Machine learning algorithm for Autonomous Underwater Vehicles operations

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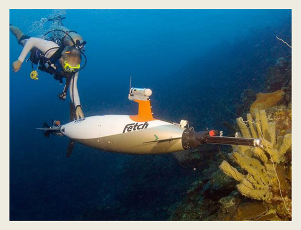
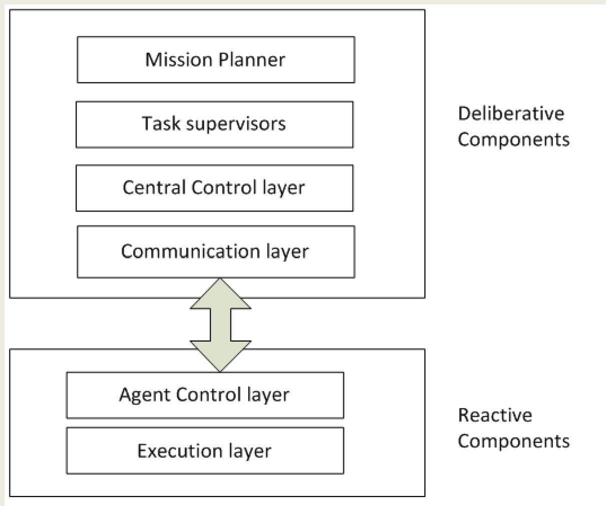
Introduction

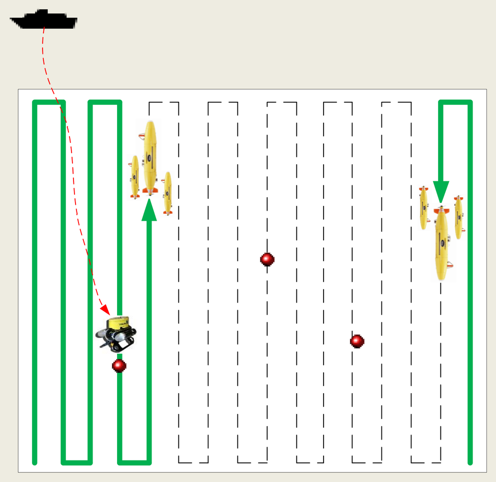


Autonomous Underwater Vehicles (AUVs) play an important role in military missions, especially in underwater Mine Countermeasure Missions (MCMs). The purpose of MCMs is to detect Mine-Like Objects (MLOs) in specified areas of interest in order to reduce the risk for potential traffic passing through the region. In our research, machine learning algorithms are applied in the automatic MLO detection and classification which will free operators from these time-consuming and difficult decision-making tasks, providing guidance for military actions to follow.

Autonomy Control Architectures for AUVs



Autonomy Control Architectures for Multiple AUVs



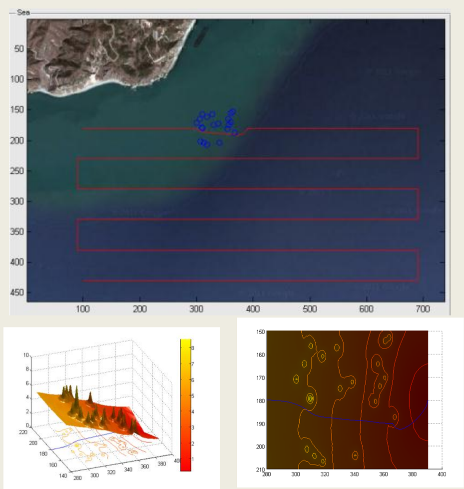
Coordination of Multiple AUVs

This hybrid architecture is close to the Autonomous Robot Architecture (AuRA) [4]. The deliberative components are built by four layers: mission planner, task supervisors, central control layer and communication layer. The mission planner is the agent who makes mission plans for AUVs. AUVs will execute the plan after the mission planner assigns the tasks of plans to them. Task supervisors are agents who supervise the execution of tasks. Central control layer is the center to control the coordination of AUVs. The communication layer is in charge of the communication between the AUVs and the control centre.

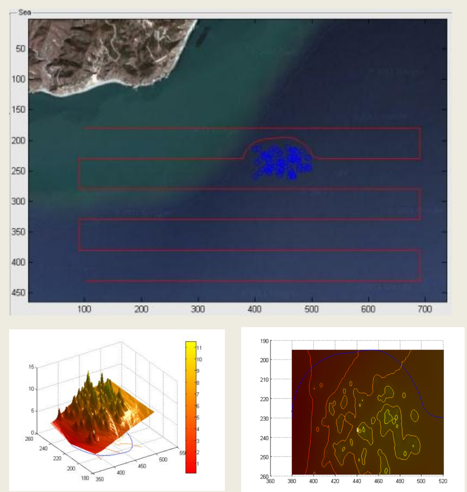
Obstacle Avoidance Behaviour of AUVs

For both transit variety AUV and intervention AUV, the ability of obstacle avoidance is important for the successful completion of their missions. Artificial Potential Field (APF) is a widely used approach in robot path planning and obstacle avoidance. The environment, (the obstacle region in MCMs) is modeled to a potential field. The AUV's motion in the region is driven by the resultant force of the APF developed from the environment.

Simulations and Results



Simulation Case 1



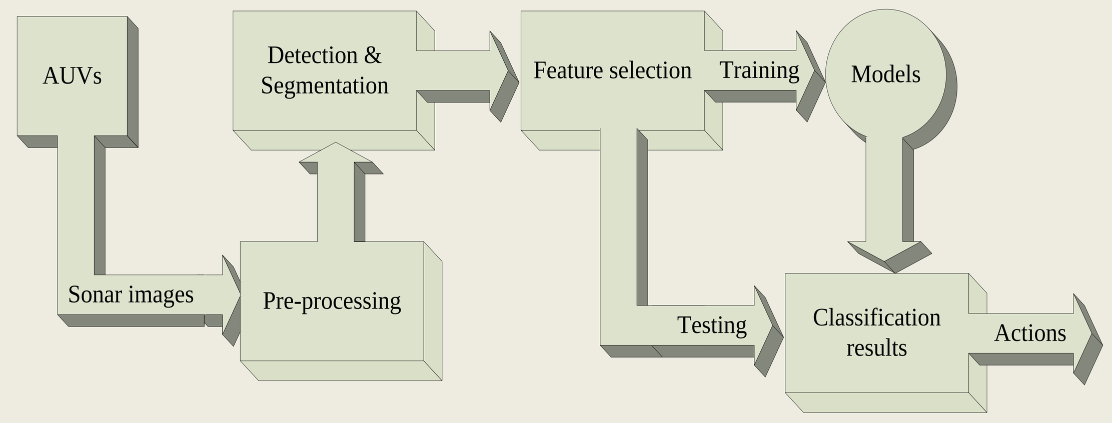
Simulation Case 2

In the simulations, an obstacle sub-region is defined. If the transit variety AUV strictly follows its pre-planed path, it will collide with the obstacles in its way, so that it will fail to complete its mission safely. The transit variety AUV is expected to adjust its path when entering this sub-region without colliding to the nearby obstacles and navigate to its pre-planed path after getting through the sub-region.

In simulation case 1, a sub-region with low density of obstacles is defined. Therefore, much between-obstacle space is left for the AUV. The result shows that AUV is able to make use of the available space to find the way out. In simulation case 2, a sub-region with high density of obstacles is created. AUV chose to detour around the high density obstacle region rather than probing into between-obstacles space which may not form a possible passageway.

The simulation results show the validity of APF approach for obstacle avoidance behaviour for the AUV. On the surface of APF of obstacle sub-region (case 1 and case 2), the obstacle will create a mountain peak at the place where it is located, in addition, the exit, at target position, will create a valley. The small contour circles indicate where the obstacles are located. The results show the ability of the AUV to adjust its path and moving direction when getting through the obstacle sub-region. It is able to follow its pre-set after leaving this region.

Computer-aided Detection and Classification



Underwater mine like object detection and classification

In our autonomy control architecture for Multiple MCM AUVs, MLOs classification and agent control are two most important behaviours. In these two behaviours, computer-aided detection and classification are very necessary. Sonar images obtained from AUVs usually needs to undergo pre-processing, which includes several steps such as de-noising, segmentation, texture analysis and object location. Furthermore, feature selection techniques are used to extract features from the pre-processed sonar image. In underwater MLOs classification, the features extracted from the pre-processed sonar image should provide us with effective information about the MLOs.

Sonar Image De-noising

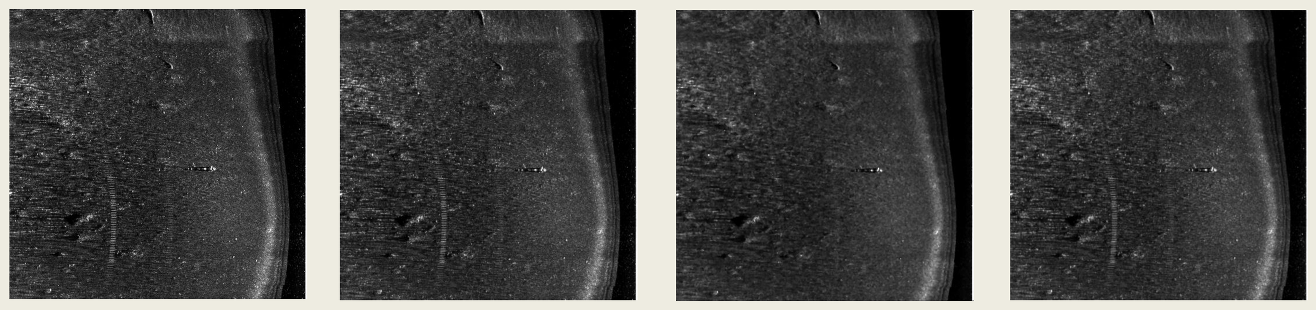
Before performing image segmentation, it is necessary to apply filters to remove noise from the original sonar image. In most cases, the operation of image filtering is to calculate the convolution between the image $\mathbf{I}(x, y)$ and the filter $\mathbf{h}(x, y)$.

Usually the sum of every number in the filter $\mathbf{h}(x, y)$ should be equal to 1, otherwise the brightness of the resulting image will change. (We are only talking about greyscale images here, as most sonar images in MCMs belong to this category.). The filtering operation can be written as

$$\mathbf{I}_{out}(x,y) = \mathbf{I}_{in}(x,y) * \mathbf{h}(x,y) = \sum_{i=-m}^{m}\sum_{j=-n}^{n} \mathbf{I}_{in}(x-i, y-j)\mathbf{h}(i,j)$$

$$\sum_{i=-m}^{m}\sum_{j=-n}^{n} \mathbf{h}(i,j) = 1$$

In our current experiment, the circular average filter is used.



Sonar Image Segmentation

After the image de-noising process, the next step is to identify and segment areas containing valuable target objects from the de-noised imagery. Usually edge detection techniques are applied in this step.

If an object lies on the background, there should be salutation in the grayscale value on its edge. The principle of edge detection is to find the discrete point of the grayscale value.

The Canny method is used to find the edges. Canny method will first smooth the image with a Gaussian filter. Then it will calculate the gradient of $\mathbf{I}(x, y)$ An edge pixel is defined to be a local maximum in the gradient direction and these edge pixels will result in a ridge which will be shrank to a one pixel wide by Canny method. Then two thresholds T1 and T2 (T1<T2) will be applied to deal with the ridge. The stronger threshold T2 will find a contour that contains more true edges, fewer false edges, but this contour is every likely to be discontinuous because of high thresholding. When the contour reaches its end, Canny method will switch to the weaker threshold T1 to grow the contour with faint edges.

The left images are the de-noised sonar images, while with lines on the right indicate the detected edges.

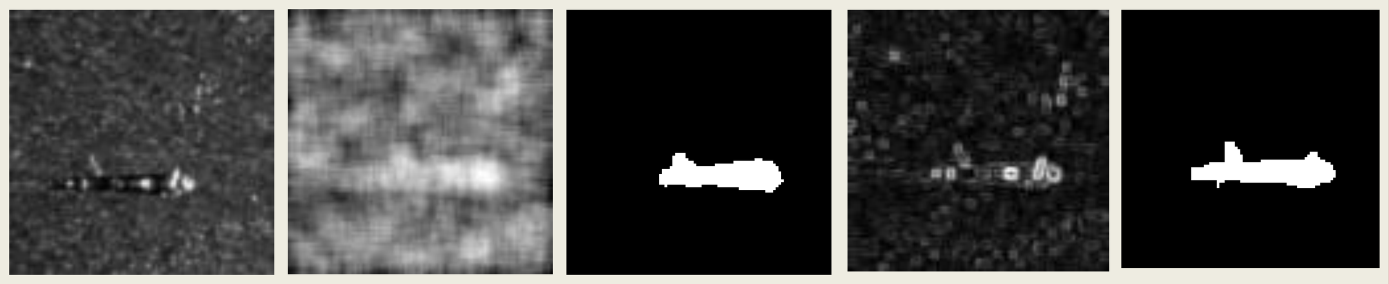
Texture analysis and Object Location

Texture analysis is an important technique in image processing. The texture contains information of the smoothness and the colour pattern of local regions in the image. The variation of grey levels can be studied by doing texture analysis. In this step, the object will be detected and extracted.

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i, \quad s.t. \sum_{i=1}^{n} p_i = 1 \qquad p_i = \frac{\text{number of pixels taking value } g_i}{\text{number of pixels}}$$

After the step of texture analysis, both dilation and erosion, two basic mathematical morphological operations, are performed to locate the object in the texture image. Closing operation, dilation and erosion with same kernel, is applied to remove small holes, the separated parts of a single object (if there is any) will merge into a whole.

$$A \bullet B = (A \oplus B)\Theta B \qquad \text{where } A\Theta B = \{x \mid (B)_x \subseteq A\} \qquad A \oplus B = \{x \mid (B^s)_x \bigcap A \neq \varnothing\}$$



MLOs Classifications

After the steps of Sonar image processing, Kernel Methods (KMs) are used in the classification step. Kernel methods are a class of algorithms for pattern analysis, whose best known element is the support vector machines (SVMs). The general task of pattern analysis is to find and study general types of relations (for example clusters, rankings, principal components, correlations, classifications) in general types of data (such as sequences, text documents, sets of points, vectors, images, etc.).

KMs approach the problem by mapping the data into a high dimensional feature space, where each coordinate corresponds to one feature of the data items transforming the data into a set of points in a Euclidean space. In that space, a variety of methods can be used to find relations in the data. Since the mapping can be quite general (not necessarily linear, for example), the relations found in this way are accordingly very general. This approach is called the kernel trick.

Furthermore, other machine learning method such as Neural Network and On-class learning are also used for this mission. More machine learning experiment results are expected in the near future work.

Discussion and Summary

According to our result, the image segmentation method can filter out over 70% of the original sonar data that contains no information on the valuable objects, while all MLOs are kept in the remaining small pieces. The computational burden for the upcoming steps is largely reduced.

This project proposes a hybrid autonomy control architecture for MCM AUVs. This architecture deals with performance measures associated with the different behaviours of AUVs. In this architecture, the coordination of different groups of AUVs is provided. This project also provides techniques for automated detection and classification of objects on the seabed from this imagery. These techniques have been developed to provide more reliable and consistent detection of significant objects, in order to free operators from these time-consuming and tedious detection tasks. Automatic detection and classification also enable real-time sonar processing to take place onboard suitably equipped AUVs, allowing for autonomous decision-making based on current observations.

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