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A Man-Portable Hybrid Autonomous Underwater Vehicle for Antarctic Exploration

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Abstract - *The present work describes the development of a Hybrid Autonomous Underwater Vehicle (HAUV) called "Spondylus" that combines the best characteristics of Autonomous Underwater Vehicles (AUV) and Remotely Operated Vehicle (ROV), good hydrodynamics and stability in the water column to perform some tasks of a ROV like get close-range images of specific objects and collect biological samples from the sea floor. The HAUV design is focused on portability for remote field deployments. The HAUV has got Inertial Navigation System (INS), Computer Vision and Artificial Intelligence algorithms implemented on FPGA and ARM processor development boards. The routines are coded by VHDL modules, assembler and C/C++ scripts running on a Linux embedded System. HAUV Spondylus has been deployed in Antarctica at the Ecuadorian Scientific Station Pedro Vicente Maldonado, austral summer 2018-2019. Results from laboratory and sea trials are shown.*

Key Words: Autonomous Underwater Vehicle, Inertial Navigation System, Computer Vision, Convolutional Neural Networks, FPGA, System-on-Chip (SoC), Antarctica.

1. INTRODUCTION

Underwater exploration in Antarctica is a challenging task due the extreme weather conditions and required logistic support. Autonomous Underwater Vehicle (AUV) and Remotely Operated Vehicle (ROV) have been used for oceanographic, biological and geological applications at polar environments [1], [2], [3], [4], [5]. One of the most important fields of study in Antarctica is benthic ecosystems, including their response of near-shore benthos to increasing water temperatures due climate change. Usually scuba divers are employed to get underwater photography and samples of benthic communities on the sea bed [6]. Typically the divers are deployed from small vessels or zodiac boats (inflatable boat) [7]. Scuba divers have got some operational limitations in Antarctica, diving time less than 30 min and immersion depths up to 40 m in water temperature near to 0°C. Also there is the risk of suddenly changes of meteorological conditions that could implies dealing with winds of 60 knots at sea on a small vessel, compromising the safety of de crew and the divers [8]. Unmanned Underwater Vehicles (UUV), frequently ROV, are employed to sample benthos without scuba divers operational constrains. The vehicle is tethered, a live signal video is send from the installed cameras in the ROV and an operator drives the vehicle and decides with determined scientific criteria what areas require close field imagery and what specimens must be collected from the sea floor [9]. Explore deep-sea benthos in Antarctica with ROV requires a large logistic support: an oceanographic vessel with a five-ton winch for the umbilical cable whose operational cost could be around USD 50000 per day [10]. At the South Shetlands Island, Antarctica most of the scientific stations have got small vessels, zodiac boats and easy-access to deep-sea waters, below 1000 m, but is not possible to deploy large ROVs that can reach deeps more than 1000 m from a zodiac boat. A more affordable alternative are AUVs. They don't depend on a physical connection to the surface vessel and can carry out a mission below the sea surface without human intervention. Man-portable AUV has got a size less than 2 m and weighted around 30-50 Kg. This kind of underwater vehicle can easily be supported by zodiac boats [11], [12], [13]. However perform the same mission of a ROV, taking close images of a scientific site of interest and collect samples with a robotic arm fully autonomously is a complex and computationally costly task that rely on artificial intelligence, machine learning and other adaptive techniques [14],[15]. Hybrid Autonomous Underwater Vehicle (HAUV) combines the best characteristic of ROV and AUV, high stability in the water column and good hydrodynamics [16]. HAUV can hover in the water column very precisely to get close images and collect samples from the sea floor [17], [18].

Performing complex task in underwater environment requires precise localization, attitude estimation and path tracking for guidance and control. Global Navigation Satellite System (GNSS) signals don't propagate trough the sea water. The main navigational aid for AUV is the Inertial Navigation System (INS), commonly strapdown INS where the gyroscope and accelerometers are rigidly mounted on the vehicle frame [19]. The INS is complemented by other sensors like sonar, pressure sensor, cameras and Doppler velocity logs [20], [21]. All sources of information for the INS are fused by Kalman Filter (KF) techniques to estimate the velocity, position and orientation. KF usage implies high computational costs using arithmetic floating point, matrix calculations and real time operation [22]. Navigation very close to the sea floor requires a Computer Vision (CV) system to detect and identify obstacles [23]. The images could come from optical cameras and acoustic devices like side-scan sonar [24]. Usually SLAM algorithms are used for this kind of underwater applications [25]. CV and INS can work together to complement each other, updating navigation state vector and generating 3D images [26], [27]. Real time underwater object identification has a great research value for marine biology applications, example identifying hydrothermal vents or unseen specie. There are various methods to extract images features based on artificial intelligence and machine learning, example an improved version of YOLOv3 algorithm for underwater ambience [28]. Convolutional Neural Networks (CNN) are often used for obstacle avoidance and object recognition using frames of a single camera mounted on small robots [29]. AUVs have onboard computers to support algorithms like navigation, obstacle avoidance, recognition patterns and mission managing. In small AUV the size and power consumption of onboard computers is a vehicle key design factor balancing between run-time performance with energy constraints. Large GPU with power consumption that excess 200 W to support CNN are not suitable for this application. Field-Programmable Gate Array (FPGA) offers a more flexible development, choosing between parallel and sequence algorithm implementation and has got lower power consumption than large GPU [30]. Soft possessors implemented by hardware described language (HDL) like VHDL or verilog are available, example: NIOS II and MicroBlaze [31], [32]. There are free soft processors architecture available, RISC-V is an open source instruction (ISA) set architecture that can be implemented using VHDL [33]. Some FPGA includes a hard-core processors fabric on a single chip [34]. Combining Soft/Hard processor with dedicated VHDL modules allows a flexible and efficient System-on-Chip (SoC) design in terms of processing time and power consumption [35].

Ecuador has got a Scientific Antarctic Station at Greenwich Island, South Shetland Island. The station has two zodiac boats for marine research and logistic purposes [36]. The basic requirements are get close-range images of scientific sites of interest like a macroalgaes group and then take small benthic samples on the sea floor without human intervention avoiding the usage of a tether, giving operational flexibility to the zodiacs boats to carry out other task meanwhile the HAUV is exploring. This paper describes the development of a Hybrid Autonomous Underwater Vehicle Spondylus for benthic sampling in Antarctica. Section 1 describes the mechanical system, section 2 onboard electronics, section 3 software architecture that was divided in INS, Computer Vision, CNN and FPGA System on a Chip.

2. MECHANICAL SYSTEMS

The vehicle has got an open frame architecture that maximizes the distance between the center of mass and center of buoyancy in order to get good stability in the water column. HAUV Spondylus has four hulls, two pressurized and two wet. The vehicle length is 65 cm and mass of 17 kg. The pressurized hulls are made of acrylic that support up to 150 m and store the onboard electronics. The wet hulls are made of PVC pipes and contain syntactic foam shape-disc to provide buoyancy. One pressurized hull is a Blue Robotics Watertight Enclosure for ROV/AUV (3″ Series) located at the upper vehicle section and mounted perpendicularly respects the vehicle longitudinal axis. The other pressurized hull is a Blue Robotics Watertight Enclosure for ROV/AUV (4″ Series) mounted on the vehicle bottom section. Inside the 4’’ hull is located the main battery and electronics protected with silica gel in order to get a low center of mass. One of its end caps is an optical clear dome for the main camera. The wet hulls are positioned at the vehicle upper section at the starboard and port bands respectively, filled with syntactic foam. This configuration generates a large righting torque to obtain a good stability in the water column during the hovering maneuvers [37]. The hulls are linked with an open-frame structure made of aluminum, PVC tubes and 3D printed parts. The propulsion system is formed by four Blue Robotics T200 thrusters rigidly mounted on the open-frame structure. A pair of thrusters is oriented with vehicle longitudinal axis, the other with the vertical axis. This configuration allows four degree of freedom: yaw, pitch, surge and heave. An underwater gripper rated for 300 m could be mounted at the vehicle bow for biological sampling. Fig. 1 shows the vehicle mechanical layout.

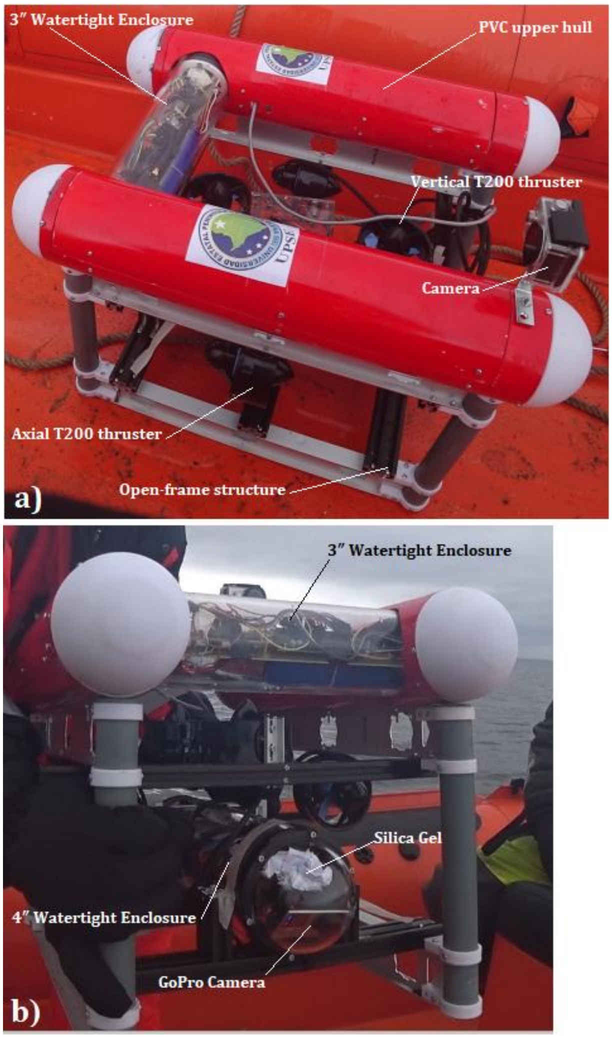

Fig -1: HAUV Spondylus mechanical layout, a) side view, b) front view.

Table -1: HAUV Spondylus dimensions and performance

Dimensions	65 cm x 40 cm x 45 cm
Cruise speed	2 knots
Max depth	150 m
Range	8 Nautical Miles
Total Mass	15 Kg
Operation temperature	-10 oC to 40 oC
Navigation	GPS/INS
Endurance	4 h
Dynamic Buoyancy	No
Obstacle Avoidance	Yes, passive system based on the CV

3. ONBOARD ELECTRONICS

The central elements of onboard electronics are the FPGA development boards. The first board is a TERASIC DE0 nano that support inertial guidance and computer vision routines. The second board is a TERASIC DE0 nano SoC where the CNN for image recognition was implemented. The DE0 nano SoC includes a FPGA with an ARM Cortex-A9 processor inside called HPS. FPGA and ARM implemented in the same chip offers great design flexibility, both are connected with a high-bandwidth backbone. The kinematics sensors are a MPU9250 Inertial Measurement Unit (IMU) that includes accelerometers, gyroscope ad magnetometer, Blue Robotics pressure sensor rated for 300 m, GPS receiver and ARDUCAM cameras. These sensors are linked to the DE0 nano board. The communication devices are RF 430/900 MHz transceivers, Wi-Fi module and a satellite module Iridium RockBLOCK 7. The PWM signals for the T200 thruster electronics speed controller (ESC) and underwater gripper are generated from DE0 nano according the commands of the inertial guidance system and mission manager. The Payload is a set of environmental sensors: temperature, pH, dissolved oxygen and conductivity from Atlas Scientific. The DE0 nano board with its peripherals is located in the 3″ Watertight Enclosure. The data from sensors and generated commands are stored in a 64 GB SD card. The DE0 nano SoC has as peripherals a USB hub, Wi-Fi dongle, external 1 TB USB hard drive and a GoPro Hero 4 camera. The GoPro images are sent to the DE0 nano SoC through the Wi-Fi. DE0 nano with its peripherals are inside the 4″ Watertight Enclosure. Both development boards are communicated with a Fathom ROV Tether that contains four twisted pairs cable for computer networks. The HAUV system are powered by a 16000 mAh 4S (14.8 V) Lithium-Polymer battery that allows autonomy up to 4 hours with a speed of 2 knots. A DC-DC converter is used to obtain regulated 5 V from the battery. The pressurized hulls have got leaks sensors near the end caps. Fig. 2 shows the electronics layout.

4. SOFTWARE ARCHITECTURE

The software architecture is divided in two major tasks: autonomous navigation and object recognition. The Autopilot for navigation tasks is implemented on the DE0 nano and the CNN for image recognition runs on the DE0 nano SoC. The Autopilot is divided in three layers. The lower layer supports communication protocols for sensors and communication devices, RAM management, SD card routines and PWM signal generation. The mid layer contains the Inertial Navigation System, automatic control and computer vision. The upper layer is the mission manager that uses Bayesian networks for decision making. A customized soft processor based on RISC-V and described by VHDL is used to support the autopilot mid and upper layers. The routines are coded by VHDL and assembler language. The software architecture is shown in Fig. 3.

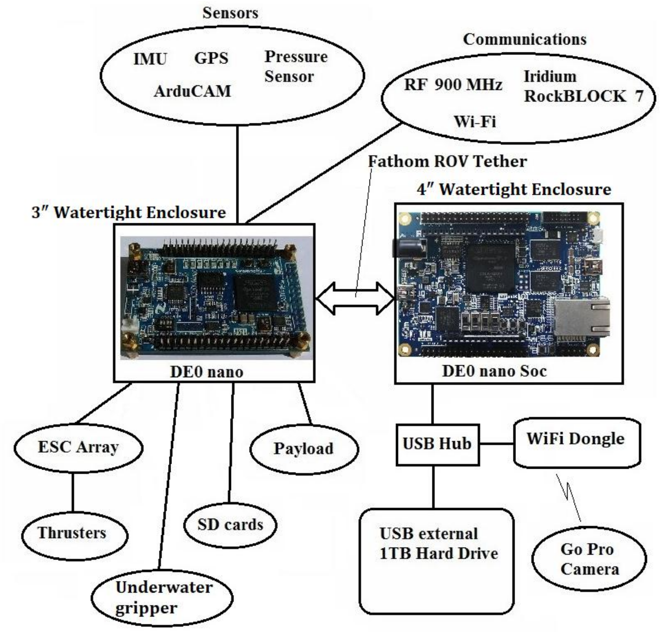

Fig -2: HAUV Spondylus electronics layout.

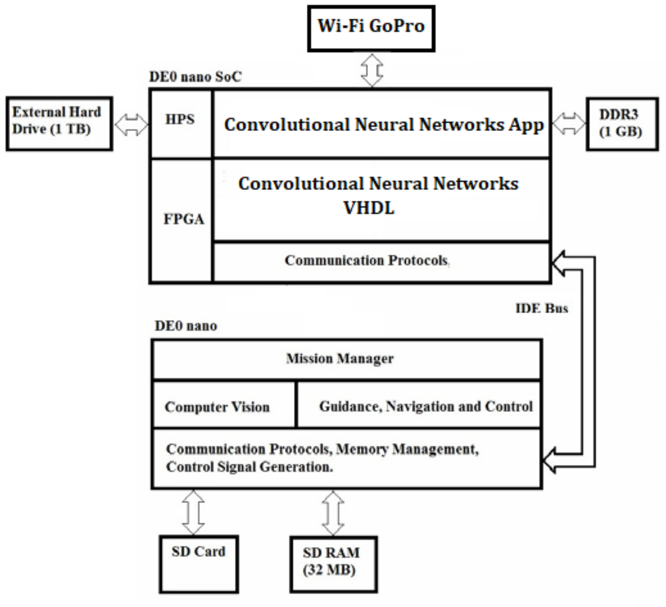

Fig -3: HAUV Spondylus software architecture.

There is a System on a Chip in the DE0 nano formed by the RISC-V soft processor and dedicated VHDL modules. The SoC is described in the following sections. The CNN are implemented by YOLO v2 running on a Linux embedded System and VHDL dedicated modules.

4.1 Inertial Navigation System

The main purpose of the HAUV Inertial Navigation system is estimate the velocity, position and attitude respect a frame of reference. The INS is divided in two algorithms: Earth Centered Earth Fixed (ECEF) frame Mechanization Algorithm and Extended Kalman Filter (EKF) [38]. Fig. 4 presents the HAUV Inertial Navigation System Algorithm.

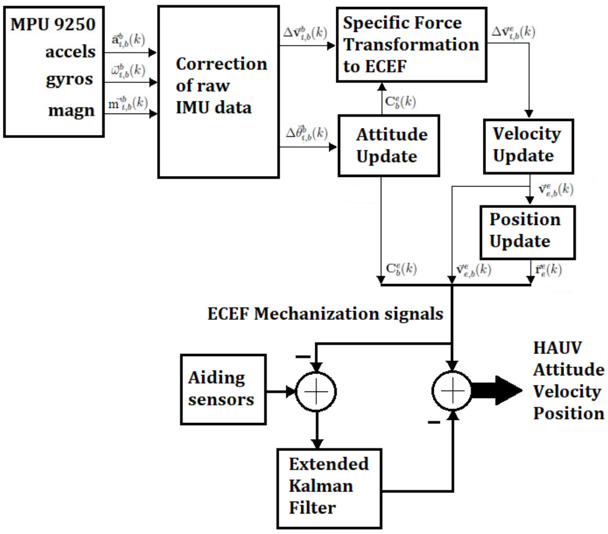

Fig -4: HAUV Inertial Navigation System Algorithm.

The IMU MPU 9250 generates kinematics signals according the actual HUAV trajectory. These signals are corrected by parameters (temperature compensation of scale factors, biases, misalignments) obtained from IMU calibration process and sensor error modeling using a test stand [39]. Then the vehicle attitude is updated, integrating the angular rate from gyros by Runge-Kutta method [40]. With the attitude updated the specified force vector is referred to the ECEF frame. Next a numerical integration step is applied to update the velocity and position. The ECEF mechanization signals are corrected by the Extended Kalman Filter. On the sea surface the aiding sensors are the GPS receiver and pressure sensor, in the water column only pressure sensor data is available. A sensor error model is used for accelerometer and gyroscope that includes bias errors, non-linearity and measurement noise. A total of 18 states are used in the Kalman Filter which could be increased as more errors are modeled. The navigation solution was simulated using GNU Octave, then with assembler language implemented on the RISC-V processor with 64 bits floating arithmetic point with a processing time less than 10 ms, achieving real time operation.

4.2 Computer Vision

The function of the HAUV computer vision implemented on the DE0 nano is for obstacle avoidance purposes. The images come from two 5MP Arducams OV5642 connected to the 40 pins IDE port. The SURF (Speeded up Robust Features Up) algorithm is employed to detect navigation obstacles along the pre-programmed trajectory [41]. Arducam SPI communication protocol was implemented by a VHDL module, another VHDL module manages the 32 MB SDRAM where the incoming frames are stored. The implementation of SURF algorithm on the FPGA has three steps: Fast-Hessian detector to found Interest points in the frames, Haar wavelet responses for x and y directions are calculated around the interest point, then the descriptor of the interest point surrounding area is calculated by Haar wavelet functions. The "Integral Image" allows filter response fast calculations. The arithmetic operations for SURF calculations are floating point running on the FPGA SoC. Due the intensive calculations the update rate is up to 29 fps. The SURF algorithm is implemented by assembler language scripts running on the RISC-V processor.

4.3 Convolutional Neural Network

The CNN are implemented on the DE0 nano SoC by VHDL modules and an optimized version of the framework YOLO [42], [43] running on the Hard Processor and Linux Embedded System. C/C++ scripts implements the stack for Wi-Fi communication between the development board and the GoPro Camera, the incoming frames are stored in the 1GB DDR3 SDRAM and external Hard Drive. The SURF algorithm and YOLO v2 works independently. The main role of CNN is detection and identification of benthic samples on the sea floor. Some problems arise with the use of YOLO v2 to detect underwater targets. The network structure is complex for an embedded system so the processing speed is low. In turbid sea water environment some features could be miss complicating the detection of desired targets. The underwater biological specimens are usually distributed with occlusions causing misdetections. Previously an improved version of YOLO v2 algorithm to address these problems is developed, then some optimizations are made by VHDL modules to make suitable for a HPS/FPGA embedded system. A VHDL manages the On-Chip RAM for the quantized weights of the CNN in order to reduce the accessing time. One of the mayor challenges is accessing a large underwater images datasets of Antarctic sea bed. In order to increase the dataset for reliable testing, underwater images of Ecuadorian marine reserves are obtained by the HAUV during the sea trials.

4.4 FPGA System on a Chip

Inertial Navigation System and Computer Vision algorithms running on the DE0 nano are compute-intensive. They are running for real time vehicle operation. ALTERA mega-functions were used for IEEE 754 64 bits arithmetic floating point operations. A pipeline of four 64 bits adder-multiplier accumulator or MAC VHDL modules are used for matrix multiplication operations allowing complex calculations under real time conditions. The incoming data from the sensors is transformed from fixed-point to floating-point by VHDL modules. Every VHDL module is connected to a central bus trough tri-state buffers. The systems runs at 100 MHz. CORDIC algorithm for trigonometric and other transcendental functions calculations is employed [44]. The routines for matrix operations like multiplication, addition, transpose, inverse and Jacobian are implemented by state machines, every operation has an 8 bits operation code. A customized RISC-V processor, described by VHDL manages the hardware resources for mathematical operations. The M9K On-Chip memory is divided in two sectors, program memory and operation variables following Von Neumann architecture due space constrains in the FPGA. A compiler for the customized RISC-V processor was developed by C/C++ scripts, converting the assembly mnemonics to operations machine code. Updated versions of the assembler code can be sent over-the-air during the sea trials for testing and debugging purposes. Fig. 5 shows the FPGA SoC.

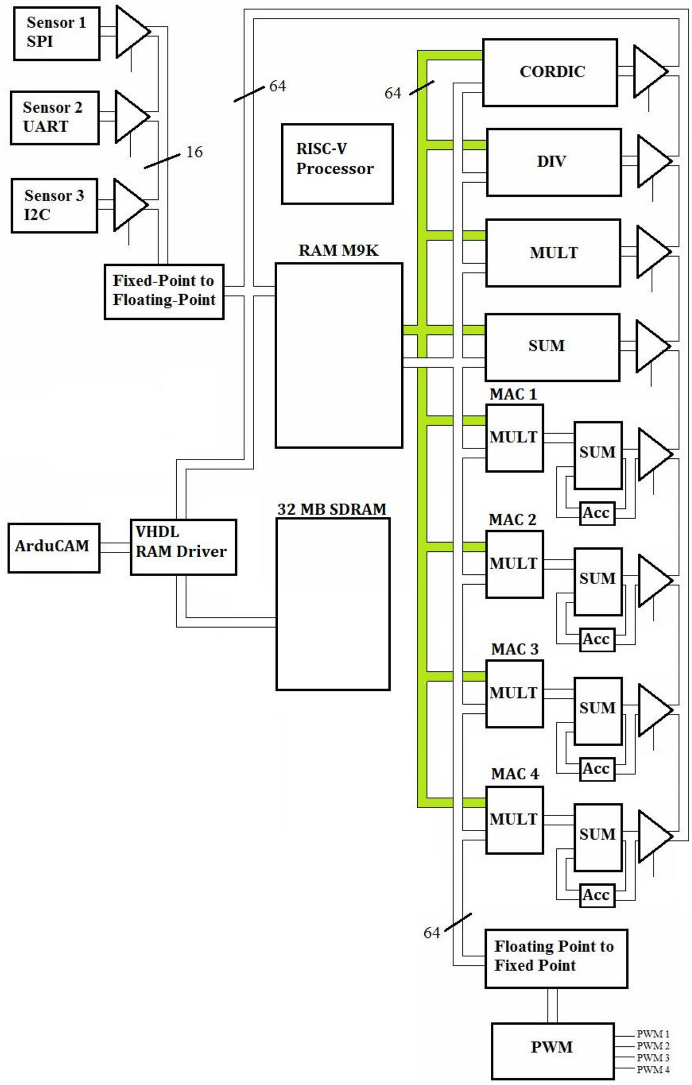

Fig -5: HAUV FPGA SoC.

5. RESULTS

The FPGA SoC required 90% of the logic elements, 100% of on-chip memory and 100 % embedded multipliers resources. After inspections of pressure vessels and onboard electronics sea trials in Ecuadorian waters were carried out. The INS accumulated error at sea was 6% of the travelled distance after 1 hour. The HAUV successfully avoided navigation obstacles on the sea floor. During the sea trials underwater images of the sea floor were collected for the dataset to train the CNN model. Data Augmentation was used to obtain more test images. The YOLO v2 algorithm was tested first on a Nvidia Geforce GTX 1080 GPU and Intel Core i7-4.00 GHz to evaluate the detection performance achieving over 95% of detection with a clear line of sight. With the optimized framework of YOLO v2 by VHDL modules the obtained processing speed was 8.1 fps on the FPGA DE0 SoC board. After the sea trials and some software updates, the HAUV was delivered to Antarctica by airplane. Mission profiles for Antarctic environment near Maldonado Station are stored in the SD Card, information like currents, recuperation coordinates, landing sites, etc. The HAUV was deployed from zodiac boats, every 10 min the robot went to the surface for GPS position refresh, report its situation and listening for new orders. The HAUV successfully followed the trajectories, taking images, avoiding obstacles and taking biological samples using its CNN for benthic image recognition in Antarctic environment. Fig. 6 shows HAUV operations in Antarctica.

Fig -6: HAUV in Antarctica, a) deployment from zodiac boat, b) benthic samples recognition from Antarctic sea floor.

6. CONCLUSIONS

In this paper, the development of a man-portable Autonomous Underwater Vehicle for Antarctic exploration was exposed. The mechanical system, onboard electronics and software architecture are described. An optimized version of YOLO v3 for marine application running on a FPGA is used for real time underwater object recognition. The HAUV can navigate fully autonomously in the water column and near the sea floor avoiding navigation obstacles, identifying and collecting benthic samples in Ecuadorian waters and Antarctic environment. Future applications are plastic garbage removing like bottles, fishing lines and increment its operational depth to 400 m.

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