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Vision-based discrimination of tuna individuals in grow-out cages through a fish bending model

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ABSTRACT

This paper proposes a robust deformable adaptive 2D model, based on computer vision methods, that automatically fits the body (ventral silhouette) of Bluefin tuna while swimming. Our model (without human intervention) adjusts to fish shape and size, obtaining fish orientation, bending to fit their flexion motion and has proved robust enough to overcome possible segmentation inaccuracies. Once the model has been successfully fitted to the fish it can ensure that the detected object is a tuna and not parts of fish or other objects. Automatic requirements of the fishing industry like biometric measurement, specimen counting or catch biomass estimation could then be addressed using a stereoscopic system and meaningful information extracted from our model. We also introduce a fitting procedure based on a fitting parameter – Fitting Error Index (FEI) – which permits us to know the quality of the results. In the experiments our model has achieved very high success rates (up to 90%) discriminating individuals in highly complex images acquired for us in real conditions in the Mediterranean Sea. Conclusions and future improvements to the proposed model are also discussed.

1. Introduction

In recent years, great progress has been achieved in all underwater applications (Zion, 2012). However, most of them currently require human intervention in some of their stages which is critical for obtaining valid results. Applications and techniques which need human intervention are described in the literature as semi-automatic. But some authors like Lines et al. (2001), Shortis et al. (2013) and Zion (2012), remark that further progress in fisheries management and research into aquatic biodiversity requires fully automatic processing of underwater video recordings to extract the most meaningful information for an application proposal.

A real challenge for this kind of application is the automatic discrimination of isolated fish in the image, ensuring that the object identified is a whole fish (hereinafter "good-fish") rather than a portion of it, or two or more overlapped fish (hereinafter "bad-fish") (Costa et al., 2006). The characterisation of a single fish is an essential processing step in the most significant applications of underwater video, such as fish detection, species identification (Spampinato et al., 2010; Zion et al., 2007), biometric measurements (Tillett et al., 2000; Harvey et al., 2003; Costa et al., 2006), biomass estimation in fish cages or tanks (Lines et al., 2001; Martínez-de-Dios et al., 2003), tracking and counting fish (Lee et al., 2004).

Our goal is to develop a vision-based application to automatically discriminate individuals or whole tuna in underwater images acquired under real conditions. This application has to overcome the fact that real underwater fish images are generally poor quality because they suffer from limited range, non-uniform lighting, low contrast, color attenuation and blurring (Shortis et al., 2007) which represent a challenge for researchers. Fig. 1 shows some color[1] video frames used in this work which illustrate some of these difficulties. We need to be able to assure that the object detected is a whole fish because, once the fish has been discriminated, the process can be continued performing biometric measurements for the purpose of species identification, biomass estimation or fish counting. Image processing and computer vision methods can be used for these purposes.

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[1] For interpretation of color in 'Figs. 1, 3, 7 and 8', the reader is referred to the web version of this article.

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Fig. 1. Some examples of video frames (left VideoA, right VideoB) used in this work.

Commercial biomass estimation systems most widely used in aquaculture are VICASS (AKVA group, 2014) and AQ1 (AQ1 Systems, 2013) which belong to the above mentioned semi-automatic category. These systems need human operators to manually inspect different frames in which a particular isolated fish appears (Harvey et al., 2003). Then, they mark the fish snout and tail, and the fish length and span are automatically computed. To reduce the effect of swimming motion on length measurements only frames in which the body of the fish appears to be straight are considered. If the system works with stereo vision, the marking process is made on corresponding points in the image pair. These systems determine size distributions based on simple length and span measurements, and thereby deduce biomass from an estimated number of fish in the cage or tank.

Currently, Bluefin tuna catch quotas are monitored to compute two statistical factors: the number of fish caught and the catch weight. The number of fish is obtained by counting all the individuals transferred from tow cages to grow-out cages. Bluefin tuna transfers are usually made by joining tow and grow-out cages through gates that allow fish to pass from one cage to another, while experienced divers equipped with video cameras monitor these underwater tasks. Subsequently, these films are watched by human inspectors in order to manually count the number of fishes transferred. The average weight of these live samples is usually estimated by collecting a given number of fish from the tow cage (Harvey et al., 2003). The individuals counted during a transfer are multiplied by the average weight to derive total biomass per tow cage.

Nevertheless, we consider that video cameras could be attached to gate sides given that it is mandatory to record the fish swimming through during the transfer. These films could be analysed automatically by computer vision techniques. These techniques have the advantage of not stressing the fish (stress can cause death) and provide continuous, objective and reproducible results.

Another interesting scenario that benefits from non-intrusive vision-based weight estimation is fish fattening monitoring. It can be used to control the feeding process without the need to stress or sacrifice specimens.

Tuna monitoring does not require precise counting of individuals because the objective is to obtain statistical estimations of fish weight. Espinosa et al. (2011) present real values for obtaining the relationship between Bluefin tuna length (L) and its mass (W). This relationship has been investigated for many years (Zion, 2012) and the most common mathematical model is $W = aL^b$, where the values of coefficients a and b depend on the fish species.

The first step in automating any process is the detection of candidates and be able to ensure that each one corresponds with a whole individual. Furthermore, body bending while free-swimming means that the same individual can be observed with very different shapes and fish size and orientation can vary in relation to the visualized frame. So, robust fish detection methods which cannot be affected by these variations are required.

The influence of swimming motion on fish shape can be minimised by designing a robust deformable fish model (Lines et al., 2001) to fit fish size and gesture. When the model successfully fits the object detected in the image, it can help to accurately locate its different parts and deduce useful information including, for example, whether the detected object is a whole fish or not, if the fish is straight or not and the angle of curvature of its body. With an estimation of the exact curvature of the body, biometric measures like fish length could be robustly obtained. Other advantages of the model would be to correct segmentation errors caused by noise or variable lighting and to successfully detect the silhouette of foreground fish in crowded images.

This paper proposes a deformable and adaptive robust model that automatically fits the ventral silhouette of Bluefin tuna in images acquired in natural conditions. The differences of the present work with regard to other works in literature are: (i) video images are taken in the natural environment without artificial illumination and without background screens, (ii) the image can contain fish clusters with semi-crowded situations and overlapping fish, (iii) the fish is extracted from images by a fully automatic process, (iv) all fish edges and contours considered in our process are outlined without human operators, (v) fish direction - which is unknown - is obtained automatically.

In this paper materials and methods are described in Section 2. Section 3 describes experiments and results which show that our model is able to identify Bluefin tuna fish. We discuss the results in Section 4 and present our conclusions and future work in Section 5.

2. Materials and methods

The automatic identification of individual fish in an underwater image is a complex issue. Important aspects like overlapped individuals in the image and sunlight effects that cause many segmentation problems, must be overcome to automate the process. This section describes a new deformable 2D model for identifying Bluefin tuna that adapts to the movements and variable sizes of fish.

2.1. Video system and image acquisition

The video films used in this work were taken in grow-out cages installed in Spanish waters in the Mediterranean when the fish were swimming freely. The sequences were acquired with a camera anchored at the bottom of the grow-out cage, and pointing towards the surface as shown in Fig. 2. The cages are cone shaped with a circle with a diameter of 50 m on the water surface and 30 m tall. The videos were acquired at 222 cm from the water