# Curve Recognition for Underwater Wrecks and Handmade Artefacts

Davide Moroni, Maria Antonietta Pascali and Marco Reggiannini and Ovidio Salvetti

Institute of Information Science and Technologies (ISTI),
National Research Council of Italy (CNR), Pisa, Italy

**Abstract.** In the framework of the development of autonomous vehicle in order to perform a survey of extreme environments, such as the seabed, the demand for computer vision to support the on-board decision system is increasing. In particular we devote this work to improve the existing underwater curve detection procedures. We propose a method that statistically highlights archaeological artefacts among its environment, weighting properly the persistence of meaningful curves in the video sequence.To this aim we made use of an existing parameterless algorithm ELSD, suitable for digital image processing [1].



## 1 Introduction

The recent advances in underwater robotics and communications fostered a lot of work in artificial intelligence and computer vision algorithms to be integrated in modern Autonomous Underwater Vehicles. The marine environment and the seafloor present very challenging conditions for a theoretical and experimental setting. Actually there exist many different techniques (e.g. [2, 3]) for the seafloor survey and the underwater object detection. Many choices in term of device employed, or environment settings (deep or shallow water, etc.), and the difficulty in each validation procedure produce a rich family of techniques and no settled standards(e.g. [4–7]. In particular there are not relevant methods and algorithms performing a real time detection of archaeological objects, based on their geometrical description. This is mainly due to the fact that the efforts of the scientific communities have been primarily devoted to the offline detection and classification of archaeological artefacts, e.g. based on model fitting.

This paper faces the specific problem of curve detection and recognition in the underwater environment. The focus on curve detection is motivated by the fact that a high concentration of regular curves is a marker for the presence of manmade objects or shipwrecks. Our results show that there is a nice correlation between the weighted index of detection and the groundtruth assessed in our underwater acquisitions. At the same time we propose a statistical and iterative method to give relevance to a finding in the scene with respect to its natural surroundings; this way we point to automate the parameters setting and free the AUV intelligence from the operator intervention. Our results are promising albeit preliminary because of the scarcity of available data. Anyway we aim at carrying out more interesting tests on the data that will be acquired in the AUV's surveys, planned for the ongoing projects THESAURUS and ARROWS.

Moroni D., Pascali M., Reggiannini M. and Salvetti O..
Curve Recognition for Underwater Wrecks and Handmade Artefacts.
DOI: 10.5220/0004392300140021
In *Proceedings of the 4th International Workshop on Image Mining. Theory and Applications* (IMTA-4-2013), pages 14-21
ISBN: 978-989-8565-50-1

## 2 State of the Art

The automatic detection of elementary geometric features (line segments, elliptical arcs) in images, is quite an old issue in computer vision [8, 9]. The current procedures for geometric features recognition can be roguhly classified into two categories: *Hough-based* and *edge chaining* methods.

The Hough-based algorithms implement variants of the Hough transform. These methods ensure that pixels belonging to the same geometric stucture are mapped to the same point into an appropriately defined parameter space. We can define an accumulator array in which every cell, corresponding to specific parameter values, is augmented every time that a pixel is mapped on that cell. Computing the peaks of this array allows to identify the potential candidates. Standard Hough-based implementation requires high computational burden handling, especially for elliptical shape recognition: indeed, in that case the parameter space has five dimensions, corresponding to the five parameters of the ellipse, resulting in a $O(n^5)$ complexity. Basça et al. [10] have proposed a method for speeding up the candidate identification process by implementing a random search method. This allows to lower the computational complexity more than two orders of magnitude.

A second class of detection methods relies on edge chaining techniques, which use extensively the geometric properties of the sought features, such as straightness criteria for line segments or curvature properties for ellipses. Usually these algorithms begin with a seed pixel (or a group of pixels), and subsequently, other pixels are added, provided they obey some geometric properties of the sought feature.

Nguyen and Kerautret proposed a method for ellipse detection based on a preliminary decomposition of an edge image into curve primitives followed by a fitting techniques. First the image is processed by an edge detection filter in order to extract a set of digital curves representing the image contours. The analysis is then limited to every single group of pixels representing a contour curve in the image. The curve undergoes a particular transformation that maps the contour lines into the so called *tangent space*. As it is explained in [11] the tangent space representation allows a much easier assessment of the curvature properties of the grouped contour. More in detail it is possible to decide whether a set of line segments belongs to a straight line or if these segments are part of more elliptical structures. The final assessment is carried out by a fitting procedure in order to decide whether the curve can be classified as a circle or an ellipse.

This paper is inspired by a successful parameterless approach that was introduced by Desolneux et al. [12], known as the *a contrario* approach. The detection algorithm is based on a three-stage process: first, a *candidate selection* stage is carried out by gathering groups of pixels sharing appropriate orientation properties (for example line recognition requires the alignment between pixels where as for circles and ellipses detection some curvature constraints must be fulfilled); in a second stage (*validation stage*), the candidates are further analysed in order to decide whether they are meaningful structured groups of pixels or if they represent an unstructured cluster. This is an important step since it allows the rejection of false positives by automatic computation of detection threshold. The estimation process is based on the so called Helmoltz's perception principle: it essentially states that there is no perception in white noise. In the final stage (*model selection*) the candidates are classified as belonging to a specific model (line, circle, ellipse) by considering the most suitable model as the one producing fewer false alarms.

In the following you may find a description of the implemented algorithm and the related experimental results.

## 3 Methods

As stated above the starting point of our method is the ELSD algorithm presented in [1]; it extends a previous one detecting locally straight contour in digital images to the detection of locally circular and elliptical contours: LSD (see [13, 14].

LSD is a linear-time Line Segment Detector giving subpixel accurate results. It is designed to work on any digital image without parameter tuning and it controls its own number of false detections (on average, one false alarms is allowed per image). The algorithm is based on Burns, Hanson, and Riseman's method [15], and uses an a-contrario validation approach according to Desolneux, Moisan, and Morel's theory [12]. The a-contrario model, used for line segment detection, is defined as a stochastic model of the level-line field satisfying certain properties. The generalization of the theoretical approach to the detection of circles and ellipses is clearly explained in [1]. The most interesting feature is the accuracy in the ellipse fitting, due to a non-iterative technique that uses gradient orientations and the algebraic formalization of the conic fitting.

We experienced quite good performances of ELSD on synthetic and natural images. Then we tried to apply it in order to get an automated curve detector for on-board optical analysis to be performed during the AUV survey. As we already said, this is not an easy task because of the several variables making each part of the survey very different from the previous one. To overcome such randomness in the boundary / natural conditions, we propose the following pipeline:

1. image acquisition and preprocessing
2. ELSD for a sequence of 10 adjacent frames - fine tuning of internal parameters (e.g. $\rho$ gradient magnitude threshold, $\tau$ angle tolerance, $D$ minimal density of aligned points for each candidate region), computation of the discovery threshold (based on weighted sum of curve detections)
3. ELSD for a sequence of 90 adjacent frames - reporting suprathreshold detection

The core step in the proposed method is the definition of the $discovery\ threshold$. This threshold is newly defined at each cycle as the weighted sum of the number of curve detected and recognized. We set $\{3, 2, 1\}$ as weights for each type of sought curve $\{$ ellipse, circle, line $\}$. This choice is motivated by the strong belief that elliptical and circular arc are more meaningful (and rare) than line segments in the archaeological object we look for (e.g. amphoras, and plates, commonly found in the cargoes of ancient vessels). Then we compute the weighted average over the detected curves $WA$ for the test set of 10 frames, take as discovery threshold the $WA$ incremented of a $20\%$; this threshold is applied to each frame (included the first 10 fs on which it is computed) and a warning is produced for each frame containing a suprathreshold number of detections. As shown in the graphics of the next Section there is a nice correlation between all

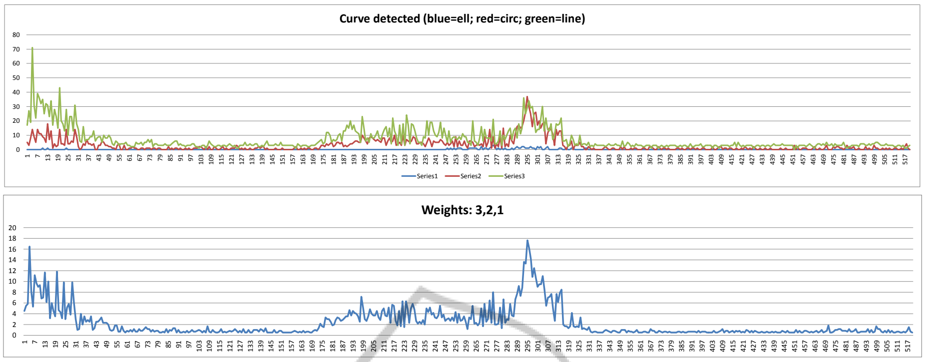


**Fig. 1.** Graphs of the Curve Detection, and of the Weighted Curve Detection (computed on the first video acquisition).

these three sets of data: detections, discovery threshold, and groundtruth of discovery (manually evaluated with four degrees of interest).

In particular we decided to increase ELSD sensitiveness to intensity changes suitable modifying the internal parameters, such as $\rho, \tau, D$.



## 4 Results

Our first results were achieved thanks to some experiments held in a pool in Pistoia, and near the Elba island, in Tuscany. In both cases data were acquired through an analogic colour camera (precisely **Bowtech**) designed for underwater environment, with high light sensitivity (it is the same optical device that has been integrated in the AUV acquisition platform, and the acquisition is part of the experiment preliminary to the HW/SW integration).

To the aim of an integration in the AUV acquisition platform, we need to consider at least two important preprocessing steps:

- Perform a frame extraction from the whole frame sequence, according to AUV speed and to the consumption time of the algorithm (that depends on each image size);

- Select the balance between RGB channels, and then the proper intensity to be used for the gradient field computation and the contour extraction. This results in an enhancement of the video quality, and it depends on the natural environment and it could be set only once per survey.

We processed only 5fps, because the slow speed of the boat allowed a large overlap between two adjacent frames. Also we applied the ELSD algorithm to an intensity obtained as a balance between the RGB channels that solves the problem of diverse degree of absorption of colours in underwater imaging. This last preprocessing was not needed in the second video, because the distance between the optical device and the target is not large, and the optical device was equipped with proper filter.

### 4.1 Pool Experiment

The pool has a depth of about 2 m, and we placed on the pool bottom a set of mock-up objects (amphora, plates, and small carpets). As you can see in the images below, the algorithm used is quite efficient in detecting the geometric curves in the scene.

**Fig. 2.** Results of the primary curve detection applied to a frame in which an amphora is visible.

### 4.2 Elba Shipwreck Site

We processed a video of a known archaeological site near Elba. The video shows a survey of the area, large and rich in amphoras and plates. Actually, it shows many amphoras and plates in the 90% of the images. Even if the video sequence is not representative of a simulation of a discovery (the real setting for which this method has been thought), the suprathreshold detections give account of the geometric richness of the seabed satisfactorily. In the following images it is shown the result of detection, Fig. 3; then, in Fig. 4, the graphics comparing the weighted detection with the groundtruth, and the suprathreshold detections with the groundtruth.

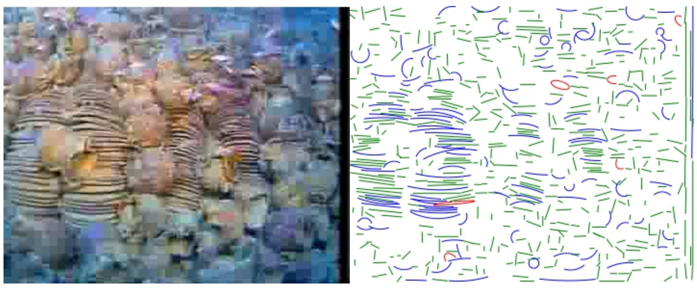

**Fig. 3.** Results of the primary curve detection applied to a frame in which a set of plates is visible.

### 4.3 Elba Survey

A mock-up target (modern amphora) has been placed on the sandy seabed. Due to favorable water and weather conditions in Elba, we could acquire a nice set of data, at about 24 fps, in PAL resolution, despite the distance between the optical device and the target (about 9 m). In the following images it is shown the result of detection, Fig. 5; then, in Fig. 6, the graphics comparing the weighted detection with the groundtruth, and the suprathreshold detections with the groundtruth.

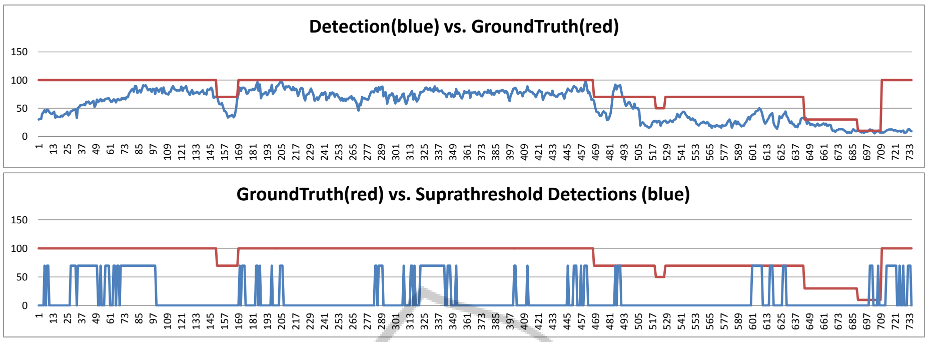


**Fig. 4.** Graphs of the video sequence of the shipwreck near Elba island: Detections and Suprathreshold vs. GroundTruth

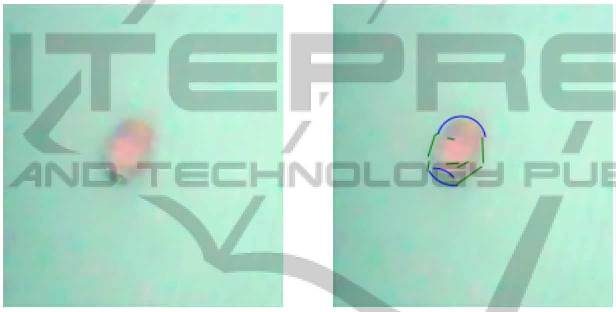

**Fig. 5.** Results of the primary curve detection applied to a frame in which an amphora is visible.

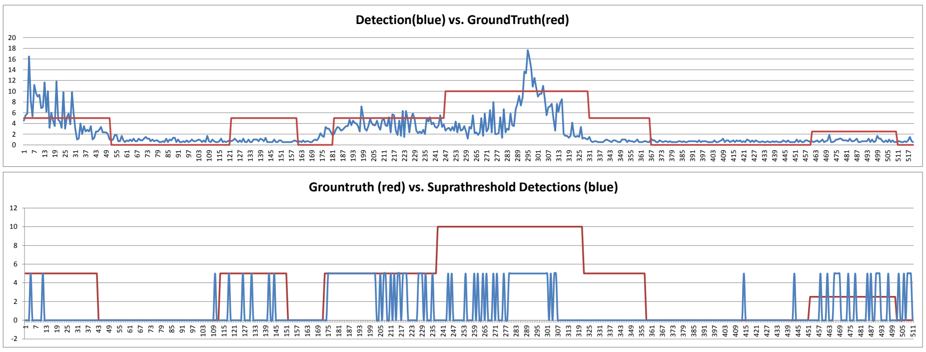


**Fig. 6.** Graphs of the Elba experiment: Detections and Suprathreshold vs. GroundTruth.

## 5 Conclusions and Further Work

In this paper we have presented a new method for man-made object recognition in underwater environment. More in detail our research was inspired by the work of Patraucean et al. [1], who developed a robust and efficient curve recognition algorithm able to detect and recognize line-segments, arcs of circle and ellipse in images. Starting from that we implemented a procedure for automatic recognition of interesting objects in the video streams captured during a survey mission. The method is based on the estimation of statistical parameters from a set of images in which interesting geometric shapes have been highlighted: in particular a descriptor based on the detected number of circular shapes has been produced and tested.

In the framework of our research work we aim to produce new technologies for underwater archaeological survey, and we believe that the exploitation of standard supplementary survey sensors, such as acoustic sensors, can be promising: since the pictorial quality of well-captured sonar images is often comparable to the optical ones, computer vision algorithms can be applied to both the data typologies. We aim to develop a data fusion model in which the information provided by the multi-sensor platform can be exploited for a higher level interpretation of the underwater scene.

Since our multi-sensor system is actually composed of a pair of cameras we aim also at developing a procedure based on the 3D reconstruction of the captured scene. At the resulting estimation we aim to apply 3D fitting procedures in order to recognize specific archaeological models (amphoras, etc..) and assign a score to the scene depending on the number of recognized models. This can be thought as a 3D extension of the method presented in this paper.



## Acknowledgements

This work has been partially supported by PAR FAS Tuscany Project “THESAURUS” – *Techniques for Underwater Exploration and Archaeology Through Swarms of Autonomous Vehicles* and by FP7 Project “ARROWS” – *ARchaeological RObot systems for the World’s Seas*. We would like to thank our colleagues from Centro Piaggio in Pisa for their contribution in a large part of the work, and also Dr. Michele Cocco e Dr. Lavinio Gualdesi (EdgeLab s.r.l.) for their kind support and for providing access to the testing area.

## References

1. Patraucean, V., Gurdjos, P., von Gioi, R. G.: A parameterless line segment and elliptical arc detector with enhanced ellipse fitting. In: ECCV (2). Lecture Notes in Computer Science, Springer (2012) 572–585
2. Pizarro, O., Eustice, R., Singh, H.: Large area 3-d reconstructions from underwater optical surveys. IEEE Journal of Oceanic Engineering 34 (2009) 150–169
3. Bonin, F., Burguera, A., Oliver, G.: Imaging systems for advanced underwater vehicles. Journal of Maritime Research VII (2011) 65–86
4. Zhang, Q.: Extrinsic calibration of a camera and laser range finder. In: In IEEE International Conference on Intelligent Robots and Systems (IROS. (2004) 2301–2306
5. Williams, S., Mahon, I.: Simultaneous Localisation and Mapping on the Great Barrier Reef. In: IEEE International Conference on Robotics and Automation (ICRA). (2004)
6. Fusiello, A., Murino, V.: Augmented scene modeling and visualization by optical and acoustic sensor integration. IEEE Trans. Vis. and Comp. Graphics, Vol (2004) 625–636
7. Negahdaripour, S., Sekkati, H., Pirsiavash, H.: Optiacoustic stereo imaging: On system calibration and 3-d target reconstruction, in review. In: Proc. IEEE Beyond Multiview Geometry. (2007)

8. Hough, P.: Machine analysis of bubble chamber pictures. In: Proc. Int. Conf. High Energy Accelerators and Instrumentation. (1959)
9. Ballard, D.: Generalizing the hough transform to detect arbitrary shapes. Pattern Recognition 13 (1981) 111–122
10. Basca, C., Talos, M., Brad, R.: Randomized hough transform for ellipse detection with result clustering. In: Proceedings of the EUROCON 2005. (2005)
11. Nguyen, T., Kerautret, B.: Ellipse detection through decomposition of circular arcs and line segments. In: International Conference, ICIAP'11, LNCS, Ravenna, Italy (2011)
12. Desolneux, A., Moisan, L., michel Morel, J.: Gestalt theory and computer vision. In: Seeing, Thinking and Knowing, Kluwer (2002) 71–101
13. Grompone von Gioi, R., Jakubowicz, J., Morel, J. M., Randall, G.: LSD: a Line Segment Detector. Image Processing On Line 2012 (2012)
14. von Gioi, R.G., Jakubowicz, J., Morel, J., Randall, G.: On straight line segment detection. Journal of Mathematical Imaging and Vision 32 (2008) 313–347
15. J. Brian Burns, Allen R. Hanson, E. M. R.: Extracting straight lines. IEEE Transactions on Pattern Analysis and Machine Intelligence 8 (1986) 425–455