Achieving Turbidity Robustness on Underwater Images Local Feature Detection

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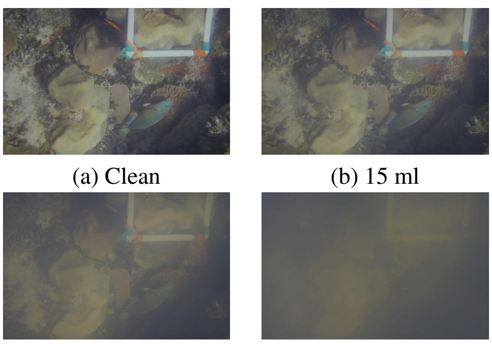
Methods to detect local features have been made to be invariant to many transformations. So far, the vast majority of feature detectors consider robustness just to over-land effects. However, when capturing pictures in underwater environments, there are media specific properties that can degrade the visual quality the captured images. Besides the shortening of information imaged, a corruption of information also happens. The main phenomena, the *Backscattering*, happens when reflected sources from outside the captured scene are scattered in a wide angle eventually reaching the image plane. This effect creates a characteristic veil on the image that reduces contrast and suppress fine structures on the image.

Little work has been made in order to study the robustness that the popular feature detectors have to underwater environment image conditions. In addition, applications benefited by finding descriptive feature points in underwater environments grows every year. They are essential for many applications like 3D reconstruction [4], visual odometry [6] and tracking [7]. Most of these applications rely on the best over-land feature detectors, without considering the water photometric properties. It is likely that some algorithms have a better behaviour than others when applied on images degraded by specific underwater conditions.

As stated before, underwater phenomena also create structural degradation. Further, it tends to eliminate all the *finer scale structures*, which is equivalent to the scale changing phenomena. Consequently, we propose the invariant points detected by some scale invariant detector can have also a good robustness to turbidity.

In this context, to evaluate feature detectors, we propose a new dataset called *TURBID*. This dataset is based on real underwater scenes photographs. The pictures are placed on the bottom of a tank filled with a milk-water solution and then are re-photographed with the degradation controlled by the amount of milk. The generated dataset for one of the printed photographs is show in Fig. 1. This dataset is an improvement in terms of visual diversity when compared to previous efforts [8] and is one of the main contributions of this work.



(a) Clean (b) 15 ml

(a) 50 ml (b) 100 ml

Figure 1: The images captured over different levels of degradation due to turbidity controlled by milk addition. We photographed three different printed pictures. (a) Clean Image, no milk. (b) *Low Turbidity* with around 15 ml of milk. (c) *Medium Turbidity* with around 50 ml of milk. (d) *High Turbidity* with around 100 ml of milk.

In order to analyze the robustness to turbidity we use the repeatability criteria on each obtained image. This criteria is proportional to the number of feature points found in the same spot given a error ε. The repeatability towards turbidity is calculated by the ratio of the number of points found in the clean image (Fig. 1(a)) and the number of points repeated in a turbid image, hence:

$$R_i = \frac{N_i}{N_0}, \tag{1}$$

where N_0 is the number of features on the clear image, and N_i is the number of features *repeated* on the image T_i.

For three different photos we computed the repeatability results. An example of this computation is show for Fig. 2.

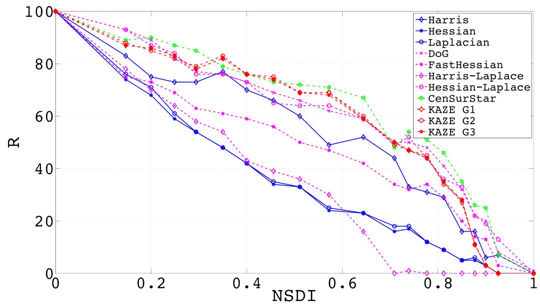


Figure 2: Results for $N = 100$ and $\varepsilon = 5$, showing the repeatability with respect to the ranging of the image degradation. For this case the *CenSurStar* [1] and KAZE [2] got the best results.

As we conjectured earlier, the *Harris* [9], the *Hessian* [5] and *Laplacian* approaches performed poorer than the scale invariant methods. *Harris* is generally used as very precise detector and is used in underwater tracking applications [7]. However, we show that, on the present scenario, the use of scale is useful also for precision.

Finally, we found that, finding scale invariant points is a useful way to find structural degradation robust points. We elected KAZE [2], *Center Surround Extremas* [1], *Difference of Gaussians* [10] and *Fast Hessian*[3] as good feature points detectors for underwater environments in all tested situations.

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