Optimal pattern design for automatic estimation of water transparency through photograph using crowdsourcing data

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Abstract: *Based on crowdsourcing data, the study aims at developing a simple method to automatically compute the water transparency. With underwater camera pictures, an image processing technique should provide robust estimations of parameters related to water transparency. Here, we will mainly see the first step: estimating the distance from the image to the camera and the optimal choice of a pattern to photograph.*

Keyword: *Image processing, Distance estimation, Crowdsourcing, Underwater imaging, Pattern optimisation*

Fig. 1: Secchi 3000 Device. The pole weights 1.7kg + the camera, total length is 1.56m.

I. INTRODUCTION

Water quality (WQ) of the sea is of great interest as there are many social and economic impacts associated to WQ decline (fishing, harmful algal bloom, leisure, drinking water, etc.). Environmental problems such as WQ should not be tackled by scientists or policy makers alone. Involving the general public in observing and understanding our changing world, and encouraging citizen stewardship for the (marine) environment are crucial elements for a sustainable way of facing current and future problems. Following this idea, various studies have developed low-cost devices based on commercial digital cameras to be used by general public to estimate WQ related parameters [1]. However, the instruments developed for such applications are usually cumbersome and difficult to handle, see Fig. 1 for example from [2]. This device was proposed for measuring water transparency but the whole large and heavy instrument has to be put into the water to obtain the measurements.

The study presented in this article is part of the *Citclops* FP7 European project [3] which aims at using crowdsourcing optical data to assess WQ in the sea. The project is focused on retrieving, through crowdsourcing, data on three main optical properties related to sea-water quality: colour, transparency and fluorescence. Moreover, involving citizens to collect WQ data leads to unprecedented levels of spatial and temporal coverage. But to make the project viable, easy-to-use and easy-to-carry devices should be used, coupled with robust image and data processing techniques that allow to retrieve information in a wide range of measuring scenarios an for a large amount of data.

Here, we analyse one of the *Citclops* goals: the development of a robust method to estimate transparency related parameters based only on image processing of pictures obtained with underwater digital cameras. To achieve it, we will let waterproof cameras to diving clubs that divers will be allowed to freely use as they wish. The only requirement will be to stick a pattern on the bottle of one of the divers and ask another one to take few pictures of the pattern at different distances. It is of course very complicated to ask people to take a picture at a specific distance so a first step is to estimate the distance from the camera to the pattern from the mere pictures. This work is centred on this step.

In section II, we will motivate our study. Section III describes how to pass from the raw picture to the selected pattern, section IV explains how to choose the optimal pattern and section V how to estimate the distance from it.

II. ESTIMATING THE ATTENUATION

Following the method proposed in [1], the light diffuse attenuation parameter K for each colour band (RGB) can be estimated as:

$$K(\lambda) = -\frac{1}{z_1 - z_2} \ln \frac{L(\lambda, z_1)}{L(\lambda, z_2)} \quad (1)$$

where z_1 and z_2 are two different distances and L is the measured brightness (radiance) for each particular band. In [2] the distances z_1 and z_2 were fixed in the pole structure (Fig 1). In our application, it is not the case anymore so a first crucial step is to get an estimation of the distances which will give the information necessary to compute the light diffuse attenuation parameter $K(\lambda)$ in (1).

III. PROCESSING THE RAW PICTURES

If necessary, pictures might be denoised with classical image denoising techniques such as median filtering. They are then converted to grayscale. A histogram is used to select a threshold and binarise the image, see Fig. 2. In order to select the area of interest, we first detect all the different components of the image using [4]. As the pattern is a circle (see section III), we use the eccentricity to detect the circle and select the area around it. The eccentricity is the ratio of the distance between the foci of an ellipse and its major axis length. The value is between 0 and 1, 0 representing a circle.

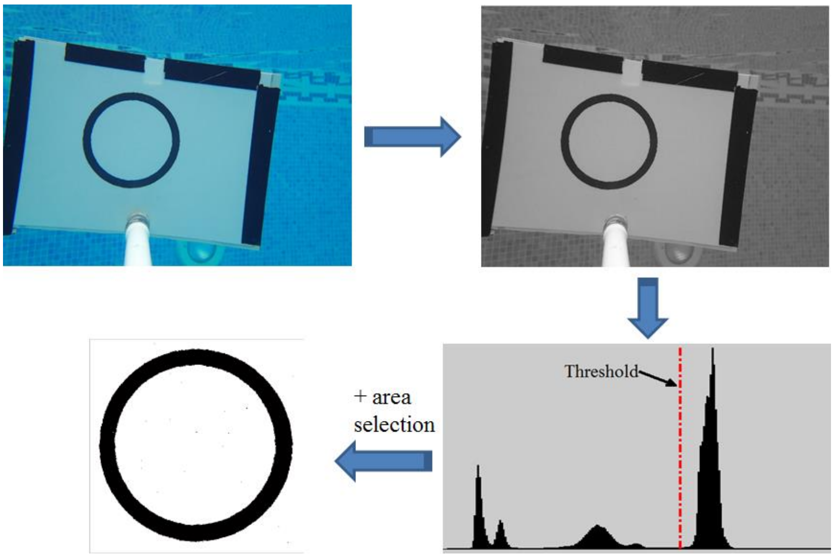

Fig.2: Processing of an underwater image before distance estimation. The picture is first converted to grayscale then to black and white using thresholding and finally the area of interest is selected

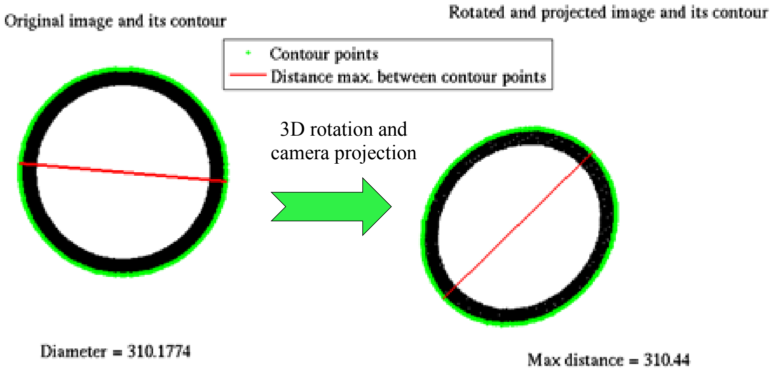

Fig. 3. Optimal design of the pattern. The original figure has been rotated along the three axes and then projected on a plane defined by two axes so that RHS figure is the one seen by the camera after the rotation.

IV. OPTIMAL DESIGN OF THE PATTERN

In [5], we used a rectangular pattern and computed the area size to estimate the distance. The results were quite good but distortions due to camera orientation were complex to compensate. We have now switched to circular pattern and we will show why this choice is optimal. Underwater pictures are supposed to be taken perpendicular to the selected target, but non-professional photographs are likely to obtain most of the images with an angle deviation. In Fig. 3, we demonstrate that even with an important angular distortion where the circle is converted into an irregular ellipsoid, the maximum distance between points of the ellipsoid stays equal to the diameter of the original circle. In this plot, the camera angle of view has been deviated from the centre along two axes, x and z.

In Fig. 3 above the contours are computed and the maximum distance between the points of the contour deduced in the RHS plot. In the LHS plot as the pattern is circular, we just take two opposite points to calculate the diameter. It can be seen that its value (310.44) is very close to the diameter of the original circle (310.1774) in spite of the modification of the shape of the original circle.

We will use this fact and estimate the maximum distance between two points of the distorted circle on the image to deduce the distance between the camera and the target.

V. DISTANCE ESTIMATION

We made some tests taking pictures outdoor and in a swimming pool with different cameras. In order to test our method, the distances between the target and the camera were exactly known. In Fig. 4, we vary the angle between the camera viewpoint and the target to show how sensible the angle of view is. All pictures of this example have been taken at 20 cm from the target.

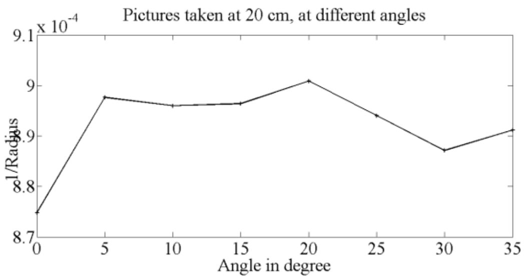

Fig. 4. Pictures are taken at a distance of 20 cm but at different angles of view, from 0º to 35º. The inverse of the maximum distance between two points of the target is computed and plotted versus the total angle of rotation

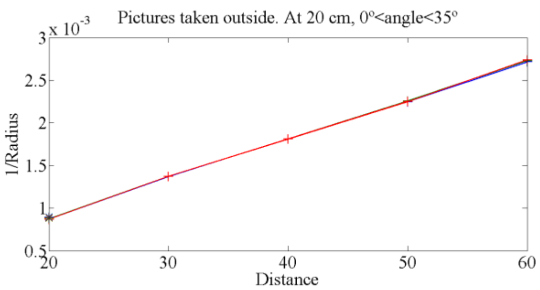

Fig. 5. Pictures are taken outside at distances varying from 20 cm to 60 cm. At 20 cm, the angles of view vary from 0º to 35º. The inverse of the maximum distance between two points of the target is computed and plotted versus the distance between the target and the camera

Fig. 5 represents the inverse of the radius versus the distance for pictures taken outside at a distance varying from 20 to 60 cm. Fig. 4 is combined with this figure. We can thus see the little influence of the angle in the

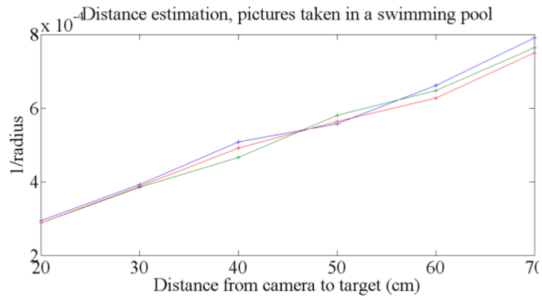

Fig. 6. The inverse of the maximum distance between two points of the target is computed and plotted versus the distance between the target and the camera. It can be seen that there is a linear dependence.

estimation of the distance.

In Fig. 6, the inverse of the radius is plotted versus the distance for pictures taken underwater in a swimming pool. At each distance, three pictures have been taken varying the angle of the pattern with respect to the camera angle of view.

In these two examples, we see that there is a linear dependence between the distance from the target to the camera and the inverse of the length of the (deformed) circle. Once the camera calibrated, we will then be able, from the pictures, to deduce the distance from the camera to the target using linear plots such as the one from Fig. 6.

VI. CONCLUSIONS

The results obtained indicate that it is possible to obtain distances estimations with automatic image processing techniques. The circle is a very simple and robust pattern to be used for distance estimation.

Further research has to be done to analyse the robustness of the estimation to different uncontrolled parameters (noise, turbidity…).

For longer distances than the ones shown in the examples, section IV, distortions might appear in the results. We are studying using great circle distances instead of the radius to compensate these possible distortions.

More complex processing may also be required (for example using wavelets) but robustness and simplicity are priorities in our design, in a crowdsourcing framework, as we will have to deal with imprecise pictures and large data sets.

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