Issues in High Performance Vision Systems Design for Underwater Interventions

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***Abstract*— This paper describes the design and evaluation of a vision system conceived to provide perception in Autonomous Underwater Vehicle (AUV) intervention tasks. Due to the accuracy requirements inherent in manipulation tasks, high performance vision systems, enabling adequate perception capabilities, are needed to cope with underwater interventions. However, vision systems are challenged by the difficulties and variability of underwater environments as well as by the need to operate in a sealed canister. The vision system described in this paper addresses design issues like computational performance, energy power consumption, heat dissipation, and network capabilities. Even though the system has been designed to support stereovision, experiments in several underwater contexts have shown that stereovision is seldom applicable, due to the many problems faced by light propagation in water. Developing a system for underwater operation emphasizes the need for tradeoffs between computational performance and power consumption and dissipation, as well as the need for flexibility to support multiple vision processing pipelines and adapt to the specific underwater context.**

I. INTRODUCTION

In spite of the technological advancements in many robotic technologies, operating in underwater environments remains a very difficult endeavor for autonomous robots. Key technologies like localization and perception must tackle problems which are not fully solved in the underwater context. Water influences the mechanical and electrical design of systems, interferes with sensors by limiting their capabilities, heavily impacts on data transmissions, and generally requires systems with low power consumption to enable reasonable mission duration.

Increasing need of long term and long range underwater operations implies the unsuitability of manned vehicles as well as ROVs (Remotely Operated Vehicles), for both costs and risks, and has pushed research in autonomous underwater robotics. So far research has been mainly focused on exploration and survey tasks with applications in oceanographic, geological, biological and archaeological sciences. Vehicles equipped with multiple state-of-the-art sensors and capable to autonomously plan missions have been deployed in the last ten years and exploited as observers e.g. for underwater fauna, seabed, ship wrecks [1]–[4].

Contrasting with observational tasks, underwater interventions such as object recovery and equipment maintenance are challenging tasks without human supervision, since they

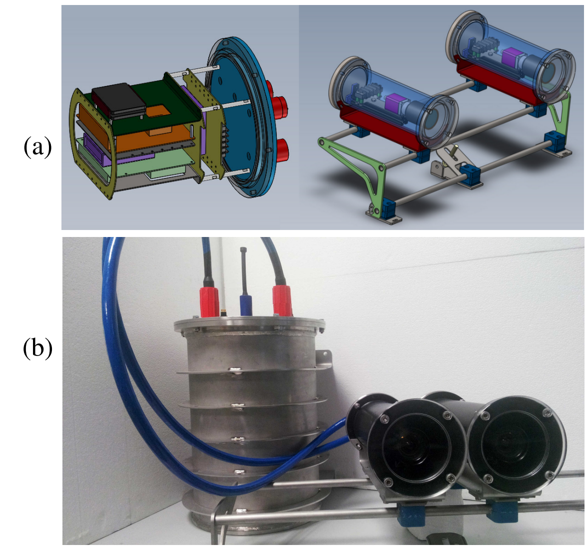

Fig. 1: (a) 3D CAD model of the vision system: internal view of the vision canister (left) and stereo rig (right). (b) Underwater vision system.

require object perception and localization with higher accuracy and robustness, to a degree seldom available in AUVs. Adequate scene perception and environment understanding are key requirements for autonomous intervention, under as well as above water. In underwater systems, main issues are related to the ability of retrieving robust and reliable perceptual data while providing adequate real-time data processing and coping with all constraints arising in the specific environment. Indeed, inadequate perception capability is one of the main obstacles hindering progress in autonomous underwater interventions.

This paper reports the design, deployment and evaluation of a general purpose and configurable platform conceived for stereovision perception in underwater environments. More specifically, the paper discusses the system design issues arising in this endeavor and how they relate to the specific operational environment. We focus on flexibility, computational performance, power consumption and dissipation, and communication requirements of the vision system. The vision system discussed in the paper has been developed in the frame of project MARIS (Marine Autonomous Robotics for InterventionS) [5], which aims at cooperative autonomous manipulation by two AUVs. The vision system has been successfully tested both standalone (for waterproof operation up to a depth of $50\ m$) and integrated in the MARIS AUV

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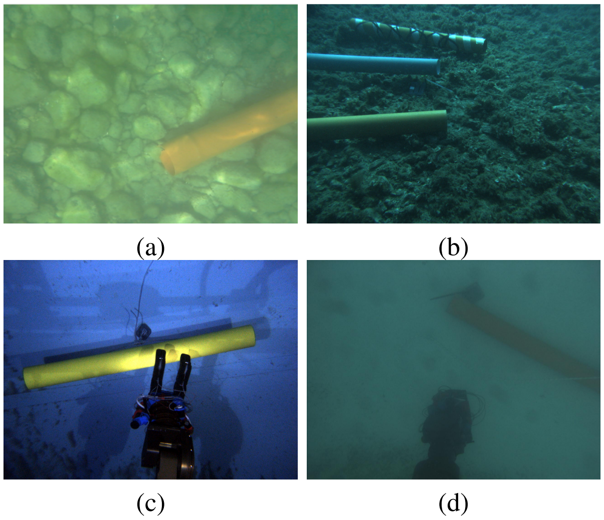

Fig. 2: (a) A raw underwater image of an object in shallow waters with attenuation and backscattering. (b) Another example of underwater image acquired at medium depth (about 10 m). (c) Image of a pipe in a pool with reasonably clear waters and artificial illumination by the AUV. (d) A similar yellow pipe in a pool with turbid water.

prototype (carrying out manipulation tasks in a pool tank). We refer to our earlier work [6] for a detailed description of the mechanical construction and internal arrangement of the canisters hosting the cameras, of the stereo camera rig, and of the canister hosting the computational unit, which are shown in Figure 1.

A. The variability of underwater environments

Unless in an artificially controlled setup, a vision system providing exteroceptive sensing to an AUV may be required to operate in remarkably variable underwater environments. Without any claim of completeness, Figure 2 shows a set of underwater environments that we have met in testing our vision system prototypes. Image in Fig. 2.a shows a cylinder-shape pipe in clear, shallow open waters. The image was taken in experiments carried out in a sunny day. Due to the strong light backscattering, feature-based methods are largely unusable for detecting and localizing objects of interest in this type of images. Specific objects of interest must be detected taking advantage of any prior information about color or shape. Generic human artifacts can perhaps be detected exploiting assumptions on contour regularity.

Image in Fig. 2.b shows a few pipes in clear, medium depth (about 10 m) open waters. Although the image refers to experiments carried out in a sunny day, here light backscattering is much lower compared with the image in Fig. 2.a. Indeed, unless artificial illumination is used (such as a synchronized flash), at 10 m depth light only comes from the top. In Fig. 2.b the bottom part of the pipe is dark and border almost invisible. Simple shape-based methods for object detection and recognition may prove inapplicable. Moreover, since color distortion increases with depth, object detection based on comparison with original color in air may be also difficult. Therefore, color restoration techniques are likely to be required.

Image in Fig. 2.c shows a pipe laying at the bottom (a few meters) of a pool with reasonably clear waters. The end-effector of the AUV manipulator is also visible. Here object color, camera perspective (top view), and artificial illumination help in simplifying detection and recognition of the yellow pipe. However, image in Fig. 2.d shows a similar yellow pipe in a pool with turbid water. Shape is completely blurred so that only a yellow stain is barely visible [7]. Bright and contrasting colors do help, but cannot always be relied upon, not even in shallow waters.

Of course, additional underwater environments could be brought as examples, each of them with its own peculiar characteristics which affect vision-based object detection and recognition. We take the position that flexibility of the vision system is dictated by the variability of underwater environments, where water conditions can range from clear to turbid, light backscatter varies substantially with daylight and depth, color distortion is related to water conditions, and other variable environmental elements factor in the perceptual problem.

The vision system described in Section III takes into account this requirement as well as other domain-specific requirements. It is a modular and configurable platform built with off-the-shelf components for both the imaging sensors and the computational unit, linked by a high performance ethernet network bus.

II. Related work in underwater computer vision

Although computer vision is a major sensing modality in robotics, in underwater environments it is far from being a mainstream approach, especially in applications in which perception should support manipulation tasks for autonomous interventions.

Indeed, artificial vision has been successfully adopted in underwater tasks that do not require online processing. Tasks of seabed mapping with image mosaicing [4], [8] can be planned with a preliminary environment exploration for images and data collection followed by an offline image processing task. Since the system does not face strict timing constraints for real-time image processing, this approach can be pursued with any processing system providing image acquisition and storing. Complex techniques for image restoration, enhancement and deblurring, as well as for feature detection and association, can be adopted since they are deferred to offline processing. Applications of seabed mapping are typically based on feature detection and association between multiple images with techniques translated from standard, out-of-water computer vision methodologies.

Feature-based vision techniques have also been proposed in underwater navigation methods based on SLAM [9]. In underwater environments, navigation is challenging due to generally poor vehicle odometry and lack of GPS signal. Pure navigation tasks, however, are somewhat more tolerant of errors than manipulation tasks, since they usually do not require the same degree of accuracy. The underwater environment indeed brings difficulties that prevent an easy re-use of technologies and methodologies already validated in other robotic fields like ground, air, and even space. These difficulties mainly come from water and its response to signal transmission which results limited and distorted.

Water turbidity, color aberrations, light reflections, and backscattering phenomena are major problems with underwater computer vision applications [10]. Furthermore these problems depend on aspects like working depth, weather conditions, water surface movements, sandy or rocky seabed, and, in general, the natural environment in which the application is deployed. The design of a reliable underwater computer vision system, able to operate in non-controlled, generic underwater environments and in such different conditions, must take care of these aspects and should therefore be powerful enough to support multiple processing pipelines.

Stereo vision systems have been proposed for underwater applications [11]–[14], although they face the additional challenges of calibration and of the required computational performance. The 3D reconstruction achieved by underwater stereo vision may prove adequate to represent the main elements of a scene, but its accuracy is often not sufficient for the detailed perception required in object detection and recognition, not to mention object manipulation. In the EU project TRIDENT, manipulation experiments have been successfully carried out in clear waters, both in laboratory tanks [15], [16] and in the sea [17], [18], targeting an object with contrasting color and well-defined features. Object detection could take advantage from previously acquired underwater images of the target object. A commercial stereo camera (Bumblebee) was used, but to our understanding no on-line stereo processing was performed during the manipulation task.

A. *Embedded systems for underwater vision*

An underwater computer vision system can be effective in real-world contexts only if it is able to cope with the variability of environment conditions, for example by exploiting multiple algorithmic approaches. So far, however, the processing units deployed with underwater autonomous vehicles have been endowed with fairly limited computational power, only allowing simple predefined perceptual tasks. Due to their very small form factor (90×96 mm), their modularity, and the definition as a standard in the early nineties, PC/104 boards are widely used in underwater applications [19]–[22]. Recent PC/104 systems exploit mobile, ultra-low-power CPUs. These CPUs, however, still offer limited computational power with respect to available CPUs e.g. for desktop or notebook systems.

In our view, processing systems with limited performance are a bottleneck for underwater perception as required by autonomous manipulation. Therefore we investigate the trade-off between computational power and power consumption of a computer vision system for underwater object detection tasks. The goal is pursued by developing a high performance hardware architecture whose deployment in an underwater sealed canister is feasible. High-performance computing in a sealed canister is not a trivial issue: safe working conditions, including operation within thermal limits, must be ensured to the system when it works both in air and in water. Indeed, autonomous underwater vehicles are inevitably maneuvered in and out water and the various robot subsystems must run safely across all operations.

III. Computer Vision System Design

The deployment of computer vision systems suitable for real underwater environments requires that system-related issues are investigated and addressed. The proposed vision system has been conceived as a versatile hardware platform for computationally-demanding underwater applications. Regarding the imaging subsystem, camera synchronization is mandatory as well as the possibility to intervene on the optical configuration in order to adapt the cameras to the specific working context. Earlier experimental trials of underwater object detection also showed the importance of color as a distinctive feature for submerged targets [7], [23].

The imaging subsystem is based on two AVT Mako G125C GigE cameras, an ultra compact device whose dimensions are $60.5 \times 29 \times 29$ mm. The connection bus is a standard ethernet link with support to PoE (Power over Ethernet). Cameras mount a Sony ICX445, 1/3", high resolution color sensor, capable of acquiring frames at 30 fps in full resolution of 1292×964 pixels. For higher flexibility, varifocal lenses have been chosen. Kowa LMVZ4411 lenses have a focal length range between 4.4 mm and 11.0 mm, a manual focus and iris controls and a minimum focusing range of 0.3m. Iris maximum aperture of f /1.60 suggests very luminous optics. Lenses fit requirements of mega pixel cameras, up to 1/1.8" sensor size. By using these lenses with smaller imaging sensors, like the ones in Mako cameras, a reduced Field of View (FoV) is compensated by less distorted images. AVT Mako firmware provides several useful features, including the possibilities to manually tune exposure time, white balance and gain, to trigger the frame acquisition with a digital signal, and to perform an on-board color correction by acting on hue and saturation channels. Image processing at a lower resolution is supported directly onboard by sensor-level image binning. Cameras are housed in separate canisters arranged in a rig allowing configuration of baseline and pitch (see Fig. 1).

The underwater computational unit has been designed balancing power consumption, thermal dissipation and system performance. The ECU inside the vision canister is a modular system comprising two x86 CPUs, an ARM-based board and a microcontroller (Fig. 3). The main computational unit is an Intel Core i7-4770TE @3.33GHz with 4 physical cores and Hyper-Threading technology, mounted on an industrial Mini-ITX board. The mainboard (BCM MX87QD) features two independent network controllers which are exploited for splitting the system network from the camera network. This PC is equipped with 8GB of 1600MHz DDR3 RAM and two 120GB Samsung 840 Pro series SSDs. The CPU heat sink is a low profile Zalman capable of cooling up to 120W. The heatpipe is placed in direct contact with the CPU dye and

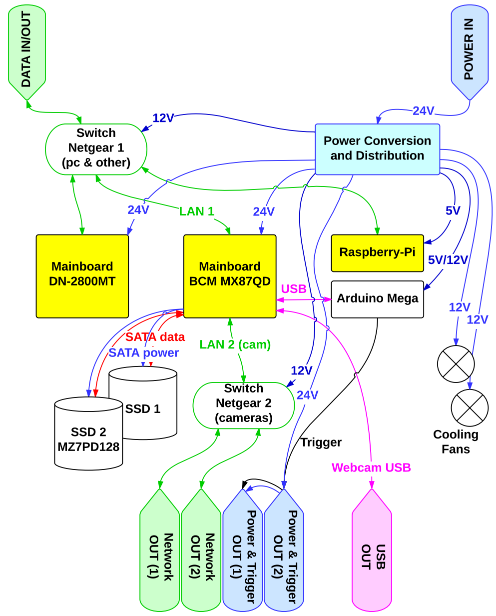

Fig. 3: Vision system architecture.

ensures efficient heat transfer from the CPU to the heat sink fins.

The microcontroller (Arduino MEGA 2560) is responsible for camera triggering and temperature monitoring inside the canister. Several internal temperatures are measured inside the canister both close to and farther from the i7 chip. The ARM-based board is a small size Raspberry-Pi providing onboard H.264 video encoder with minimal impact on heat generation and power consumption. Raspberry-Pi features a BCM2835, ARMv6 700MHz CPU, 512MB RAM and is equipped with a 16 GB Class 10 SD-CARD running Raspbian Linux operating system. The Raspberry-Pi board is in charge of remote streaming an encoded video for monitoring purposes. A final computational unit is based on an Intel DN2800MT Mini-ITX mainboard with an ATOM N2800 64bit 1.86GHz processor (TDP 6.5 W). This unit has been included to support lightweight computation tasks when the canister is being operated out of water, as well as to investigate the feasibility of simple vision algorithms in underwater perception.

Network connection is managed by two independent gigabit networks using Netgear GS-105 switches. Due to the high traffic rate generated by the vision system, the two cameras and the i7 ECU are connected by a dedicated network to avoid traffic jams. The second ethernet interface is used to enable communication between the vision system and the AUV. The vision system is housed in a cylinder stainless steel canister with soldered bottom and accessible from the top where all marine connectors are located (see Fig. 1). The canister includes small fans and is based on a careful 3D design to maximize heat exchange with the surface and then with the outside medium. We refer to [6] for further details on the canister design. Fig. 3 shows the block diagram of internal components and connections.

IV. Algorithms

The proposed computer vision system has been used to acquire images and to execute algorithms for detection and pose estimation of target objects with cylindrical shape. Several approaches [23]–[25] have been investigated for image pre-processing, object detection and pose estimation in different conditions (see Fig. 2). The most challenging step in the algorithm is the evaluation of the target position and orientation, since it affects the computer vision system requirements and relies on the previous steps in the processing pipeline. Experiments showed that dense stereo vision processing is unsuitable for the noisy and varying conditions of underwater environments. Thus, the approach adopted in generic underwater condition exploits the object geometry and, in particular, the projection of the cylindrical shape in the image [25].

The main goal of the final image processing pipeline, shown in Fig. 4, is the accurate identification of the object contour. After color restoration using grey-world hypothesis, the region-of-interest (ROI) is selected according to the known object color (Fig. 4.a-c). The approximate dominant direction of the ROI edges is used to rotate the image (Fig. 4.d-e). For better accuracy, the lines delimiting the long and short sides of the target objects are found in the rotated image (Fig. 4.f-g). The object pose is computed from the intersection of the planes corresponding to these lines. A tracking algorithm provides additional robustness to the approach.

V. Experiments

Results in this section refer to system-level evaluation experiments. We refer to [24], [25] for algorithm evaluation.

A. *Basic hardware evaluation*

Long-term experiments have been conducted in a laboratory setup to evaluate power consumption, heat dissipation, working temperature, and network performance. Power consumption and heat dissipation have been tested by stressing the CPUs at a high load using the Linux `stress` command. Results are reported in Table I and show that the total power consumption is well below 100 W. We consider this value a reasonable tradeoff between available computational performance (ensured by the i7 CPU) and power consumption / heat dissipation, thereby enabling effective integration of the vision system in AUVs for interventions.

The maximum temperature registered in the vision canister in water with all the CPUs stressed was $60°C$, far from a dangerous value. However, in the laboratory setup, with the vision canister in air and external temperature at $25°C$, temperature inside the canister after 15 minutes of CPU stressing reached $72°C$ and was still increasing. This test suggests that the system cannot support heavy computational loads in air with external mild temperature for an extended time. It should be remarked that with no stress of the CPUs the temperature remained stable at a lower, safe value. Hence,

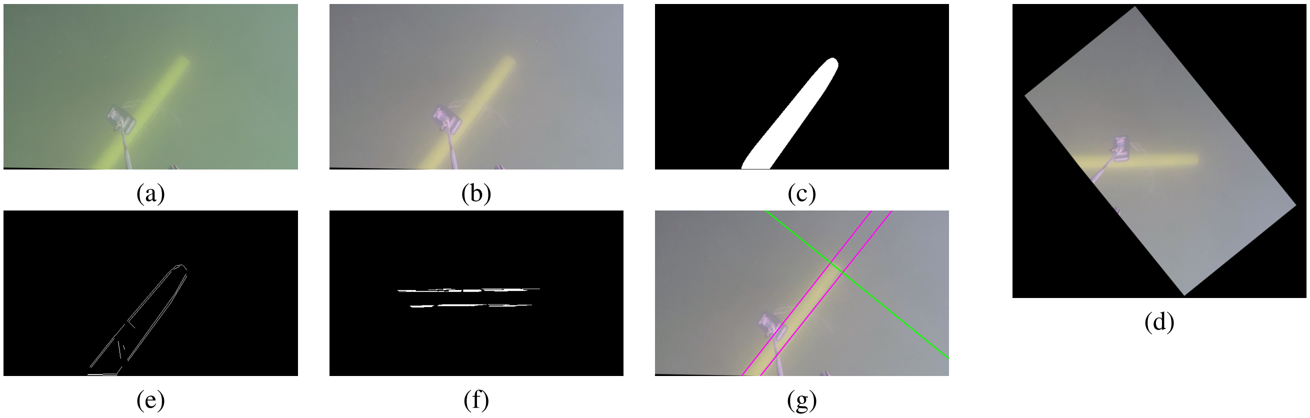

Fig. 4: Outline of pipe detection algorithm: (a) input image of target object; (b) color restoration with grey-world hypothesis; (c) color ROI detection; (d) image rotation according to the main orientation given by (e) the contours of ROI; (f) horizontal line extraction in rotated image; (g) line border of pipe.

Test	Power (W)
Idle	43.2
CPU stress - 1 core - i7	65.0
CPU stress - 2 cores - i7	78.0
CPU stress - 4 cores - i7	79.2 (peak 86.4)
CPU stress - 4 cores/8 threads - i7	79.2 (peak 86.4)
CPU stress - 2 cores/4 threads - Atom	44.9
Stereo Vision frames acquisition	46.6
CPU stress on all cores/CPUs	**81.6 (peak 91.9)**

TABLE I: Power consumption tests at different CPU loading levels

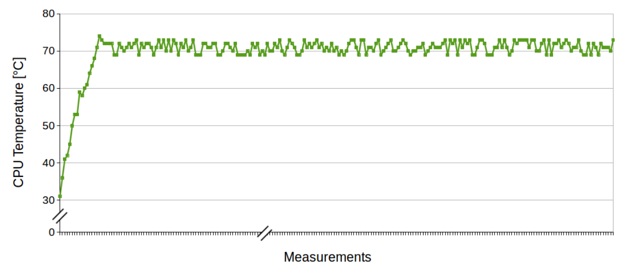

Fig. 5: i7 CPU temperature of the vision system logged during an AUV intervention experiment. A stationary average value of $71°C$ is reached and maintained during the whole session.

the vision canister can also be operated in air at standard CPU load level for an extended time, as long as no intensive computation is requested.

Bandwidth throughput of both networks was tested exploiting `iperf` [26] using both TCP and UDP protocols, half and full duplex communication and different packet size. Despite cable soldering and usage of marine connectors, data transfer rate was about 850 Mbps, full duplex, for both system-to-cameras communication and system-to-vehicle communication. The performance of the vision system to reconstruct a disparity map was tested using the standard Absolute Differences (SAD) correlation method. A throughput of 12.5 frames per second (at full 1292×964 resolution) has been achieved.

B. Stand-alone underwater vision system experiment

An underwater image acquisition campaign took place in off-coast sea waters, near Portofino (Italy). The seabed was roughly flat, with submerged cliffs and a water depth of approximately 10 m. Despite the presence of sand on the bottom, water was clear and visibility perfect. The main canister buoyancy is slightly negative, so it tends to sink. For this reason it was also tied to a rope and held from the surface at mid-water, in order to ease divers maneuvering. The main canister was connected to the control station on the support dinghy with a power supply cable and an ethernet link. A set of cylindrical pipes with different colors, patterns and radii ranging from 5 to 6 cm was submerged and laid on the seabed. The stereocamera rig was slowly moved around in order to collect images of both the environment and pipes, from different distances and angles.

Cameras were configured with a small baseline due to rather proximity of target objects in the workspace. Images were acquired at the maximum feasible resolution of 1292×964 pixels, in Bayer encoded format. An example of grabbed frame is shown in Fig. 2.b. Although cameras would be able to grab images up to 30 fps, they were configured at 15 fps because in underwater intervention applications images must be processed online, and a target frequency of 10Hz is already challenging. The underwater testing session lasted approximately 22 minutes. The dataset, cleared from useless frames of the initial sinking and final raising of the equipment, comprises 10,123 stereo images. The collected dataset has been made available for download, accompanied with camera calibration parameters in yaml file format [6].

C. Experiments with vision system mounted on AUV

Several MARIS experimental sessions were carried out in a pool with the vision system mounted on the AUV. During these experiments, the vision system did not exhibit any hardware problem and showed a reliable behavior. With the algorithmic pipeline discussed in section IV the system was able to process images with 1292×964 resolution at 7.5 Hz, while at the same time images were stored and compressed with bzip algorithm. The file compression task saturated one of the eight available CPU logic cores. During the experiments the i7 CPU temperature was logged and the resulting trend (Fig. 5) showed a stable average value of $71°C$, reached with a very short transient. This limit temperature is well below the CPU warning temperature of $82°C$.

VI. Conclusions

Working in underwater environment is a challenging task. Making every device ready for water implies that electronic components need to be sealed in appropriate canisters, generating heat dissipation and maintenance issues. Components must be chosen taking into account their performance as well as their power consumption and operating temperature specification.

AUVs, indeed, require a constantly updated representation of the environment and therefore a real-time processing of perceptual data. On the other hand, underwater intervention tasks are characterized by the same requirements in terms of perceptual accuracy as manipulation activities performed out of water. Designing a computer vision system for underwater perception is therefore a challenging problem, especially if the goal is to develop a reliable architecture able to cope with real environments and different working scenarios.

The vision system described in this paper has been evaluated in real world environments. In a real submarine scenario, at approximately $10\ m$ depth, a dataset of stereo images of submerged objects has been collected. The computer vision system has been also integrated into the autonomous underwater vehicles developed by the MARIS project.

VII. ACKNOWLEDGEMENTS

We thank the members of the MARIS consortium for the engaging experimental activities and discussions.

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