precious help and time savings it can bring. So the idea is to design a system that would be able, from a video source, to automatically extract high-level semantic information that could be directly studied by scientists.

Automatic fish recognition by image processing and analysis is a widespread problem that can be devided in several successive stages. We can distinguish three such stages:

1. *Fish detection* : the first step is to detect and to isolate the fish from the remaining of the scene.
2. *Fish tracking*: once fish is detected, the idea is to provide a correlation between successive images. In other words, we try to track the fish from one image to another.
3. *Fish recognition* : the last step is to identify for each detected and tracked fish, its species, from a database identifying a number of images of each species of fish. Mostly, algorithms based on the concept of learning are used.

It should be noted that the description above is about the full fish recognition system but very few publications address the problem in its entirety. This type of system is still very marginal in the underwater environment. Indeed, it is an environment that has a lot of difficulties to be able to easily perform complete underwater image processing. The water absorbs light, that is why we must expect to get less bright contrasting images. It is also likely to have more noisy images because the water is more or less disturbed, it may be due to the presence of chlorophyll, sludge or pollution for example. Moreover, in a video, it is rare that there is only one fish at a time; it will be expected to see fish overlap in the two-dimensional plane of the camera. There will also be a submarine background that includes rocks, algae, etc. so the fish can hide behind objects. All these elements make recognition very complex. Some works as in [1] start of thumbnails images of fish segmented by hand to go directly to the phase of tracking. In other cases, the methods presented are not generic; they take into consideration the nature of the scene that can be very different from one situation to another.

Our interest will be focused in this paper to the fish recognition using the fish outline only. The outline is a very precious tool for fish discrimination but this tool faces several problems. Shape characteristics mainly depend on the fish orientation. Therefore shape analysis tool should be robustly invariant to geometric transformation. Moreover, there could be little difference between fish species and relatively high intra-class difference between fish of the same species. In previous works, the fish outline was described by the moments (first and second moment of Hu) [2, 3], geometric parameters [4], the shape context [5], the morphological descriptors [4, 6, 7], etc. We propose in this paper to perform fish shape recognition based on shape geodesics [8]. Performances of the proposed method are compared to those obtained with Fourier descriptors, moments and other more recent methods tested on a benchmark of marine shapes, the SQUID database. It is the only benchmark in the literature when recognition is done using the fish outline without other features. Some retrieval examples of our proposed method are given in Fig. 1.

This paper is organized as follows. In section 2 we describe our proposed method for automatic fish recognition based on attributes coming from the geodesics-based shape registration. Validation and comparison experiments on the SQUID database are given in section 3. Finally, conclusions and perspectives are given in section 4.

2. SHAPE-BASED FISH RECOGNITION

In most cases, we can extract from fish shape some points of specific features or attributes that correspond to similar points on the shapes of different instances of the same species. It is useful to benefit from this information about points correspondence for the shapes comparison. The main idea behind this framework is to perform an optimal matching of curve points in order to use this correspondence for shape comparison. We consider here the Geodesics approach recently proposed in [8] which proved to give very good performances for shape classification and retrieval experiments on the part B of the MPEG-7 shape database. The proposed approach based on shape geodesics has been compared to state-of-the-art schemes and we showed that it outperforms reported schemes in terms of correct classification rate and the *bull's eye* score for shape retrieval. This approach is adapted here for fish shape recognition.

2.1. Geodesics-based metric for shape recognition

The geodesics are widely used in analyses concerned with studying variations and changes in the shape of organisms, for instance morphometrics and image warping [9], because a morphometric variation can be considered as a geodesic path in the shape space. Geodesics in the shape space are defined as paths between two shapes with respect to some metric. This metric is chosen to be invariant for a given set of transformations.

Given a curvilinear parameterization s which has a value between 0 and 1 independently of the original contour length, it comes to a registration issue of $\theta(s)$ and $\tilde{\theta}(s)$, the angle functions that encode the two considered shapes S and $\tilde{S}$ respectively. Formally, the problem is stated as the minimization of an energy $E(\phi)$, involving a data-driven term, E_D, that evaluates the similarity between the reference and aligned signals and a regularization term, E_R. The similarity measure between the two shapes is given by [8]:

$$E_D(\theta, \tilde{\theta}(\phi)) = 2 \arccos \int_s \sqrt{\phi_s(s)} \left| \cos \frac{\theta(s) - \tilde{\theta}(\phi(s))}{2} \right| ds \qquad (1)$$

where $\phi_s(s) = \frac{d\phi(s)}{ds}$.

To improve the registration robustness with respect to the outliers data we have introduced a robust norm $\left\| \theta(s) - \tilde{\theta}(\phi(s)) \right\|_\rho$ instead of the simple difference $(\theta(s) - \tilde{\theta}(\phi(s)))$. The principle is supported by the use of a function that adjusts a weight ω in order to penalize the data points with high variation compared to other points. Several forms of the robust estimator ρ were proposed [10]. We will use the Leclerc estimator given by:

$$\|r\|_\rho = 1 - exp(-r^2/(2\sigma^2)) \qquad (2)$$

with σ is the standard deviation of data errors r.

The shape registration issue resorts to minimizing:

$$\begin{aligned} E(S, \tilde{S}, \phi) &= (1-\alpha) \arccos \int_s \sqrt{\phi_s(s)} \left| \cos \frac{\|r(s)\|_\rho}{2} \right| ds \\ &\quad + \alpha \int_s |\phi_s(s)|^2 \, ds \end{aligned} \qquad (3)$$

where $r(s) = \theta(s) - \tilde{\theta}(\phi(s))$.

Finally, for shape recognition, we propose here to compare shapes on the basis of a metric that takes into consideration the optimal robust shape matching. Formally, the distance between two shapes S and $\tilde{S}$ is defined as:

$$d(S, \tilde{S}) = E_D(S, \tilde{S}(\phi^*)) \textbf{ where } \phi^* = \underset{\phi}{argmin}\, E(S, \tilde{S}, \phi) \qquad (4)$$

This modification on the distance proposed in [8] is necessary because fish shape changes very little from one species to another. The robust norm will be useful for the optimal matching but it should not be used for shape comparison once the registration is performed. It was used in both steps in [8].

2.2. Pose and initial point estimation

Minimizing $E(S, \tilde{S}, \phi)$ can be done by an incremental iterative scheme as detailed in [8]. This algorithm is able to ensure the rotation invariance of shape alignment regardless of starting points. However, the number of required iterations for convergence increases as the degree of non-aligness increases. To reduce this computing time, we propose here to estimate in advance, as a preliminary step, the pose and the initial point by a technique of rigid registration between the two shapes to align.

Unlike the matching problem, the initial point estimation remains somewhat studied in the literature. This task is often carried out by complex optimization procedures followed in some cases by manual correction. Our technique of pose and initial point estimations uses an algorithm described in [11] for rigid alignment of a pair of $2D$ shapes. This algorithm has the main advantage to be computationally efficient as it provides closed-form expressions for the estimates of the initial point and pose parameters without the need of complex optimization procedures.

3. EXPERIMENTS ON MARINE (SQUID) DATABASE

In our experiments, we use the SQUID database provided by Petrakis [12]. This database firstly introduced by Mokhtarian [13] consists of 1100 shapes of marine species including Seamoths, Sharks, Soles, Tonguefishes, Crustaceans, Eels, U-Eels, Pipefishes, Seahorses, Rays with others. The benchmark has 20 query shapes, shown in Fig. 2. This benchmark is used in the literature to evaluate the effectiveness of retrieval for proposed methods for fish shape recognition.

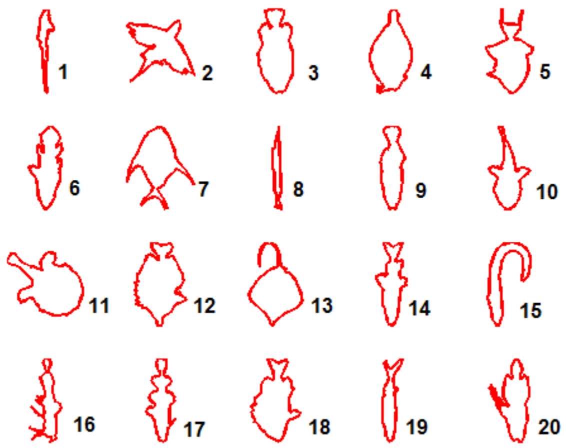

Fig. 2. Queries of the marine (SQUID) database. This database [12] consists of 1100 shapes of marine species.

We tested first the pose and initial point estimation method (section 2.2) on SQUID database where fish shapes have large deformations and different sizes and angles of rotations. The rigid alignment and initial point estimation are correct. Moreover, on average, the computational time is improved by 90%, a reduction by a factor of 10 compared to the original scheme without pose and initial point estimation. Examples of pose and initial point estimation on two queries with two shapes of the database are given in Fig. 3. As shown in this figure, the estimated rotation and initial point allow a perfect initialization for the Geodesics-based matching described in section 2.1.

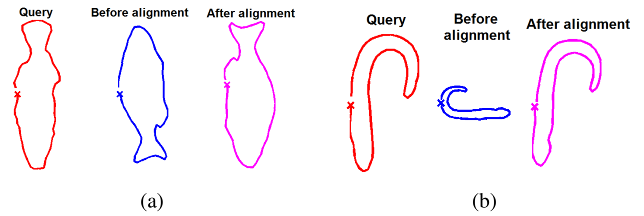

Fig. 3. Examples of pose and initial point estimation. (a) and (b): left to right: a query example, an original shape instance before and after alignment w.r.t. the query with the initial point estimation. Initial points are marked by $\times$ mark.

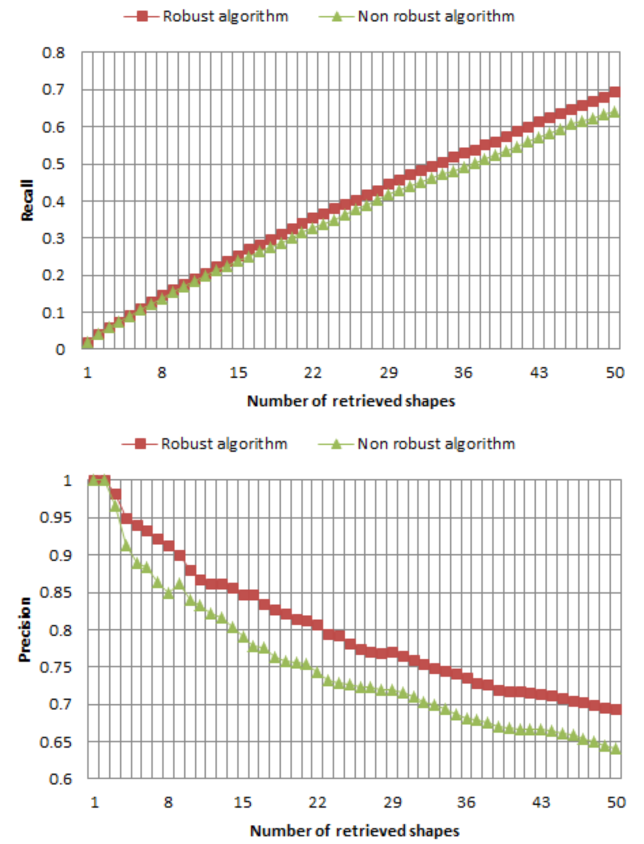

Fig. 4. Average Precision and Recall obtained on the SQUID database.

As in previous works for recognition evaluation on SQUID database, we calculate the distance (Eq. (4)) between the queries and each shape of the database. Each query retrieves the 50 most similar shapes. Then to evaluate the effectiveness of retrieval, two measures are computed :

1. **Precision:** the ratio of similar shapes retrieved with respect to the total number of retrieved shapes.
2. **Recall:** the ratio of similar shapes retrieved with respect to the total number of similar shapes in the database.

Precision and Recall measures are calculated on the test queries using our proposed method either with or without the added robust norm (Eq. (2)) to the matching process. Average values of Precision and Recall measures are reported in Fig. 4 for both cases in correspondence of the number of retrieved shapes (1 to 50). Each point in the plots is the average over the 20 queries.

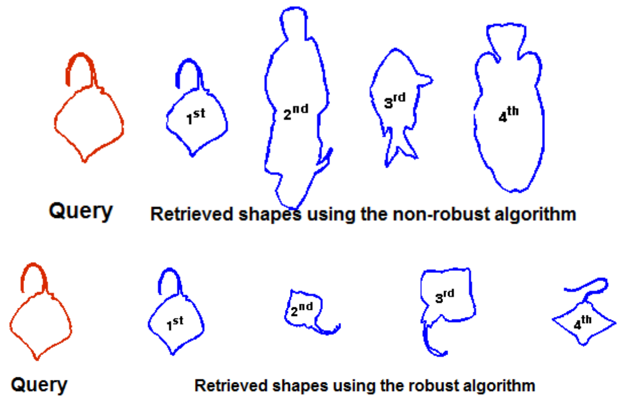

Fig. 5. Illustration of the robust criteria effect. For the same query, the first four retrieved shapes by the non-robust algorithm are false while they are relevant with the robust one.

A method is better than another if it achieves better precision and better recall. In general, the robust criteria we added to the similarity measure permits to retrieve a higher number of relevant shapes (Fig. 4). In order to give a deeper idea of the retrieval behavior of our method in the case of using the robust estimator or without using it, we show in Fig. 5 two sample results. For the same query (on the left), the first four retrieved shapes are shown for both cases. As we can observe, three of the retrieved shapes with the non-robust algorithm are false. On the other hand, the first four retrieved shapes with the robust proposed method are relevant. The ray instances are all with different positions of tails, that is why non-robust algorithm totally fails to deal with this shape. Other retrieval examples of our proposed robust method are given in Fig. 1.

In order to compare the results of our proposed method to previous works, we refer to [14] where comparative results for the method proposed in [14] itself and the methods described in [15] (Fourier descriptors) [16–18] (moments) and [12, 19, 20], are given using the SQUID database as benchmark. In this work, the same queries and the same measurements are used. Comparison is done by Precision-Recall plots for each method in Fig. 6. The horizontal axis corresponds to the measured Recall while, the vertical axis corresponds to Precision. Each plot contains exactly 50 points corresponding to precision and recall values computed from each answer set (1 to 50). The n^{th} point of a Precision-Recall curve corresponds to the Precision-Recall values for the n nearest shapes in the database for the queries. The precision-recall plot curves shown in Fig. 6 indicate that our method outperforms previous methods for shape matching and retrieval.

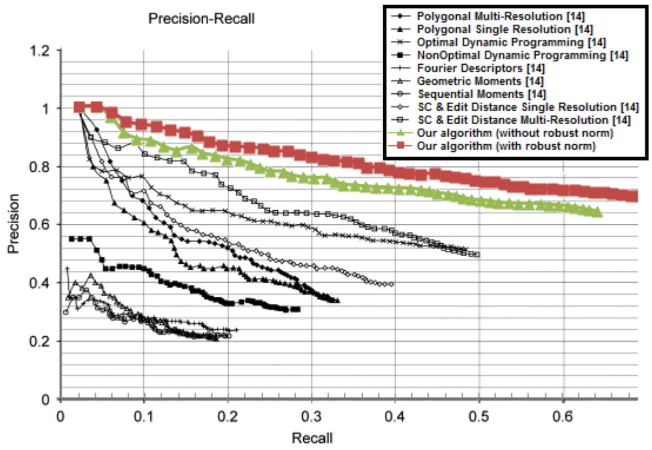

Fig. 6. Precision-recall curves for SQUID database. Our method outperforms all previous algorithms.

We note that the previous methods achieved lower values of precision and recall on the SQUID database contrarily to other benchmarks where performances were much higher. The shapes of the SQUID database present a lot of noise and contour details [19]. From results, we observe that our method is less sensitive to noise and contour details. However, we can see that when we do not use robust norm in the matching process, the method becomes sensitive to details which reflects a drop in quality of the performance. The performance of our approach is mainly due to its invariance to geometric transformations (translation, rotation and scaling) and its good deal with local shape features. In particular, high curvature points play a key role. Another important property of the proposed metric, compared to others, is in the fact that we look for the optimal path (in shape space) of minimal cost of deformation aligning the two shapes. It is a suitable way of modeling inter-individual variation in fish shapes. This cost of deformation is relatively low when we consider fish of the same species while it is higher when we consider fish of different species.

Finally, the experiments show that fish shape outline can be very efficient for fish recognition, but several fish cannot be easily distinguished by their shape outline only (especially the case of the species *Seamoth* and *Crustacean*). For these species, other features than the shape should be involved in the recognition process. Among most discriminative features, we can find color statistics [7,21], texture (co-occurrence matrix) [3, 7], spatial signature [21], etc.

4. CONCLUSION

We proposed in this paper to use an approach based on shape matching and geodesics for fish recognition. Our approach is independent of translation, scale, rotation, and starting point selection. We carried out performance experiments on a benchmark for marine shapes. The experiments show that our approach is well suited to marine shape recognition even with a lot of noise achieving higher precision and recall than traditional shape matching and retrieval methods based on Fourier descriptors and moments and more recent optimal and non-optimal methods. Future work include the experimentation with more datasets and methods involving more than shape features such as texture, color, and others.

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