Underwater Feature Point Extraction for Man-Made Structures Inspection

F. M. Codevilla , F. A. Guth, S. C. Botelho, D. Fischer, L. Silveira, P. Drews Jr. and N. Duarte Filho

***Index Terms*—Underwater Vision, Feature Detection**

***Abstract*—Underwater Computer Vision is now an important area for multiple applications, like seabed environment monitoring, underwater archaeology and also the oil and gas industry. Feature points extraction is a relevant tool for describe images which is useful for many applications.. Motivated by the lack of evaluation of the feature on specific environments, with the exception of the recent [1], this paper analyses feature extraction on underwater turbid scenes composed by man-made objects. We used a controlled pool environment and captured a scene composed by man-made objects under different levels of turbidity created by algae proliferation. The results show that color based detectors have contrasting results. And, different than concluded that hessian based detectors are better underwater for natural objects, for man-made cases this superiority does not exist.**

I. Introduction

Underwater computer vision is a growing area for multiple applications, including underwater archaeology [2] and monitoring of the seabed environment [3]. Today, computer vision also has a possible role for the oil and gas industry. While oil is currently explored at very high depths, the use of divers is no longer feasible. This create the necessity of perception in this environment, like the use of images to inspect the oil well-head structure or pipes [4]. In this context, the use of ROVs(Remotely Operating Vehicles) for visual pipeline inspection is already widely used. Additionally, there is also more elaborate examples like the Petrobras's AURI [5].

For autonomous visual inspection or any application that need to compare image information, it is useful to find points that are able to describe an object independently of the viewing condition [6]. The understanding and developing of techniques to find those points has been largely developed on the past decades.

On the early stages these points where found in order to be describe an object and be invariant to its rotation and translation. Examples of that like the Harris corner detector [7] or the Hessian blob detector [8] are largely used even nowadays. Invariance to scale was also incorporated to feature points detectors after the development of the *scale space theory* [9]. Many kind of detectors have been developed to use this theory, like the multiple scale Harris (HarissLaplace) [10] or the optimized methods like SIFT [11] or SURF [12].

However, on participative mediums like the underwater environment there are another phenomena that the feature detectors needs to take into account. The image acquisition is highly degraded by the light attenuation process. When light propagates in a participative environment, it is scattered and absorbed by the particles in suspension. It reduces the amount of light information that can be captured by imaging sensors. Moreover, the scattering phenomenon spread the captured information creating a "hazy" effect on the image.

Little study has been made about the most suited feature extractors for underwater scenes [1]. A initial study on this situations was made by *Garcia and Gracias*. Their study compared the most popular feature extractors in the literature. They found that, due to the turbidity, blob like structures (Hessian based) are better extracted on even non-scale and scale invariant methods. This happens since water turbidity tends to smooth corners and blur defined regions, making methods like Harris [7] or MSER [13] less suited. Their study focus the evaluation in a scene that is mainly composed by natural structures aiming on environment monitoring and rescue tasks [1].

However, on the present paper, we are interested on another kind of tasks which is the computer vision to sub-sea inspection of oil and gas structures. This environment is composed by a set of hand-made objects like motors, pumps, pipes, valves, etc.

This paper proposes to evaluate the performance of different feature point extraction methods associated with inspection of man-made sub-sea oil exploration scenarios. Issues associated with the water turbidity and light conditions are analysed aiming to provide a comparison of the studied methods. First, since man-made objects usually have more well defined corners and segments [14], we evaluate if the aspects of underwater environments are enough to still smooth corners on objects made by man. Second, we know that the water turbidity is dependent of the light conditions from the environment. With this, we evaluate how a totally illuminated environment differ its results from a a case with just a spot illumination

Lastly, there is no homogeneity on underwater color as lower wavelengths are more absorbed. We also evaluate how color salient features could reflect important information to be extracted from the scene.

To test our hypothesis we built an controlled pool environment where a certain turbidity level was obtained due to natural algae proliferation. A scene with a motor, tubes, grids and other man-made objects was build inside the pool. The turbidity level was measured a Structural Degradation Index(SDI) [15] [1].

The results show that color based detectors have contrasting results. And, different than concluded that hessian based detectors are better underwater for natural objects, for man-made cases this superiority does not exist.

F. Moraes , S. Botelho are from the *Centro de Ciências Computacionais(C3)* at the *Universidade Federal de Rio Grande*, Rio Grande, RS, Brazil contact (felipe.alcm@gmail.com).

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II. Feature Detection

In this section we briefly explain the feature detectors tested on this paper. *Tuytelaars and Mikolajczyk* [14] categorize the algorithms by different approaches to identify descriptive points or regions. The approaches based on high curvature points or regions are the ones most successfully used to many applications. Human cognition studies indicate that corners can be used as a descriptive and succinct features to describe objects [14]. One of the most used corner detectors was proposed by *Harris and Stephens* [7]. This method was an extension to Moravec [16] proposed to allow the finding of corners on a continuum set o angles and with more resistance to noise . A measure proportional to the auto-correlation curve eigenvalues is used to achieve this. Harris detector is invariant to translation and rotation but no scale was yet considered. Harris has been proven to be detector with the higher repeatability under various situations [17]. A blob can be defined as a region with some property holds. On the feature detection context, a blob is usually defined as a region of sufficient large area that is significantly different than its neighbourhood [18]. A Hessian matrix determinant and trace measure can be used to find blobs as described by *Beaudet* [8].Blobs are normally more invariant to blurring and perform better on scale space methods [10]. . Both Harris and Hessian detectors are only invariant to rotation and translation. However, a robust description of a scene must consider its representation on multiple scales [18]. This phenomenon of representing an image over coarser scales can be approximated by the diffusion equation. A solution to this equation is the point less diffused over time and therefore the most invariant to scales. A solution to this equation, the level of gaussian [19] , together with the calculation of Harris feature points over multiple scales was proposed by [10] as extension of the Harris detector over scales. A difference of gaussian(DoG) approach can be used to approximate the diffusion equation as proposed by *Lowe* [11]. The keypoints detected by the DoG are a local maximum considering a neighbourhood on space and scales. A further optimization is accomplished by the use of box filters based on integral images [12].

Most of the approach to detect features are luminance based where just the geometry of the scene is analysed. The use of a luminance only based approach can sometimes ignore regions that are sometimes salient just in color. The use of Color for feature points detection has already been analysed by [20]. It was concluded that color based methods usually outperforms illumination based methods on low contrast and dark images. These environments aspects match with the aspects found on underwater environments. Maybe the first color extension to a Harris corner detector was proposed by *Montesinos et al.* [21]. To improve the distinctiveness of detected features, a boosting on color saliency can performed on a illumination invariant colour space [22]. This method impose that points with more probability of containing information should have more saliency.

III. Man-Made Structures Inspection

A. Man-Made Structures

On current oil and gas exploration industry there are whole collection of objects. Structures like the wet-christmas-trees, oil pipes or oil manifolds are common on this environment. This set of structures are used to control oil flow and lifting.

Objects, like the ones described above, have the property of non-accidentalness [23]. This mean that the objects shapes are usually simple and have a smooth variation along their structure. Natural objects, on the other hand, have a long process of evolution due to erosion and other phenomenons and usually have more deformity and complex shapes.

B. Visual Inspection

These objects found on oil industry environment must be regularly inspected to find possible anomalies. It is important to consider the imaging formation aspects to further evaluate characteristic points detection on objects from this environments. When light propagates in an underwater environment, it interacts with the suspended particles in the medium creating some physical phenomenons. *Scattering* occurs when light is spread changing its original direction. Also, the light can be *absorbed* by the particles in suspension. This physical properties culminate into certain results when imaging an underwater scene. Besides the shortening of information imaged, a corruption of information also happens. Figure 1 shows the types of scattering that degrades the captured images. *Backscattering* is when sources from outside the captured scene are spread in a wide angle and eventually reaches the image plane, creating a ”hazy” effect on the image. *Forward-scattering* is when the light is spread on a short angle, blurring the information from the image scene creating a contrast reduction.

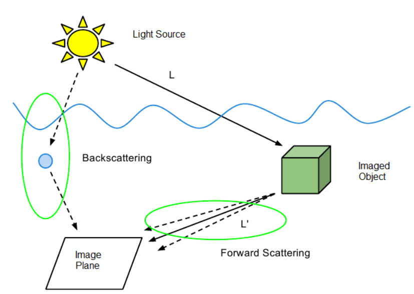

Fig. 1: Kinds of image degradation caused by the physical phenomenon of light scattering

On dark environments like deeper sea or at night, there is also the necessity to use artificial light sources. This kind of lighting can produce non uniformity on the scene illumination.

IV. Methodology

A. Image Acquisition Setup

For this evaluation, we used a controlled outdoor underwater pool environment. Approximations of well-head as man-made structures were made by submerging junk yard objects. A picture of the scene is showed at Figure 2. Of this scene, two pictures were taken, a *turbid image* and a *clear image*. The underwater images were taken using a Go Pro Hero3 Black Edition camera with 12Mpixels of resolution. This camera is optimized for low illumination photography. Together with this, we tested two illumination configurations. Setup 1 was made with with just one underwater flashlight placed at a fixed distance from the camera as show on Figure 2. This setup is created in order to minimize the backscattering effect on the scene. Setup 2 was made adding two 15 Watts fluorescent lamps around the pool to further illuminate and test a situation with increased backscattering. To keep objects remaining on the same position marks were made on the floor of the pool.

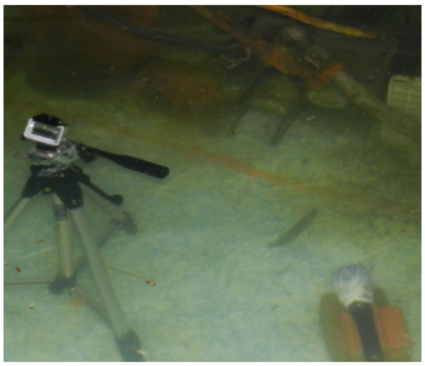

Fig. 2: The organization of the image acquisition process: a camera is set on a static position with a flashlight at a fixed distance. The pictures were captured with and without outside illumination.

The turbid image was captured after a few days. The turbidity was obtained due to algae proliferation. Sodium bicarbonate was added to the pool to accelerate the proliferation. A region of interest was defined and a brightness normalization was made in order to reduce intensity difference caused by the turbidity phenomenon itself. Figure 3 and 4 shows the images that were captured for each setup.

B. Image Turbidity Assessment

We define *turbidity* as the measure used to evaluate the amount of "haziness" or "cloudiness" existent on water environments. The turbidity is dependent of the quantity of floating sediment (SSC) existent to scatter the incident light. Thus, the illuminated volume and the intensity of light are also applicable to calculate turbidity [1]. Many methods have been developed to measure the turbidity. A traditional method to measure is by the *secchi disk*. The amount of turbidity is measured by the distance that the disk is still visible underwater. A more quantitative measure of the turbidity is by the quantity of light beans that are scattered as done on a nephelometer turbidimeter [24]. None of the described alternatives consider that turbidity is also scene dependent. Under these consideration we choose to measure the degradation by *Structure Degradation Index* proposed by [1] and [15].

C. Evaluation

The results are evaluated as the repeatability criterion described on [17] and also similar as made by [1]. This analysis is made by counting the number of features found on the *clear image* that can be still found on *turbid image*.

For each test the N best features are extracted. For each detector, these N features are detected on both days of test. For each feature to be considered as resistant, it has to be detected on the *turbid image* and not move more than a predefined radius r. The number of resistant features found at the *turbid image* are counted. With this the underwater repeatability factor for each detector is measured by $U_r = \frac{N}{ND_i}$.

V. Results

On the tests made, due to non uniformity of illumination on underwater environments, feature points tend to concentrate on certain region. Regarding to this, a no maxima suppression technique is applied. With this method only the best the points on each local neighbourhood are chosen. The radius of this local neighbourhood is adjust by a factor δ. The visual attention saliency criteria [25] was used to decide the best feature point from a local neighbourhood. The SDI index between the *clear image* and the *turbid image* was of for the *Setup 1* and of 99 for the *Setup 2*.

For Setup 1 (Figure5, Figure 5(a) shows the results for the best selected parameters. The bar graphs plots the underwater repeatability (U_r) for each tested feature detector. The following detectors were tested: Harris,Hessian,DoG,FastHessian(FastHes),Harris Laplace(HarLap),Color Harris(ColHar) and Color Harris with saliency boosting(ColHarB). A number of features $N = 400$ was choose in order to best fitted the capture scene. To avoid mismatches due to camera movements, a radius r of 10 was chosen. For the non maxima suppression radius we set $\delta = 20$.

It is possible to notice that none of the detectors had a high contrast toward others. The colored version of Harris seems to be a bit more accurate. The HarrisLaplace is clearly the one with less underwater repeatability towards turbidity. Besides the a little better results of the color Harris its, saliency boosted version showed no contrasted results.

For the Setup 2(Figure 6), the harris color little accuracy superiority is not perceivable anymore. This probably is due to more uniform illumination conditions found on this setup.

VI. Conclusion and Future Works

This paper presented an evaluation of the best feature point detectors for underwater environments specifically concerning man-made objects.

Previous experiments concluded that, since the turbidity phenomenon usually smooth borders, blob based detectors should be a better option. Our results shows that this conclusion is considerably weaker for man made objects. Corner detectors are still robust for detecting more structured objects even under a certain .

Color methods seem to improve repeatability for underwater situations, specially for low illumination cases. However,color boosting is not efficient since a low percentage of distinctive points were found.

Further experiments with more levels of turbidity are still need to be done.

(a) Clear Image (b) Turbid Image

Fig. 3: A clear and turbid image captured with different amounts of algae proliferation. This setup was captured with just flashlight illumination.

(a) Clear Image (b) Turbid Image

Fig. 4: A clear and turbid image captured with different amounts of algae proliferation. This setup was captured with outside illumination as well.

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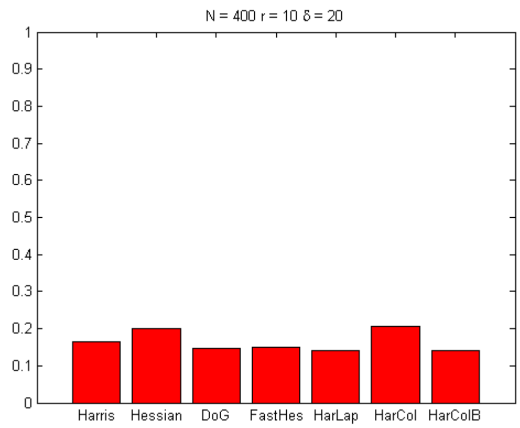

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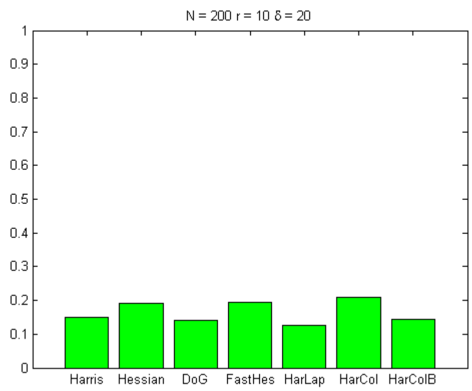

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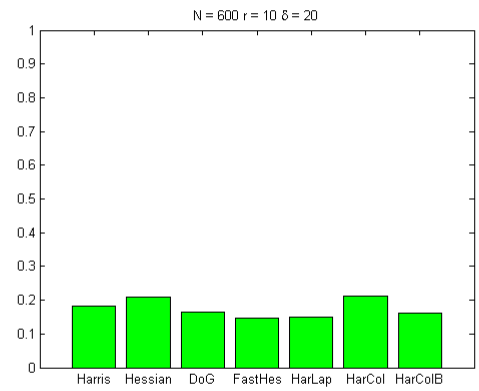

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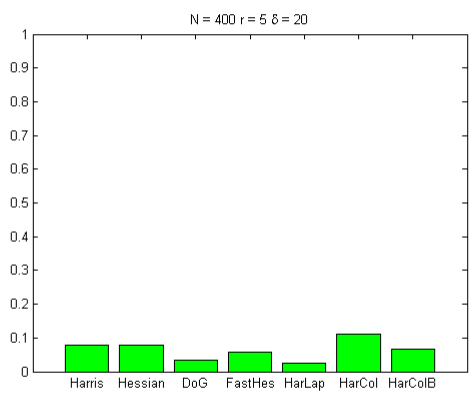

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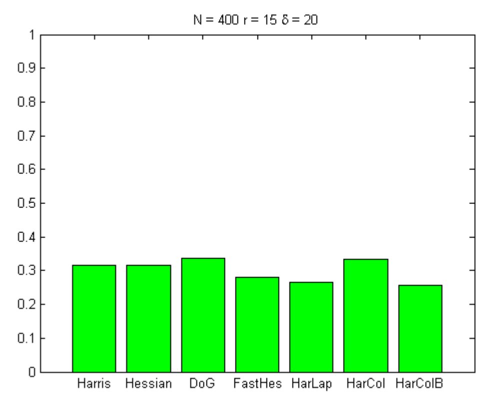

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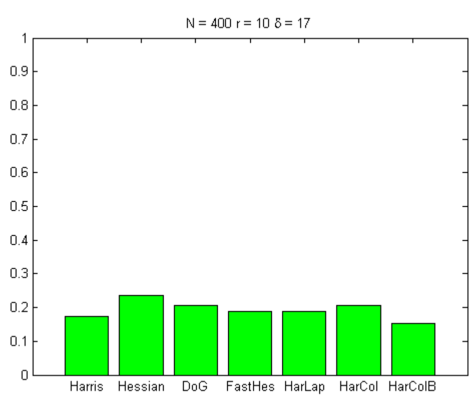

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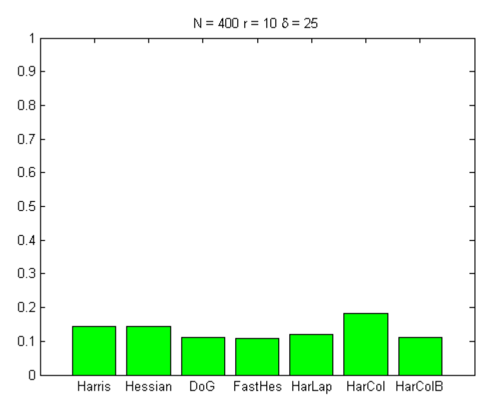

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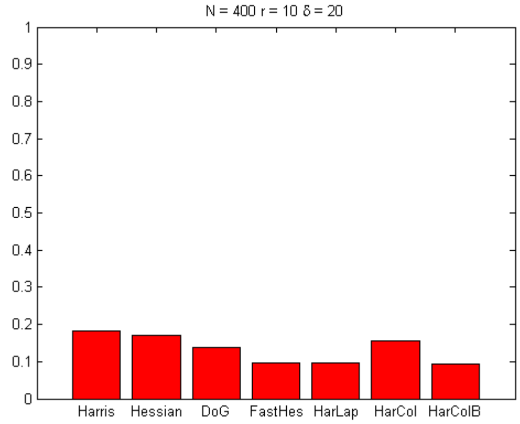
Fig. 5: Number of repeated features for Setup 1. The graphics show variation of the parameters r, N and δ



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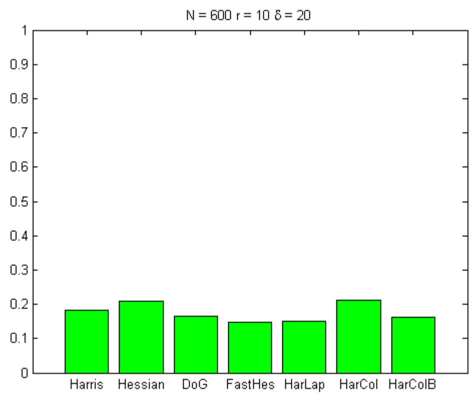

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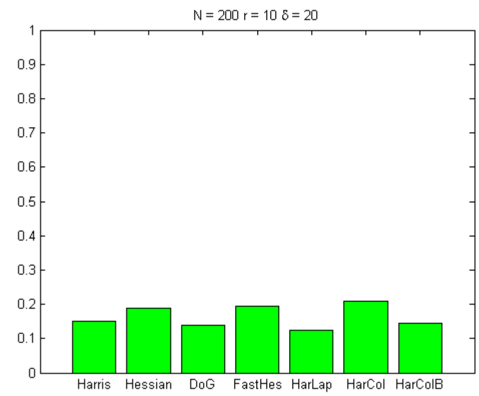

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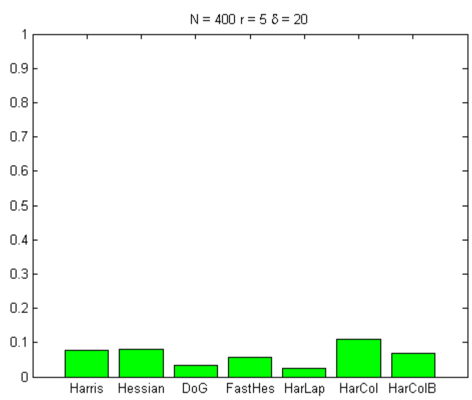

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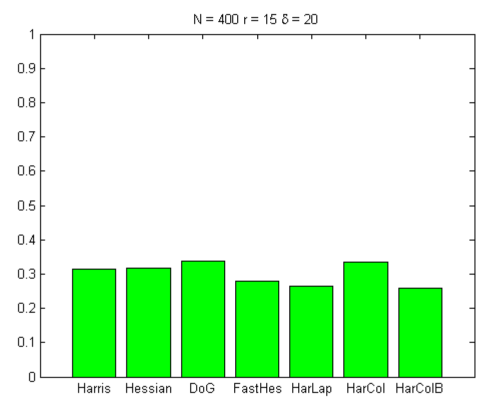

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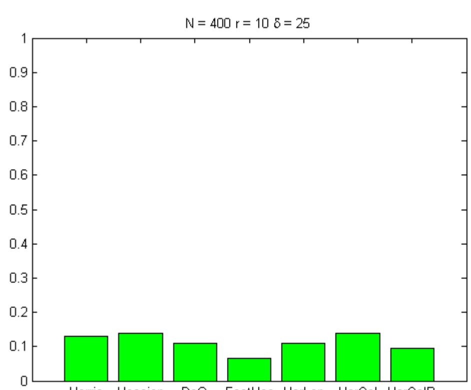

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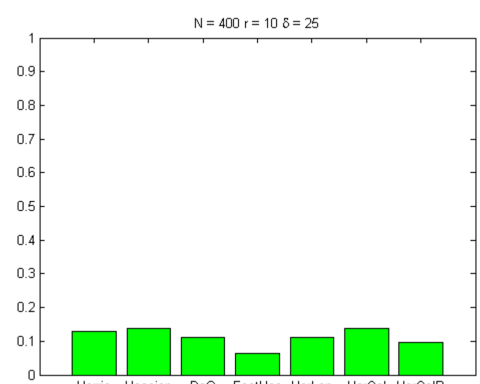

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Fig. 6: Number of repeated features for Setup 2. The graphics show variation of the parameters r, N and δ