

# Cognitive knowledge representation under uncertainty for autonomous underwater vehicles

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**Abstract**—This paper presents an early approach for marine cognitive robots, in order to incorporate uncertainty into an ontological representation of the world. The proposed system is based on a signal processing module and an ontology-based knowledge framework, which is queried and updated according to the processed sensor data. It has been successfully demonstrated post-processing data from a mission of *Nessie*<sup>AUV</sup> at The Underwater Centre, in Fort William, west of Scotland. The system shows its ability to process sensor data, identify basic features (lines and circles) and populate the ontology model. Additionally, from the ontology side, the basic information are elaborated in order to arrive to more complex concepts, like pillars and crossbeams.

## I. INTRODUCTION

Recent advances in robotics have resulted in machines capable of performing many tasks autonomously, such as preparing food [1], searching for objects and knowing what rooms they are likely to be found in [2], and searching for underwater mines [3]. However, a significant obstacle to intelligent robots being used in real-world scenarios is their limited ability to cope with unexpected events and environments. The aim of this paper is to present a semantic knowledge-representation system that will make it easier for robots to handle such situations, and therefore achieve more persistent autonomy.

The target domain is the inspection of subsea structures such as oil platforms using autonomous underwater vehicles (AUVs). In this domain, the original plans for structures can generally be made available to the AUV in advance of a mission, but frequently they have changed or moved when the AUV actually reaches them. If the robot has a pre-programmed survey path, then unexpected obstacles can cause it to abort the mission. To avoid this, a probabilistic semantic representation is used, which enables the robot to model and reason with the uncertainty in the world.

In parallel with a work focused on planning and dynamic re-planning [4], this paper focuses on extract information from noisy sensors, convert this into objects which are stored in an ontology, and then repeat the process when new observations of the same object are received. Sonar is a commonly used sensor for underwater structure inspection, as it provides 3D data on objects. However, compared to laser scans which can be used by land and air robots, sonar is very noisy and hard to interpret. This makes an abstract representation of objects in the world, isolated from direct sensor data, even more useful.

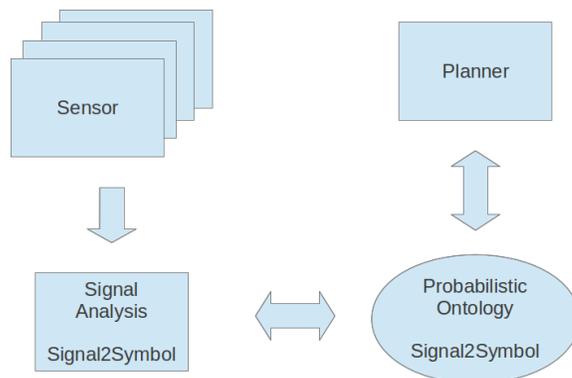


Fig. 1. Computational architecture for persistent autonomy

An ontology format for semantic data is used for several reasons:

- it is easy to create and examine the concepts used by the system, and the attributes available for each concept, without having to have programming knowledge.
- many tools exist to perform logical reasoning within the knowledge base.
- an ontology represents a well-specified central data store that all the software components comprising the agent can make use of.
- common ontologies (such as the IEEE robotics ontology currently under development [5]) are very useful for exchanging data between robotic systems created by different organisations.

Most work on ontologies has not used any representation of uncertainty, but several authors have added the ability to store probabilities to the standard ontology language OWL [6] [7]. In robotics, the KnowRob system [8] uses a sophisticated base ontology, an extensible reasoning system, and interfaces closely with the ProgCog probabilistic reasoner [9]. Ontologies have been applied in the AUV domain by [10], but to the best of the authors' knowledge, no marine robotic systems incorporate a probabilistic semantic representation.

The rest of this paper is organised as follows: in Section II, an overview of the system architecture is given, then in Section III the operational setup for AUV testing is described. Section IV details how sensor data is identified and uncertainty values are assigned to the outputs, and finally Section V covers the core semantic reasoning system.

## II. ARCHITECTURE

The general proposed architecture of the system is highlighted in Figure 1. Sensor data are collected and analysed.

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Fig. 2. The Underwater Centre, in Fort William. The pier leg are mainly concrete round pillars, of which some are connected through crossbeams. Other underwater structures are also present, requiring a throughout exploration in order to correctly classify the different objects.

The first block *Signal2Symbol* is able to extract basic features and information from the raw sensor data. An interaction with the ontological representation of the reality is needed, in order to decide whether to add a new instance, to update an already existing instance, or to remove an instance. Inside the Ontological framework a second block *Signal2Symbol* runs. This is to infer more complex symbols, based on the current knowledge. This kind of inference is not possible processing directly the sensor data, but it is more related to the overall domain and the overall knowledge over the domain. The planning system therefore can query the ontological representation and use the acquired information for planning.

### III. OPERATIONAL ENVIRONMENT

The domain of interest is an underwater environment with subsea structures. Features of interest are underwater pillars and crossbeams, which can connect the pillars. The ideal scenario is at The Underwater Centre, located in Fort William, on the west of Scotland, in Fig. 2. The structure that supports the Centre is mainly made by pillars and crossbeams, and it is similar to offshore underwater structures, thus making it a favourable test facility. The autonomous underwater vehicle *Nessie VII* was used both in teleoperation mode, or requesting a list of waypoints to be followed. Data from the vehicle were recorded for after-mission analysis. For the purpose of this paper, important data are the vehicle state, given by the navigation system, and the sonar images, acquired through a BlueView MB2250 multibeam. The vehicle location is calculated integrating sensor data from a Doppler Velocity Log, which provides very accurate relative motion. The following sections will explain the process which goes from the raw sensor data into semantic high-level concepts, taking into account uncertainty and partial views. Although the results shown are given by post-processing the gathered data, the algorithms were designed and implemented in the ROS based vehicle's architecture, thus enabling future integration.

### IV. SENSOR PROCESSING

As shown in Fig. 1, the first block dealing with the process of extracting symbols from the signal given by the sensors is naturally the sensor processing unit. Sensor processing techniques vary according to the type of features the robot

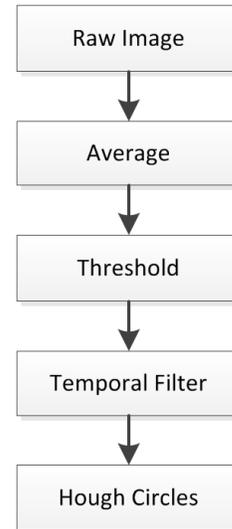


Fig. 3. The various steps in signal processing

is interested in. In the case of underwater robots, the noisy acoustic data with poor resolution makes the process much more challenging than using high resolution video cameras. Specific algorithms for Autonomous Target Recognition (ATR) can be employed, as shown in [3]. In the case presented in this paper, the key elements in the environment are represented by pillars and crossbeams. The focus in the sensor processing is therefore towards the detection of geometric features that characterise those elements: circles and lines. The following steps were applied to the raw sonar images:

- **Average:** this is done over a window of images, in order to remove some of the noise;
- **Threshold:** this is done in order to focus only on the high intensity returns of the sonar image, filtering out the portions of the image with little interest;
- **Temporal Filter:** this is used to detect static objects. All images are put in the same reference frame. Each sonar image has the vehicle's state associated with it, so it is transformed into global coordinates. The next processing block is called only when a static object is consistently detected.
- **Hough Transform:** this is done to detect basic features: lines and circles, which are indicators of crossbeams and pillars. The function returns the list of circles, with centres and radius, or a list of segments, expressed by two points.

Fig. 3 shows the process for circle detection. Fig. 4 shows the transformation of an image following all the steps, with the resulting identified circle. The OpenCV library [11] was used for all image processing functions.

Due to the noisy nature of the sonar data and the limited field of view, false positives are not unusual, as shown in Fig. 5. A mechanism to quantify the uncertainty in the detected feature is therefore employed. The example of pillar features is the most interesting, as the vehicle can only see a portion of it from any position. Additionally, a view from one position only may



Fig. 4. The various steps in signal processing. From left to right: raw image, average, threshold, hough circle.

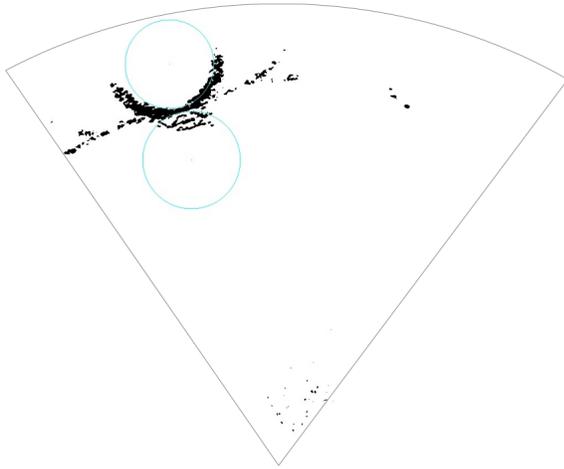


Fig. 5. Hough circles: the presence of false positive in noisy and low-resolution sonar data is almost unavoidable.

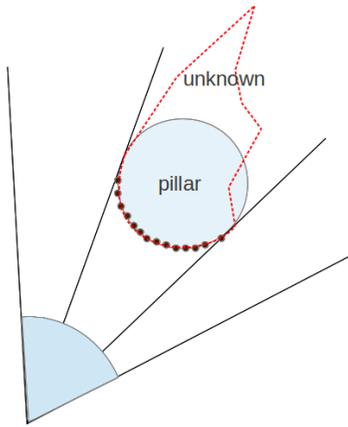


Fig. 6. A sonar observation. Field of view in light blue (gray). Points detected highlighted. A single sonar image is not enough in order to discriminate among a pillar and another structure with a round end. The system needs to take into account the uncertainty derived by the partial observation.

not be enough to discriminate between a pillar and another structure, as shown in Fig. 6.

Two factors are considered when evaluating the uncertainty in a sensor reading:

- 1) how well the perceived image represents the feature, so an estimate of the confidence in the results given by the Hough functions;

- 2) in case of pillars, which part of the circumference of the circle is seen by the sonar.

The first case represents how likely is the perception of that image, given that a pillar is present in the environment and is located at the coordinates given by the Hough transform function. Given a circle detected by the system, the visible portion of the associated pillar is defined as the sector of the pillar visible from the sonar, i.e. in a sonar image, the arc of the circle limited by the two tangents from the sonar location. Mathematically, the system of equations to find the visible portion can be expressed as:

$$\begin{cases} (x-x_c)^2 + (y-y_c)^2 = r^2 \\ y-y_0 = m(x-x_0) \\ \Delta = 0 \end{cases} \quad (1)$$

The first equation represents the circle with radius  $r$  and centre in  $(x_c; y_c)$ . The second equation represents the lines with angular coefficient  $m$  passing by the point  $(x_0; y_0)$ , which is the observation point, i.e. the sonar location. The third equation represents the condition of having one and only one solution for the intersection between a line and a circle. Defining the observation point as  $(0;0)$ , and constraining the discriminant  $\Delta$  of the resultant quadratic equation to zero, the two angular coefficients of the two tangent lines are therefore represented by the following equation:

$$m = \frac{-x_c y_c \pm \sqrt{r^2 x_c^2 + r^2 y_c^2 - r^4}}{r^2 - x_c^2} \quad (2)$$

It is to be noted that fixing the observation point at the origin simplifies the resulting equation from a 4<sup>th</sup> order to a *quadratic* equation, with a simple translation of references.

For the sonar image to be a good match to the detected circle, the sections of the sonar image which correspond to the visible portion of the pillar should show high intensity. Consider the two tangent lines that define a field of view where there is an expected pillar at a certain distance. Moving from the Cartesian  $XY$  space into the polar  $\rho\phi$  space, the two tangent lines becomes two vertical lines, and it is therefore easier to work within the concerned area, as shown in Fig. 7 and Fig. 8.

Knowing the distance of the circle from the the origin, it is possible to calculate the coordinates of the expected points with high intensity in polar coordinates.

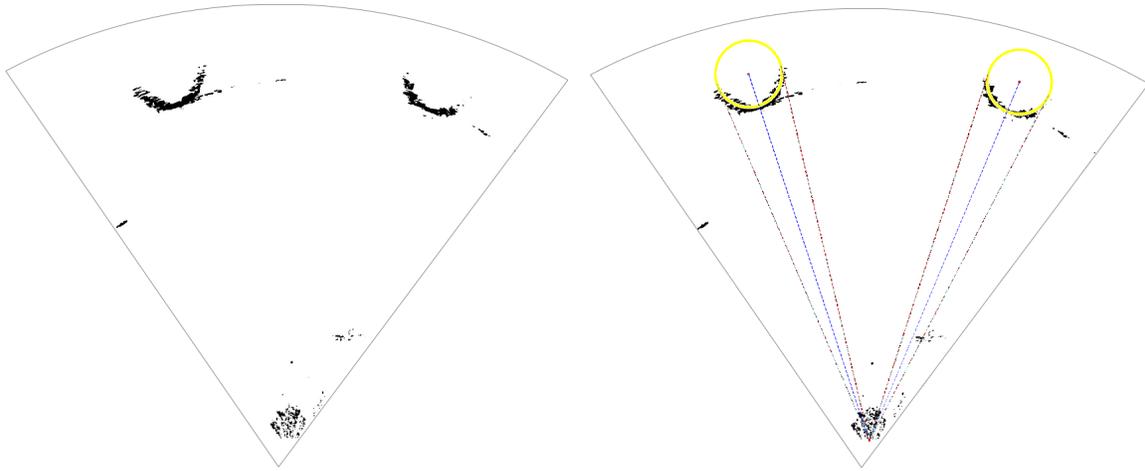


Fig. 7. (left) Original sonar image in Cartesian coordinates, after the transformations described in Fig. 3; (right) Circle detection, with calculation of the visible portion; (right) the visible portion identified by the tangents in the Cartesian space is converted into lines in the polar space, making the analysis computationally efficient.

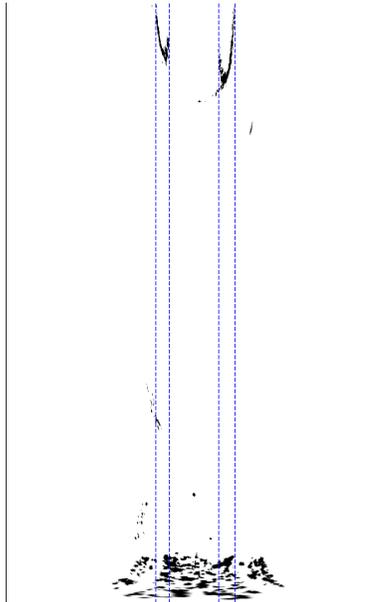


Fig. 8. The visible portion identified by the tangents in the Cartesian space is converted into lines in the polar space, making the analysis computationally efficient.

The uncertainty associated to the detection is given therefore by the following formula:

$$p(\text{pillar}) = \max \left\{ \varepsilon, \frac{n \text{ column with high intensity}}{n \text{ total columns}} \right\} \quad (3)$$

where  $\varepsilon$  is a small number to prevent the result being 0, which can cause numerical problems.

The second component of the uncertainty is given by the observed sector. In the case of pillars, this module therefore returns all the circles detected, with an associated uncertainty, and the related visible portion, given by the position of observation, with the relative field of view.

The field of view could also be incorporated in the uncertainty measure expressed in Eq. 3, for example with a coefficient  $\alpha$  representing the visible portion. For a single image, combining the two measures would certainly result in a better estimate of the confidence of the perceived portion of the environment being a pillar. However, considering the vehicle's motion, it is important to keep them separate, in order to use domain specific knowledge to improve the total knowledge. This will be explained in more detail in section V.

## V. ONTOLOGY

This section is focused on the ontological representation, the access to it, and the benefits in designing a cognitive system based in an ontological way. The module described in section IV returns basic features: lines and circles, with an associated confidence level. This paper focuses mainly on the case of circles / pillar. As discussed previously, and shown in Fig. 6, only a portion of the pillar is visible with the sonar. The sonar provides a regular stream of images; if the visible portion data was combined with the confidence value for each image, the system would not be able to discriminate between observations which increase the portion of observed object, and those taken close to the previous location.

Fig. 9 shows an example of this. The transition from  $A$  to  $B''$  should bring more confidence about the pillar being present rather than the transition from  $A$  to  $B'$ , as the unknown/unexplored area is significantly reduced. However traditional techniques cannot cope in general with domain specific information, which can be formalised inside an ontology.

An alternative way of addressing this immediate issue of combining multiple sensor readings would be to use a Bayesian filter such as a particle filter. Unlike traditional particle filters in robotics, in this case the random variable would represent the class of object that had been detected by the sonar. However, this would require the definition of the number and type of objects that could be observed, whereas much less severe restrictions are required for the ontological case. Further, particle filters will only handle this specific application of

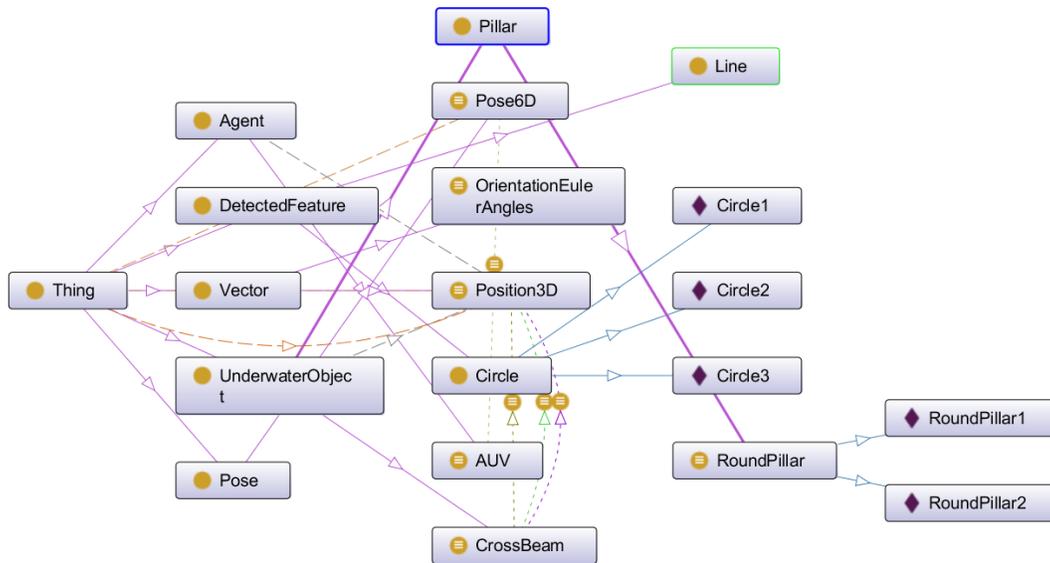


Fig. 10. The OWL file built representing the knowledge. Blue diamond are the instances of classes (yellow circles). As it is possible to see, there are three instances of *Circle*, but only two instances of *RoundPillar*. This is normal, because not all the detected circles are then associated with the concept *RoundPillar*.

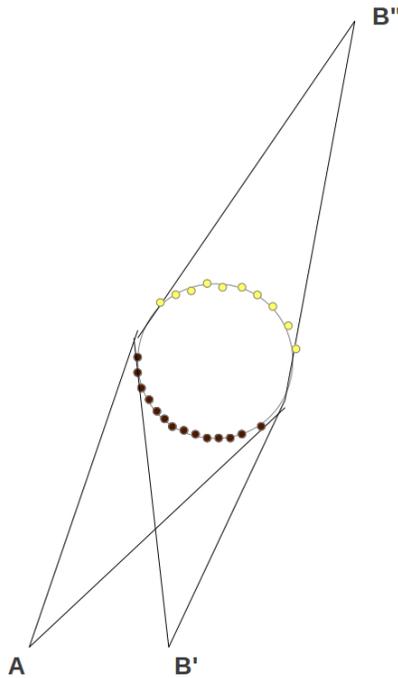


Fig. 9. The transition from  $A$  to  $B''$  should bring more confidence about the pillar being present rather than the transition from  $A$  to  $B'$ , as the unknown/unexplored area is significantly reduced.

domain knowledge, whereas the use of an ontology provides a basis for dealing with a wide variety of situations.

Fig. 10 represents a graphical view of the ontological representation, using the software *Protégé*. The ontology is then accessed and manipulated through the JENA library. A domain based rule is inserted in the *TBox*, such as a circle represents a pillar only if at least 65% of its circumference has been perceived by the sonar. This helps to discriminate among pillars and, for example, walls with a round end or

other unknown objects with a round face. Additionally, domain specific knowledge can specify the minimum distance among two pillars.

#### A. Access and Update

When a new feature is detected a module takes care of its insertion into the ontology. Considering the case of a circle, three cases can arise:

- 1) there is already a circle in the ontology with parameters close to the current ones;
- 2) there is already circle in the ontology with parameters violating the domain specific knowledge, for example the minimum distance between pillars;
- 3) there is no circle in the ontology with parameters either close to the current ones or violating domain specific rules.

In case 3, the operation is of a simple insertion into the knowledge base. Case 2 is the most problematic, as it represents an inconsistency, which cannot be resolved at semantic level. Case 1 is, on the other hand, the most interesting, because it might require an update in the confidence level, as well as in perceived areas.

Two basic situations are defined:

- 1) The two observed portions perfectly overlap: in this case the resultant confidence level is an average of the two.
- 2) There is no overlap among the two observed portions: in this case the resultant confidence level is a weighted average, with the field of view represented by the weight.

All other situations, like partial overlap or one subset of the other can be formalised according to the two base cases. Fig. 11 shows a partial overlap of two observed portion of a pillar.  $AC$  represents the field of view from the instance in the

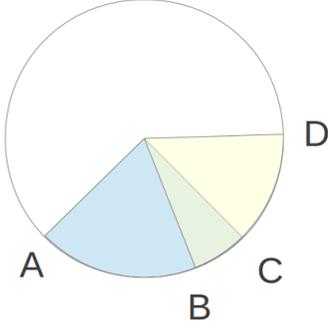


Fig. 11. Partial overlap of observed portions among two detected circles in the same position, with different uncertainty.

knowledge base, which has confidence  $p$ , while  $\hat{B}\hat{D}$  represents the field of view of the current instance, which has confidence  $p'$ . Defining the angle  $\theta$  as the total field of view given by the sum of the field of views, as in the following equation:

$$\theta = \hat{A}\hat{C} + \hat{B}\hat{D} - (\hat{A}\hat{C} \cap \hat{B}\hat{D}) \quad (4)$$

it is possible to merge the two formulations together in order to arrive to a general one, as expressed by the following equation:

$$p(\text{pillar}) = p \frac{\hat{A}\hat{B}}{\theta} + p' \frac{\hat{C}\hat{D}}{\theta} + \frac{p\hat{B}\hat{C} + p'\hat{B}\hat{C}}{2\theta} \quad (5)$$

It is also possible to define a weight according to the trust on the knowledge base vs the trust on the sensor data. In this case, a coefficient  $\alpha \in [0, 1]$  is defined and the formulation described above would have the following changes:

$$\begin{aligned} p &\leftarrow \alpha p \\ p' &\leftarrow (1 - \alpha)p' \end{aligned} \quad (6)$$

### B. Reasoning

The possibilities given by an ontology are not limited to domain based rules, as shown in the previous section, but they are also related to the possibility to *reason* on the data, and to arrive to new concepts previously not present in the knowledge base. In our domain from the sensor data up to the detection of a pillar, the only manipulated data in the ontology are instances of *Circle* and *RoundPillar*. However, using a reasoner on the ontology, each instance of *RoundPillar* becomes also instance of *Pillar* and *Underwater Object*, as shown in the ontology model in Fig. 10. Using a DL formalisation typical for ontologies, this relation can be expressed as:

$$\begin{aligned} \text{RoundPillar} &\sqsubseteq \text{Pillar} \\ \text{Pillar} &\sqsubseteq \text{UnderwaterObject} \end{aligned} \quad (7)$$

This is essential for obstacle avoidance and for planning. The planning system can actually query the ontology, receiving for example all underwater objects, regardless of the type.

Reasoning however does not mean only a reclassification of an existing instance. The creation of an instance of a complex class is a typical example of augmenting the knowledge. A specific set of components can identify a specific structure. This is certainly the case of complex subsea structures, composed of several valves, panel, crossbeams, pillars, etc. The vehicle can therefore identify the atomic components and then

the high-level reasoning at the ontological level is able to infer the presence of a complex structure, previously unknown in the knowledge base.

## VI. CONCLUSIONS AND FUTURE WORK

This paper has presented an early approach for marine cognitive robots, in order to incorporate uncertainty into a probabilistic ontological representation of the world. The proposed system is based on a signal processing module and an ontology-based knowledge framework. The case of round pillars has been analysed in detail, with a proposed solution in order to estimate the confidence of the detections. Partial view of the target objects are considered, with domain specific knowledge rules. The system has been tested successfully post-processing data from an underwater mission of the *Nessie*<sup>AUV</sup> at The Underwater Centre, in Fort William. Circles and line features were detected, as well as pillars and crossbeams, considering uncertainty in the sensor measures and reasoning at the ontological level. The code was integrated into the general vehicle architecture, so it is possible to easily integrate it in the vehicle itself. Future work includes the link among the knowledge base and the planning system, with in-water trials scheduled in the next months.

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