Machine Learning Algorithms for Multiple Autonomous Unmanned Vehicle Operations

Research Proposal

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DRDC CORA CR 2012–154
June 2012

Defence R&D Canada
Centre for Operational Research and Analysis

Maritime Operational Research Team
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Canada

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PWGSC Contract Number: W7714-115078/001/SV
CSA: F.-A. Bourque and B. U. Nguyen, Defence Scientists, 613-992-3206/613-947-9759

Defence R&D Canada – CORA

Contract Report
DRDC CORA CR 2012-154
June 2012

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Abstract

Autonomous Underwater Vehicles (AUVs) are expected to be used by military forces to acquire high-resolution sonar imagery for the detection of mines and other objects of interest on the seabed. This document reviews progress in the development of automated detection and classification techniques for side-looking sonar mounted on AUVs. While considerable progress has been made in both unsupervised and supervised (trained) algorithms for data processing and classification, this report focuses on the areas that are still lacking and require further research. From our analysis, a clear direction for future research is mapped. In particular, we explain what the classification algorithms that we plan to develop will aim to achieve.

Résumé

On s’attend à ce que les forces militaires se servent de véhicules sous-marins autonomes (VSA) pour acquérir des images sonar à haute résolution afin de détecter les mines et d’autres objets d’intérêt sur le fond marin. Le présent document examine les progrès réalisés dans le développement de techniques de détection et de classifications automatiques pour les sonars latéraux installés sur les VSA. Des progrès considérables ont été accomplis à l’égard des algorithmes supervisés et non supervisés (instruits) de traitement des données et de classification. Cependant, le présent rapport se penche surtout sur les aspects qui présentent encore des lacunes et qui nécessitent davantage de recherche. Notre analyse nous permet de tracer une voie claire pour les recherches futures. En particulier, nous expliquons ce que l’algorithme de classification que nous nous proposons de mettre au point tentera d’accomplir.

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Executive summary

Machine Learning Algorithms for Multiple Autonomous Unmanned Vehicle Operations: Research Proposal

X. Wang; H. Shao; DRDC CORA CR 2012-154; Defence R&D Canada – CORA; June 2012.

Background: Autonomous Underwater Vehicles (AUVs) are powerful tools that perform undersea tasks, for both commercial and military purposes. Requiring no operators, they are ideally suited to perform dangerous tasks remotely. Mine countermeasures operations is one such mission. Presently, AUVs are used to collect sonar images of the sea bottom, which are then processed on the mother ship. Processing includes two stages: detection of mine-like objects (MLO) (Stage I) and classification of MLOs into several categories (Stage II). One of the major challenges with the first stage is to design fast algorithms that allow on-board processing of images. Furthermore, analyzing one sonar image is in general insufficient to properly classify objects, especially in difficult environmental conditions. One way to improve the likelihood of classifying mines is to fuse several images of MLO taken at different aspects. However, current classification algorithms lack this capability.

Purpose: The aim of this contractor report is to document the research proposal to develop a fast detection algorithm (Stage I) and a classification algorithm (Stage II) when several images at different aspects are available.

Significance: With the help of AUVs, the efficiency of mine countermeasure missions can be improved. More importantly, the risks to humans can be reduced. Properly designed algorithms will improve the effectiveness of AUV search and lay a solid foundation for the whole mine countermeasure mission. Using proper training data and algorithms, the capability of AUVs on mine-like object recognition and classification can get close to or even exceed the accuracy that humans currently obtain for this task.

Future plans: Several classification algorithms, including unsupervised and supervised learning methods, will be explored. Related algorithms including data pre-processing, image segmentation, and feature selection will also be used. Other researchers' approaches will be tested and extended with new insights that we will have gathered from our analysis.

Sommaire

Machine Learning Algorithms for Multiple Autonomous Unmanned Vehicle Operations: Research Proposal

X. Wang; H. Shao; DRDC CORA CR 2012-154; R & D pour la défense Canada – CORA; Juin 2012.

Contexte : Les véhicules sous-marins autonomes (VSA) sont des outils puissants qui accomplissent des tâches sous-marines à des fins commerciales et militaires. Comme ils n'ont pas besoin d'opérateur, ils conviennent parfaitement à l'exécution de tâches dangereuses à distance. Les opérations de lutte contre les mines sont une de ces missions. Actuellement, les VSA servent à recueillir des images sonar du fond marin, qui sont ensuite traitées par le navire-mère. Le traitement comporte deux étapes : la détection des objets ressemblant à des mines (étape I) et la classification des objets détectés selon plusieurs catégories (étape II). Un des principaux défis de la première étape consiste à mettre au point des algorithmes rapides permettant le traitement des images à bord du VSA. De plus, l'analyse d'une image sonar ne suffit généralement pas à classifier correctement les objets, particulièrement quand les conditions environnementales sont difficiles. On peut notamment améliorer la probabilité de classification des mines en faisant la fusion de plusieurs images des objets prises selon différents aspects. Les algorithmes de classifications actuels sont toutefois dépourvus de cette capacité.

Objectif : Le but du présent rapport d'entrepreneur est de rendre compte de la proposition de recherche sur la mise au point d'un algorithme de détection rapide (étape I) et d'un algorithme de classification (étape II) lorsque plusieurs images prises selon différents aspects sont disponibles.

Portée : Les SVA peuvent améliorer l'efficacité des missions de lutte contre les mines; qui plus est, ils peuvent réduire le risque que courent les humains. Des algorithmes correctement mis au point augmenteront l'efficacité de la recherche par SVA et constitueront une base solide pour la mission de lutte contre les mines dans son ensemble. Avec des données d'apprentissage et des algorithmes appropriés, la capacité de reconnaissance et de classification des objets ressemblant à des mines peut s'approcher ou même dépasser la précision qu'obtiennent actuellement les humains pour cette tâche.

Recherches futures : Plusieurs algorithmes de classification, y compris des méthodes d'apprentissage supervisé et non supervisé, seront étudiés. Des algorithmes connexes, notamment des algorithmes de prétraitement des données, de segmentation d'image et de sélection de caractéristiques seront aussi utilisés. Les approches d'autres chercheurs seront mises à l'essai et approfondies au moyen des nouvelles connaissances issues de notre analyse.

Table of contents

Abstract …….. i
Résumé ….... i
Executive summary iii
Sommaire iv
Table of contents v
List of figures vi
1 Introduction 1
2 STAGE-I: Fast detection of targets to support autonomous decision making 2
2.1 Challenges 2
2.2 Proposed fast target detection approach 2
3 STAGE-II: Multi-aspect observation policies for classification of MCM targets 5
3.1 Relationship between conditions and MLO classification performance 5
3.1.1 Sea-bed topographies 5
3.1.2 Object shape 6
3.1.3 Aspect angle 6
3.1.4 Incident angle 6
3.1.5 Resolution 7
3.2 Related work 7
3.3 Proposed approach of Multi-aspect observation policy for classification of targets under various conditions 8
3.3.1 Sonar image generator 9
3.3.2 Fusion of classification 9
3.3.3 Extension of Dempster-Shafer theory for multi aspect classification 9
3.3.4 Classifier for Multi-aspect classification 10
3.3.5 Challenges 10
References 11
List of acronyms/initialisms 13

List of figures

Figure 1: Fast target detection 3

Figure 2: Sea-bed topographies [4] 5

Figure 3: Sonar images of targets in different sea-beds [5] 5

Figure 4: Sonar images in pixel of a cylinder at different aspect angles (30° increments) [6] 6

Figure 5: The shadow regions under different incident angles [7] 6

Figure 6: Steps of proposed approach 8

Figure 7: Multi-aspect classification. 9

1 Introduction

Autonomous Underwater Vehicles (AUVs) are powerful tools that perform undersea tasks, for both commercial and military purposes. Requiring no operators, they are ideally suited to perform dangerous tasks keeping humans away from potential dangers. Conducting Mine CounterMeasures (MCM) operartions is one such mission.[1]

At present, high-resolution side-looking sonar systems, such as Side Scan Sonars (SSS) and Synthetic Aperture Sonars (SAS), are the tools of choice for imaging the seabed to detect Mine-like objects (MLOs). SAS has the operational advantage of allowing for high-resolution surveys of the seabed with an increased detection range, enabling AUVs with these sonars to survey the seabed faster.

Processing of sonar images includes two stages: detection of MLOs (Stage I) and classification of MLOs into several categories (Stage II). Presently, AUVs are used to collect sonar images of the sea bottom, which are then processed on the mother ship by human operators. Automation of these tasks is currently the focus of active research.

In the future, it is expected that Computer-Aided Detection and Classification (CAD/CAC) techniques will be employed to highlight areas of images that warrant close inspection by a human analyst, obviating the requirement for the analyst to scan through all the data. This procedure will greatly increase the speed and efficiency of mine countermeasures operations and other operations requiring seabed feature detection.

Moreover, it can be envisioned that CAD/CAC systems could be incorporated into real-time processing systems on board AUVs, making the vehicles able to make autonomous decisions based on detection of seabed features.

One of the major challenges to enable this vision is to design fast algorithms that allow on-board processing of images. A second is to properly classify objects in difficult environmental conditions.

The aim of this contractor report is to document the research proposal to develop (1) an on-line detection algorithm (Stage I) and (2) a classification algorithm (Stage II) which fuses several sonar images taken at different aspects to improve accuracy.

This report is structured into three sections. Section 2 describes the proposal for fast detection of targets to support autonomous decision making, while Section 3 describes the proposal for multi-aspect observation policies for classification of MCM targets.

[1] Mine countermeasures missions involves deploying assets (manned or unmanned) to detect, classify and neutralize mines. For this project, the focus is on the first two phases of the mission.

2 STAGE-I: Fast detection of targets to support autonomous decision making

2.1 Challenges

One of the challenges for this project is the quality of available sonar images, which are low resolution SSS (Side Scan Sonar) images rather than high resolution SAS (Synthetic Aperture Sonar) imagery. A better sonar image can provide more accurate and detailed information about the MLOs such as the size, shape, location, shadow, et cetera. Low quality and noisy SSS images will limit the performance of the image processing and machine learning algorithms that will be subsequently applied.

Scarcity of MLO data is another problem. In other target detection tasks, like face recognition, a template can be built based on the large amount of existing data. If the MLO data is insufficient, no reliable template can be created. In addition, the lack of MLO data is likely to result in an imbalanced data set, causing problems to the training of a machine learning algorithm.

Furthermore, in other target recognition systems, face recognition for instance, it is known in advance that there will be, for example, two eyes, one nose and one mouth as well as their approximate location and size on a face. Unfortunately, no such prior knowledge is available in MLO detection. The uncertainty of the orientation, size, location and shape of MLO will make the task more challenging.

Another challenge is processing the sonar images before the next set of images is acquired.

2.2 Proposed fast target detection approach

One of the main objectives of MCM operations is to detect and classify the MLOs in a specified area of interest. Unfortunately in MCM operations, a large part of the sonar data collected by the AUVs only conveys information about the background (seabed). The background data are relevant for the seabed classification, but for MLO detection and classification, they will be less valuable compared to sonar data that directly contain information on MLOs.

The large amount of background sonar data will inevitably increase the computation time, largely impeding the fast detection process of MLOs. Therefore, it is reasonable and necessary to reduce the amount of data by filtering out the less informative background data, while keeping the MLOs data. This process, known as data reduction, makes real time target detection possible.

Data reduction can be performed by proper image processing algorithms. By analysing the texture and edge features of the sonar image, the foreground objects can be extracted from the background. This step will largely reduce the computational load for the later steps, allowing real time operations. The main purpose of this step is not to detect the MLOs; therefore, a relatively high false alarm rate is acceptable.

After the background data are filtered out, machine learning algorithms can be applied to analyse the remaining sonar data. A proper machine learning method can capture the distinguishing characteristics that depict the target pattern and lead to an acceptable learning result.

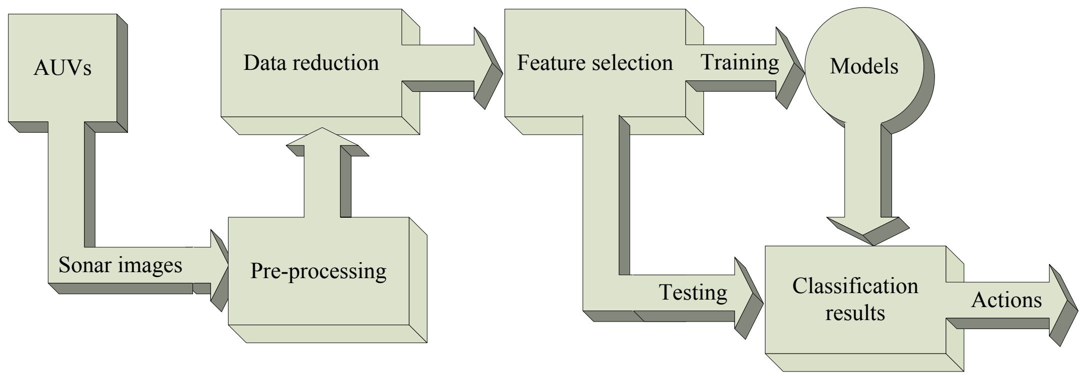

Figure 1: Fast target detection

Figure 1 shows the steps of real time target detection. The pre-processing and data reduction can be performed by image processing algorithms while the later steps are performed by machine learning algorithms.

For object detection tasks, an object should be detected through a single view, no matter where and how they lie on the seabed. Therefore, the feature used should be robust to the location and orientation of the object. In many image recognition systems, complex features such as Fourier or wavelet coefficient are used. Unfortunately, such features will inevitably increase the computational complexity. Instead, we propose using a histogram, a simple but informative statistical feature. The histogram is easy to calculate and robust to rotation. It is directly obtained from the pixel values of the target. The distribution of the backscatter intensity can be well described by this feature.

Artificial Neural Networks and Kernel Methods are the two families of machine learning algorithms that will be considered in the MLO detection task.

Artificial Neural Network (ANN) [1] is a learning method derived from the neural network structure in brains. Large amount of weights connecting the artificial neurons are designed and trained in the network. The resulting network is expected to capture the relationship between the input data and the output pattern. Over the course of their development in the past few decades, ANNs have been successfully applied to solve many real life problems.

Kernel methods are a class of algorithms for pattern analysis [2], whose best known element is the Support Vector Machines (SVMs) [3]. Kernel methods approach the problem by mapping the data into a higher dimensional feature space. In this feature 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.

Usually, SVMs will perform hard classification, but research has been done to make SVMs produce prediction (detection) probability, which is obtained by passing the distance between the actual output and the final decision boundary through a logistic sigmoid function. In this way, within limited time, further analysis time slice can be attributed to MLOs with low initial classification confidence.

3 STAGE-II: Multi-aspect observation policies for classification of MCM targets

Compared to the single-view classification described in Section 2, multi-view classification relies on multiple views of an object, which, in turn, is expected to get higher accuracy and reduce the uncertainty of the object's classification.

In classification of MCM targets, there are three key elements that need to be represented: (1) highlight structure of the target; (2) reverberation due to insonification of the seabed; and (3) shadow zones cast by the target. We propose to research the conditions that may affect these three key elements. First we will conduct research on the relationship between each condition and MLO classification performance. In particular, we will find the best range of operating values for each single condition. Then we will consider the relationship between MLO classification performance and the combination of these conditions. This research will lead to the possibility for adaptive multi-aspect observation policy for classification of targets under various conditions.

3.1 Relationship between conditions and MLO classification performance

The nature of sonar images includes the following five conditions.

3.1.1 Sea-bed topographies

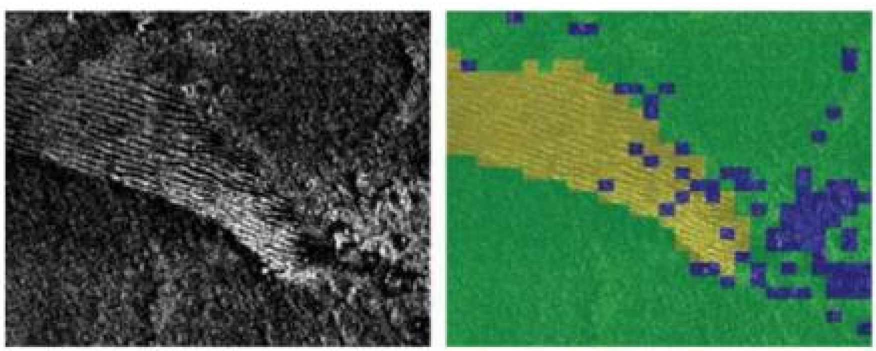

Figure 2: Sea-bed topographies [4]

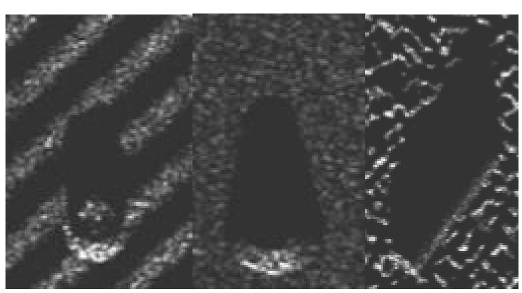

Figure 3: Sonar images of targets in different sea-beds [5]

Figure 2 [4] shows the three possible sea-bed topographies which are the flat (green area), the rippled (yellow area) and other (purple area) topographies. Figure 3 [5] shows three sonar images of mine targets on these three sea-bed topographies (rippled, flat and randomised).

3.1.2 Object shape

Different objects have different highlight structures and shadow areas in sonar images. Objects considered include rock, sphere, cylinder, wedge, cone and so on.

3.1.3 Aspect angle

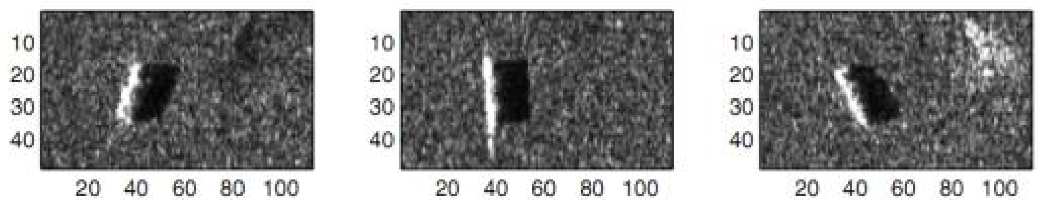

Figure 4: Sonar images in pixel of a cylinder at different aspect angles (30° increments) [6]

The polar angle between the orientation of the object and the sonar beam is the aspect angle. Figure 4 shows three images of one object at different aspect angles. From Figure 4, we can find that highlight and shadow zones are different for the same target with different aspect angles. So the aspect angle is an important factor which may affect the classification performance. Finding the best angle range for MLO classification is one of our research objectives.

3.1.4 Incident angle

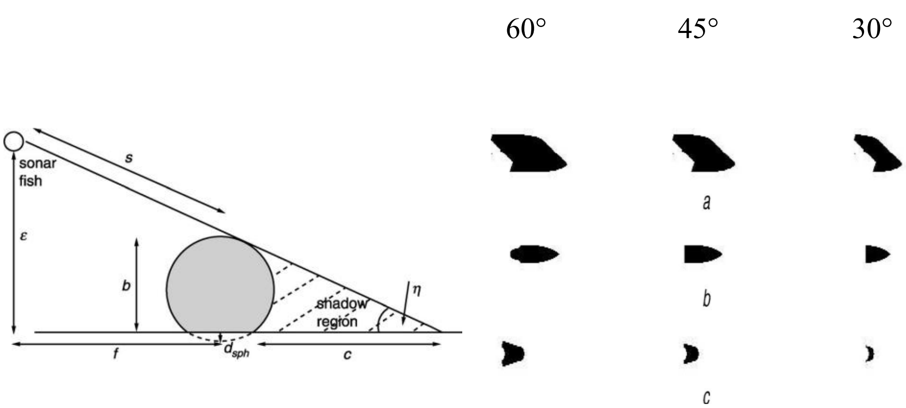

Figure 5: The shadow regions under different incident angles [7]

Figure 5 [7] shows examples of shadow regions from different types of objects on sonar incident angles of 60°, 45° and 30°. Object (a) is from the cylinder class while object (b) is from the sphere class and object (c) is from the truncated cone class.

Like in the case of the aspect angle, the incident angle can also change the shadow regions.

3.1.5 Resolution

Resolution is another factor that may affect the classification performance. High resolution generally can improve the classification performance, but sometimes the resolution may not be very good.

3.2 Related work

J. Fawcett *et al.* [6] investigated two approaches for fusing multiple views: fuse-feature and fuse-classification. In the first approach the two feature sets taken at different aspects were combined to form a large feature vector. Then a kernel based classifier was trained with this feature vector. In the second approach, they fused two individual-aspect classifications of two feature vectors using Dempster-Shafer (DS) theory, which was frequently used as an alternative to Bayesian theory and fuzzy logic for data fusion. In their work, three new methods are proposed based upon the DS fusion of the outputs from a single-look kernel-based classifier. They differ from one another with respect to the manner in which the DS masses for each view are derived from a single-look classifier. Their experiment shows that these four (fuse feature + 3 DS-based fuse classification) approaches yield very similar classification performances but the DS approaches have the advantage that they do not require explicit training with a combined set.

B. Zerr *et al.* [8]-[9] and S. Reed *et al.* [7] and [10] have also investigated the classification of a target by fusing several views using DS theory. B. Zerr *et al.* [8]-[9] described a method to estimate the three-dimensional aspects of underwater objects using a sequence of sonar images. The sonar images are segmented into three kinds of regions: echo, shadow and background.

S. Reed *et al.* [7] and [10] present a model to extend the standard mine/not-mine classification procedure to provide both shape and size information on the object. The difference between their work and others is that they generated the mass functions using a fuzzy functions membership algorithm based on fuzzy logic.

V. Myers and D. P. Williams [11] and [12] introduced a model for classifying targets in sonar images from multiple views by using a partially observable Markov decision process (POMDP). The Markov property means that the future states are entirely dependent on the present state. In the case of the POMDP proposed by them, the AUV does not keep track of the aspects it has already obtained, which can result in the situation where the same aspect is obtained more than once. This POMDP model allows one to adaptively determine which additional views of an object would be most beneficial in reducing the classification uncertainty.

J. Fawcett *et al.* [6] performed one of the most extensive works on multi-view classification. Four approaches were used for the multi-view classification. But in these approaches, only aspect angles and target shapes were considered as the factors of the multi-view datasets. B. Zerr *et al.* [8]-[9] and S. Reed et al. [7] and [10] also just considered part of the conditions we mentioned in Section 3.1. In particular, the sea-bed conditions were not considered in their approaches. The POMDP model introduced by V. Myers and D. P. Williams [11] and [12] gives AUVs the benefits to determine additional views adaptively. But as mentioned in the paper of V. Myers and

D. P. Williams [12], the model works well in specified conditions and small state space. With the increasing of the state space, more sophisticated observation models are expected in the future.

3.3 Proposed approach of Multi-aspect observation policy for classification of targets under various conditions

The approaches described above have their own weakness and strengths. This is due to the fact that each approach is based on different statistical properties and therefore emphasizes different characteristics of the data. Thus a combination of their advantages may get the benefits of increasing the probability of detection of MLO's and consequently reducing the number of false alarms.

Before we construct the multi-view classification of targets, we need to investigate the relationship between each aspect and the performance of the classifier. This work will lead us to investigate the relationship between various combinations of aspects and the performance of the classifier. Figure 6 shows the steps of our proposed approach. Since taking multi-view images by AUVs is expensive and on the other hand, large data sets reduce the speed of classifiers, it is necessary for us to create policies of multi-aspect classification. Following these policies, AUVs would have the ability to select the best ways of combining the information, taking high quality views of targets. This research also prepares us for a future stage of adaptive multi-view classification without creating too many limitations.

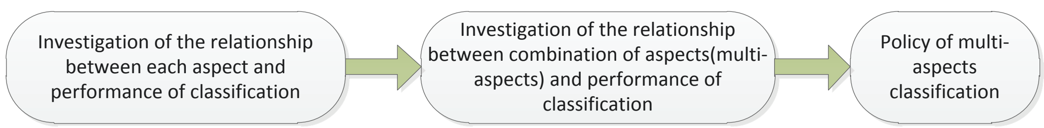

Figure 6: Steps of proposed approach

After we get the relationship between a single condition aspect and MLOs classification performance, it is necessary to make multi-aspect observation policies for classification of targets under various conditions. Figure 7 shows the steps of multi-aspect classification.

When an AUV classifies a target, the conditions on the target are static, for instance, the shape of the target, the sea-bed topography at that location, and the resolution of the SAS are all constant. However, we can adjust the AUV's position to get images with different aspect angles and incident angles. On the other hand, finding out how many images are necessary for classification to be achieved with high accuracy is also important. With more images the classification performance will be better, but the classification cost will increase as well. Therefore, choosing the best policy on how many and what kind of images to gather is a worthy endeavour. In our research, data fusion technology will be used for multi-aspects classification.

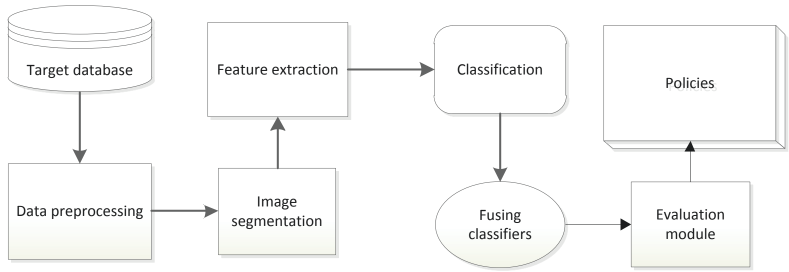

Figure 7: Multi-aspect classification.[2]

3.3.1 Sonar image generator

Since the sonar data provided by the Technical Authority is scarce and ground truth knowledge is often lacking, we will need to implement a sonar image data generator. This generator will simulate the conditions that may affect MLO classification performance which we mentioned above.

3.3.2 Fusion of classification

When we consider the aspects discussed above, we may get multi-aspects sonar images for one object. Data fusion is a technology which collates information from different sources considering the same scene in an attempt to provide a more complete description.

The most common numerical techniques used are Bayesian probability theory, Fuzzy systems and Dempster-Shafer theory [13]. Fuzzy systems contain a wealth of possible fusion operators. However, the choice of operators is case dependent and many of the operators are non-associative, meaning that the order in which the information is fused has an impact on the final result. Bayesian and Dempster-Shafer models have both been successfully applied but Dempster-Shafer theory provides some features that Bayesian theory cannot. One of the most significant features is that Dempster-Shafer theory can consider the union of classes. This feature is used to improve the separability of different classes. So in our research, we will use Dempster-Shafer theory for multi-aspect classification.

3.3.3 Extension of Dempster-Shafer theory for multi aspect classification

Dempster–Shafer theory is based on two ideas: obtaining degrees of belief for one question from subjective probabilities for a related question, and Dempster's rule for combining such degrees of belief when they are based on independent items of evidence.

The Dempster’s rule of combination is a purely conjunctive operation (AND). The combination rule results in a belief function based on conjunctive pooled evidence. This rule can also be used for multi aspect classification [14] and [15].

[2] The sonar image target database will be either provided by the Technical Authority or generated (see Section 3.3.1).

3.3.4 Classifier for Multi-aspect classification

In our proposed approach, Support Vector Machines (SVMs) is the selected classifier. Support Vector Machines are based on the Structural Risk Minimization principle from statistical learning theory. The idea of structural risk minimization is to find a hypothesis *h* for which we can guarantee the lowest true error.

As we know, the datasets in our research are highly imbalanced. In imbalanced data set, the number of false alarms are often much larger than the number of real targets. In this situation, a default classifier always predicts “negative”. In the context of MCM, D. P. William *et al.* [16] introduce an approach to deal with class imbalanced problem.

In our approach, we can apply a general method to modify Support Vector Machines by penalizing errors on positive examples more strongly than errors on negative examples. This can be achieved using cost factors C_+ and C_- to adjust the costs of false positive vs. false negatives. Such cost factors can be directly incorporated into the SVM.

3.3.5 Challenges

Since we plan to combine the benefits of others’ research and extend their work, more challenges will be created. We expect that:

- Data generation will require significant investment of resources;
- The multi-aspect policies we will create may be highly ambiguous; ands
- The use of too many aspects will increase the dimensionality of the problem and, consequently, computational load.

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List of acronyms/initialisms

ANN	Artificial Neural Network
AUV	Autonomous Underwater Vehicle
MCM	Mine CounterMeasures
MLOs	Mine-Like Objects
SSS	Side Scan Sonar
SAS	Synthetic Aperture Sonar
CAD	Computer-Aided Detection
CAC	Computer-Aided Classification
DS	Dempster-Shafer
POMDP	Partially Observable Markov Decision Process
SAS	Synthetic Aperture Sonar
SSS	Side Scan Sonar
SVM	Support Vector Machine

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DOCUMENT CONTROL DATA

(Security classification of title, body of abstract and indexing annotation must be entered when the overall document is classified)

1. ORIGINATOR (The name and address of the organization preparing the document. Organizations for whom the document was prepared, e.g. Centre sponsoring a contractor's report, or tasking agency, are entered in section 8.) Nathalie Japkowicz Consulting Services 5714 Queen Mary Road Hampstead, Québec H3X 1X6	2. SECURITY CLASSIFICATION (Overall security classification of the document including special warning terms if applicable.) UNCLASSIFIED (NON-CONTROLLED GOODS) DMC: A REVIEW: GCEC JUNE 2010

3. TITLE (The complete document title as indicated on the title page. Its classification should be indicated by the appropriate abbreviation (S, C or U) in parentheses after the title.)

Machine Learning Algorithms for Multiple Autonomous Unmanned Vehicle Operations: Research Proposal

4. AUTHORS (last name, followed by initials – ranks, titles, etc. not to be used)

Wang. X; Hang S.;

5. DATE OF PUBLICATION (Month and year of publication of document.) June 2012	6a. NO. OF PAGES (Total containing information, including Annexes, Appendices, etc.) 22	6b. NO. OF REFS (Total cited in document.) 16

7. DESCRIPTIVE NOTES (The category of the document, e.g. technical report, technical note or memorandum. If appropriate, enter the type of report, e.g. interim, progress, summary, annual or final. Give the inclusive dates when a specific reporting period is covered.)

Contract Report

8. SPONSORING ACTIVITY (The name of the department project office or laboratory sponsoring the research and development – include address.)

Defence R&D Canada – CORA
101 Colonel By Drive
Ottawa, Ontario K1A 0K2

9a. PROJECT OR GRANT NO. (If appropriate, the applicable research and development project or grant number under which the document was written. Please specify whether project or grant.) 10bz04	9b. CONTRACT NO. (If appropriate, the applicable number under which the document was written.) W7714-115078/001/SV
10a. ORIGINATOR'S DOCUMENT NUMBER (The official document number by which the document is identified by the originating activity. This number must be unique to this document.)	10b. OTHER DOCUMENT NO(s). (Any other numbers which may be assigned this document either by the originator or by the sponsor.) DRDC CORA CR 2012-154

11. DOCUMENT AVAILABILITY (Any limitations on further dissemination of the document, other than those imposed by security classification.)

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Autonomous Underwater Vehicles (AUVs) are expected to be used by military forces to acquire high-resolution sonar imagery for the detection of mines and other objects of interest on the seabed. This document reviews progress in the development of automated detection and classification techniques for side-looking sonar mounted on AUVs. While considerable progress has been made in both unsupervised and supervised (trained) algorithms for data processing and classification, this report focuses on the areas that are still lacking and require further research. From our analysis, a clear direction for our future research is mapped. In particular, we explain what the classification algorithms that we plan to develop will aim to achieve.

On s'attend à ce que les forces militaires se servent de véhicules sous-marins autonomes (VSA) pour acquérir des images sonar à haute résolution afin de détecter les mines et d'autres objets d'intérêt sur le fond marin. Le présent document examine les progrès réalisés dans le développement de techniques de détection et de classifications automatiques pour les sonars latéraux installés sur les VSA. Des progrès considérables ont été accomplis à l'égard des algorithmes supervisés et non supervisés (instruits) de traitement des données et de classification. Cependant, le présent rapport se penche surtout sur les aspects qui présentent encore des lacunes et qui nécessitent davantage de recherche. Notre analyse nous permet de tracer une voie claire pour les recherches futures. En particulier, nous expliquons ce que l'algorithme de classification que nous nous proposons de mettre au point tentera d'accomplir.

14.

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Machine Learning; MCM; AUV; Unmanned vehicles;

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