Adaptive Behaviour for an Autonomous Underwater Vehicle to Perform Chemical Mappings

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***Abstract-* Curve fitting of the measured spectrum in real time using genetic algorithms was performed to support the adaptive behaviour of an AUV equipped with an XRF. Preliminary results of the curve fitting algorithm are shown to demonstrate the algorithm using synthetic data sets.**

I. Introduction

Autonomous robots are increasingly being used to perform analysis of inaccessible environments, be it the bottom of the ocean or the surface of Mars. Because of communication constraints they need to be autonomous. This means that robots have the ability to make decisions based on available information in real time without the input of a human operator.

Engineering sensors, those that are tasked with providing information on a robot's position, depth, roll, pitch, yaw, etc, are generally used to ensure the robot navigates to the correct position, maintains the correct orientation and successfully performs other similar tasks. Therefore data from engineering sensors are directly used to influence a robot's actions.

In contrast, scientific sensors are commonly used passively, collecting their data for analysis post mission [1]. The data collected by these sensors are rarely used to directly influence a robot's behaviour during a mission. However including the data obtained through these scientific sensors in a control scheme has the potential to greatly improve the science return of missions using autonomous machines. This can be achieved, for example, through increasing the sampling resolution near areas of interesting findings or can be used to adaptively control reading frequency based on quality of data measured.

To successfully integrate the use of scientific sensors into the control schemes the robot needs to have the ability to make sense of the data. This will require the implementation of an algorithm designed to autonomously analyse data in real-time. This analysis will involve the translation of unit less numbers stored by the scientific sensors into meaningful values that provide information about the environment that the robot can use to facilitate decision making.

This paper investigates improving the control scheme used by an Autonomous Underwater Vehicle (AUV) to perform environmental monitoring. One such AUV is Starbug (Fig. 1) which has been developed by the CSIRO [2].

Figure 1. The Autonomous Underwater Vehicle (AUV) developed at CSIRO. This AUV is 1.2-m long and is equipped with different sensors.

An AUV is equipped with an X-ray fluorescence (XRF) spectrometer for performing in-situ chemical analysis of heavy metals found within marine sediment. The implemented software will give the AUV the ability to make decisions based on the results from the XRF analysis, to dynamically adjust its sampling activities, and to maximise the information on contamination from heavy metals in the studied area.

II. Motivation

AUVs provide a platform from which a wide range of marine monitoring activities may be carried out. One of the important considerations associated with AUVs is how to most efficiently use their limited resources. Battery life limits the duration of missions, and through increasing the monitoring capabilities of an AUV the drain on the batteries is increased. Another limiting factor is in the accuracy of the localisation method the AUV utilises. The underwater environment does not allow the use of GPS instead relying on alternate means of keeping track of position. Inaccuracies that may be present in these localisation methods create difficulties in revisiting the same area. These two limitations of AUVs place a requirement of accuracy and efficiency on any sampling strategy that is implemented. An improvement in accuracy can be accomplished through analysing the data in context with its real world meaning to ensure meaningful results can be interpreted from the data. Sampling in regions that yield

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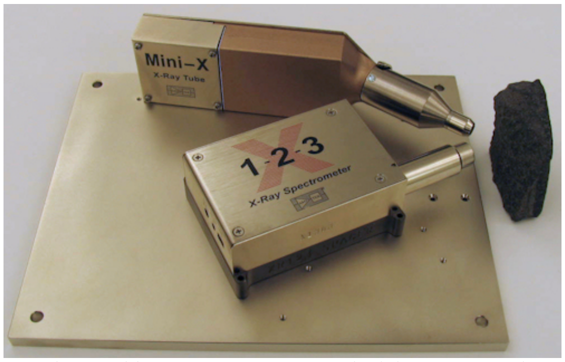

Figure 2. The portable X-ray spectrometer and miniature X-ray tube used in this study (see details at http://www.amptek.com/x123.html). The X-ray detector (X-123) has the following dimensions: (7 x 10 x 2.5) cm.

results of the highest importance will improve the efficiency of the sampling performed by the AUV.

The sampling that will be considered for this paper is chemical analysis of marine sediments. Of particular interest are the concentrations of heavy metals that are present in the sediment as a result of past industrial activities. The area of interest is the Derwent River Estuary in Hobart Tasmania. This area has a particular problem with high levels of heavy metals, in particular zinc, mercury, lead and cadmium [3]. Heavy metals can work their way up the food chain into human consumption. The proposed method of measuring these heavy metals is to use an X-ray Fluorescence (XRF) spectrometer that has been attached to an AUV platform. The X-ray spectrometer system features an X-ray detector and an X-ray emitter (Fig. 2). The X-ray emitter excites the sample which then emits its own X-rays which are detected by the X-ray detector. The energy of the detected X-rays is unique to the element that produced it and hence can allow identification of the element to occur. There may be several individual energies associated with the one element. This results from different interactions at an atomic level. X-ray fluorescence spectroscopy offers an appealing technique for chemical analysis. Many advantages exist, including the ability to identify multiple elements in a single analysis, it is non-destructive and the results can be made immediately available [4]. In-situ XRF analysis has been used in a range of applications. There have been previous studies into the use of field portable XRF spectrometers to monitor heavy metal concentrations in marine sediment [5]. This study involved retrieving samples from the sea floor and analysing them both on a research vessel and in the laboratory using XRF spectroscopy. The results indicate that the wet samples analysed in the field were comparable to the dried, homogenous samples analysed in the laboratory.

A waterproof housing has been built for the X-ray system (tube and detector) as shown in Fig. 3. This housing features a carbon cover which will allow the passage of X-rays while still being protected from water at depth. The AUV will navigate to the desired sample site, dive, and then attempt to land on the seafloor. The spectrometer and X-ray tube will be placed upon the seafloor for direct contact with the sediment and must remain in position until the measurement is taken, at which time the AUV proceeds to the next sampling site.

Figure 3. Housing for X-ray spectrometer to allow it to be attached to an AUV. Dimensions are 28 cm long, 11 cm in diameter. The X-ray tube and the radiation detector are placed in the vertical position (pointing down).

The accuracy and efficiency of the measurement, as discussed previously, can be improved through an improved sampling strategy. One of the important aspects to consider when performing spectroscopy is the integration time used for the measurement. This refers to the amount of time the measurement is performed for. Too short an integration time and the information will not be complete, and hence not accurate. Too long and valuable mission time and resources can be wasted performing redundant measurements. The focus of the proposed mission is finding regions of high heavy metal concentrations. Therefore the AUV should be able to adaptively change its sampling resolution to perform more measurements per area in regions of high interest (high heavy metal concentrations) and fewer measurements in low regions of interest (low heavy metal concentrations).

In order for this to be possible the AUV needs some way of translating the data it receives from its sensors into useful information. An algorithm is needed to perform data analysis in real time onboard the AUV.

III. PROPOSED SOLUTION

A spectrometer records counts per second over multiple channels which can be related to energy through a calibration process. This results in a spectrum which contains peaks corresponding to elements present in the analysed sample with amplitudes related to the abundance of the element present. The proposed technique consists of an automated curve fitting using Genetic Algorithms (GAs) [6, and references therein]. GAs are a powerful optimisation technique and have already been extensively used with spectral fitting with good results [6, 7]. GAs are modelled on the process of natural selection. Potential solutions to a problem are evaluated by a fitness function to determine their effectiveness at solving the problem. Solutions that have high fitness values are crossed over with other solutions of high fitness to create offspring, new solutions that have qualities taken from both their parents. Through evolving the solutions with the highest fitness values, and including such other genetic algorithm operators such as mutations, the algorithm will over time converge to a desirable solution for the problem.

The genetic algorithm attempts to fit a curve to the spectral data by approximating peaks with a Lorentzian curve shown by (1)

$$f(x)=\frac{H}{4\left(\frac{x-x_0}{w}\right)+1} \tag{1}$$

where x_0 is the peak position, H is the peak amplitude and w is the full width at half maximum. A library of expected elements is created, based on past data from the region of interest. This library contains the associated peaks with each element, K_α and K_β for example. Each of these peaks has an expected energy associated with them. This energy can be approximated to channels through instrument calibration. The genetic algorithm then attempts to fit the experimental data collected by the sensors by adjusting parameters of the Lorentzian curves.

To increase the accuracy, and decrease the number of generations required to reach an acceptable solution, the algorithm initially investigates the regions containing expected peaks to find approximations for peak amplitudes. This provides the GA with some knowledge of the data it is fitting that will allow it to perform in a much more focussed manner.

The speed of the algorithm is an important factor as it will be directly influencing actions of the AUV in real time. Precious resources can be wasted if the system has to idle for too long waiting for the outcome of an algorithm. Therefore consideration should be given to increasing the efficiency of the algorithm, even if it is at the cost of accuracy. The algorithm is used as a guide to the AUV so it can adaptively update its sampling strategy. The results at this stage do not need to be of high accuracy, just representative of the composition of the sample. A more detailed, thorough, analysis of the results will be made post mission. With speed as a high priority a method to assist the GA in converging to a suitable solution in a quick time frame would be desirable. To this end the GA has been enhanced through the addition of some simple statistical measures.

The genetic algorithm alone cannot distinguish between well formed peaks and background noise. The quality of the spectrum is a function of the integration time. During the mission planning phase it would be possible to define an integration time long enough to guarantee a usable spectrum. However this method provides an inefficient solution, especially when considering an AUV's limited resources. A more efficient method is to use a dynamic integration time. The integration time would be as long as necessary before the collected spectrum satisfies some heuristic based criteria. One method is to determine the signal-to-noise ratio (SNR) of the collected data. A low value for SNR indicates the spectrum is not well formed enough to provide usable data and a longer integration time is needed.

When a curve has been fitted to an acceptable spectrum, the relative spectral area associated with elements can be calculated. This is done through calculating the total area under all peaks (2) and finding the percentage contribution of peaks corresponding to individual elements (3).

$$A_{TOT}=A_{Fe}+A_{Zn}+A_{Si}+A_{Pb}+\ldots \tag{2}$$

$$\mathrm{Re}\,lative\ Spectral\ Area\ Fe=\frac{A_{Fe}}{A_{TOT}}\times 100 \tag{3}$$

The total area of an element may contain more than peak, for example peaks corresponding to K_α and K_β emissions. The area under a peak is found by calculating the corresponding definite integral (4).

$$\int_{-\infty}^{\infty}\frac{H}{4\left(\frac{x-x_0}{w}\right)^2+1}\,dx \tag{4}$$

It can be shown that this definite integral can be approximated by the expression shown in (5).

$$\frac{Hw\pi}{2} \tag{5}$$

These individual components related to performing chemical analysis of marine sediment will form an integral part of a larger control system aimed at successfully carrying out these measurements. The steps involved with carrying out a sampling mission are shown as a flowchart in Fig. 4. During mission planning the desired sampling area is divided into sampling sites. These could be equidistant from each other, in a grid-like arrangement, or each site could be selected for sampling based on some criteria or previous studies. During the mission the AUV will navigate to the sampling sites in order on the surface of the water using GPS. Upon reaching the site it will dive to a predetermined height above the seafloor and start analysing the seafloor for a suitable landing site using its vision system. A suitable landing site can be defined as being free from obstacles, such as rocks and seagrass, and flat enough to land safely on. Once such a site has been identified the AUV will then land on the seafloor. It will then have to maintain its position while it performs its measurement using the X-ray spectrometer. After a predetermined amount of time the collected spectrum will have its SNR assessed. Whether or not curve fitting of the spectrum occurs is dependent on the value of the SNR. A low SNR indicates that further data collection needs to take place before a suitable spectrum is produced. Curve fitting can commence if the SNR is of a high enough value. Curve fitting identifies the peaks that correspond to elements that are expected in the sample.

The resultant parameters from the curve fitting are then used to calculate relative abundances of each element. Of particular interest are areas of high concentrations of heavy metals. Therefore, when such a site is discovered, the AUV will create a new sampling site within close vicinity of the one it just analysed. This will ensure areas of high heavy metal concentrations will undergo high resolution sampling. If the area has low heavy metal concentration the AUV will resurface and proceed to the next programmed sampling site.

IV. RESULTS

To test the effectiveness of the proposed algorithm and to demonstrate how it will work synthetic spectra were created. These spectra contain Lorentzian peaks representing elements that have been identified as possibly existing in marine sediments. Calibration data was used from an existing data set and used to convert energy to channels. An example spectrum is shown in Fig. 5.

This is a spectrum containing the elements that have been identified as being the main constituents of marine sediment [8]. These are Silicon, Calcium, Titanium and Iron.

TABLE I
RESULTS OBTAINED WITH THE CURVE FITTING USING GENETIC ALGORITHM AND THE SYNTHETIC SPECTRUM DEPICTED IN FIG. 6. WSA MEANS WHOLE SPECTRAL AREA.

Element	Reference [%WSA]	Fitted [%WSA]	Absolute Difference [%]	Relative Difference [%]
Silicon	33.9	31.7	2.2	6.5
Calcium	7.9	7.3	0.6	7.6
Titanium	11.8	10.6	0.8	6.8
Iron	46.4	50.4	4.0	8.6

Fig. 6 shows the result of the fitting algorithm applied to the spectrum shown in Fig. 5. It can be seen that for some peaks the amplitude fitted curve was smaller than the synthetic data. Table 1 shows the whole spectral area of each element present in the spectrum, the fitted results and the absolute and relative difference. The average relative difference obtained with this approach was of 7.4%. These were calculated using (5). It can be seen that for some peaks the amplitude of fitted curve is smaller than the synthetic data, and this is reflected by Table 1. However the areas are still sufficient to give an accurate representation of the makeup of the sample.

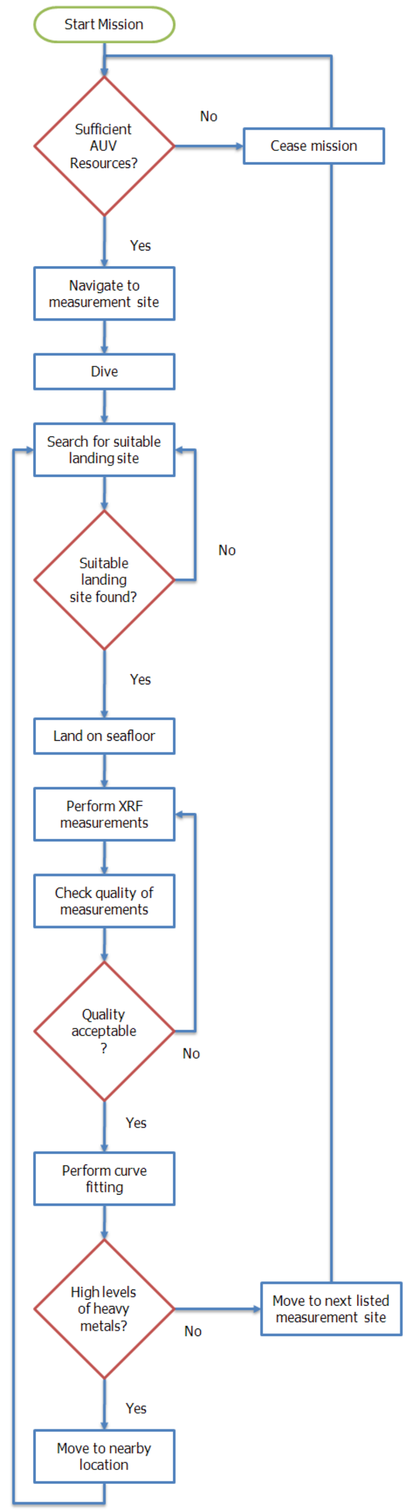

Figure 4. Simplified flowchart describing the procedure to perform sediment sampling

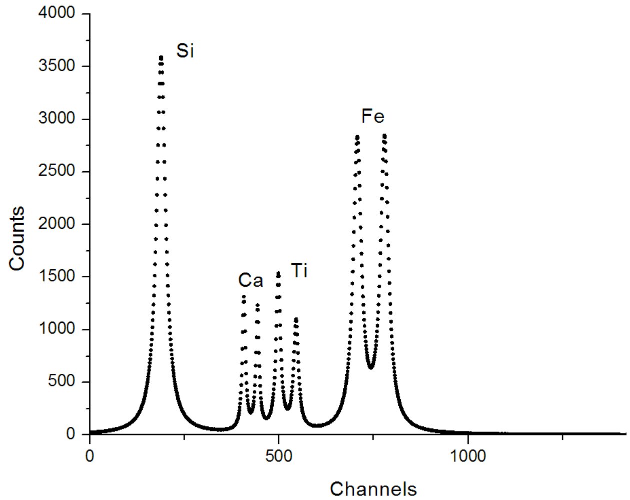

Figure 5. Example of a simulated spectrum showing major elements that constitute sediments from Derwent Estuary in Hobart, Tasmania.

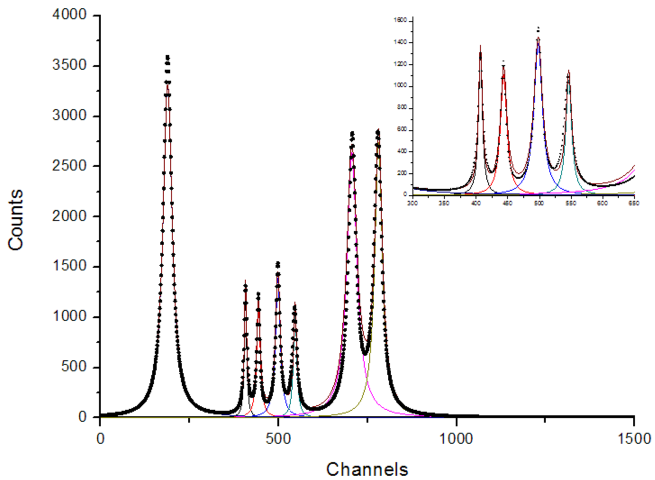

Figure 6. Result of fitting applied to spectrum in Fig. 5

In order to show the algorithm using more realistic data, elements were added to those already present. These elements are those that have already been mentioned as being of concern in the Derwent Estuary. Fig. 6 shows the results of the fitting on a spectrum that includes these heavy metals. Table 2 shows the results of the percentage spectral areas calculations.

TABLE 2

RESULTS OBTAINED WITH THE CURVE FITTING USING GENETIC ALGORITHM AND THE SYNTHETIC SPECTRUM DEPICTED IN FIG. 7.

Element	Reference [%WSA]	Fitted [%WSA]	Absolute Difference [%]	Relative Difference [%]
Silicon	30.7	27.9	2.8	9.1
Calcium	11.0	11.9	0.9	8.2
Titanium	10.3	9.9	0.4	3.9
Iron	42.4	39.5	2.9	6.8
Zinc	0.1	1.3	1.2	1200
Cadmium	1.9	3.7	1.8	94.7
Mercury	1.8	2.8	1.0	55.6
Lead	1.8	3.0	1.2	66.7

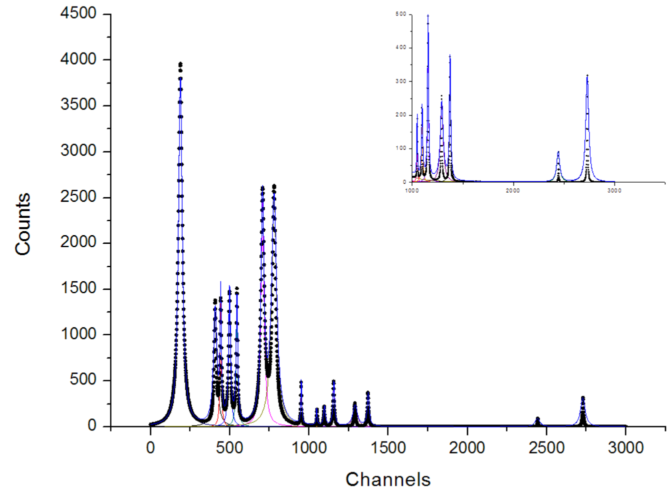

Figure 7. Result of fitting of spectrum including heavy metal elements

The calculated areas, especially for the heavy metals, tend to be higher than the actual ones. Usually, width of the fitted peak tends to be higher than the actual data, resulting in the higher calculated spectral areas.

To demonstrate the algorithm with more realistic data some background noise was added. A background level was introduced to the spectrum and then white Gaussian noise was added to that. Fig.8 shows a fitting performed on spectral data with noise added. The noise added was Gaussian distributed with a mean equal to 50% of the background component. Table 3 shows the calculated areas. It is evident that the added noise impacts the fitting, especially with the heavy metal elements. This highlights the need for checking of the spectrum quality before fitting is commenced. It also suggests that the algorithm may benefit from the addition of noise handling aspects.

TABLE 3

RESULTS OBTAINED WITH THE CURVE FITTING USING GENETIC ALGORITHM AND THE SYNTHETIC SPECTRUM DEPICTED IN FIG. 8.

Element	Reference [%WSA]	Fitted [%WSA]	Absolute Difference [%]	Relative Difference [%]
Silicon	31.7	23.5	8.2	25.9
Calcium	8.8	7.5	1.3	14.8
Titanium	10.6	12.3	1.7	16.0
Iron	44.1	40.2	3.9	8.8
Zinc	0.8	1.5	0.7	87.5
Cadmium	1.1	3.7	2.6	236.4
Mercury	1.4	6.0	4.6	328.6
Lead	1.5	5.3	3.8	253.3

Tests were also performed with real measurements. Figure 9 represents a least-squares fitted X-ray fluorescence using genetic algorithm, and Lorentzian lines shapes. Apart from a noise present between channels 1000 and 2500, there is an excellent agreement of the curve fitting and the experimental data.

V. CONCLUSION AND FURTHER WORK

This paper has introduced an algorithm that can be used to improve the environmental monitoring perform by an AUV. This algorithm will be used in the analysis of marine sediments using an XRF spectrometer. It will allow the AUV to adaptively respond to the measurements it takes through the use of curve fitting techniques to derive real world meaning from spectral data. Some synthetic results were shown to demonstrate the curve fitting aspect of the algorithm.

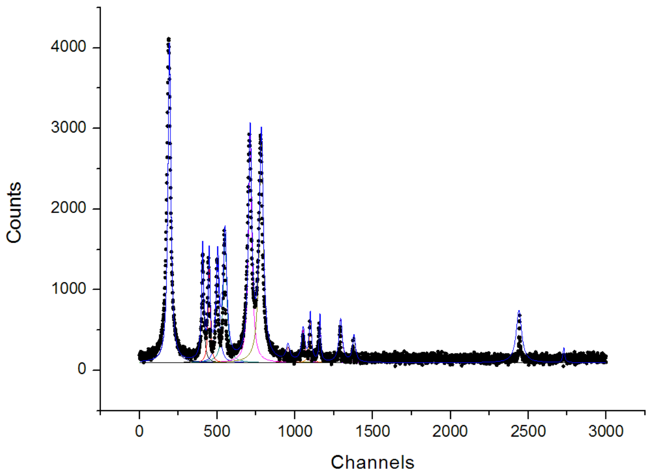

Figure 8. Result of fitting of spectrum which contains white Gaussian noise (µ 10 = % and s.d. = 5 %).

The algorithm represent is a feasible way to perform in situ data analysis. The algorithm could be improved to give better fits in the presence of noise and large number of target elements. This will include investigation into ways to increase the speed of the algorithm and algorithm simulations on the AUV hardware. Further work needs to be done using actual data sets that are representative of the area of interest, in this case the Derwent Estuary. This will allow the algorithm to be finetuned using more relevant datasets.

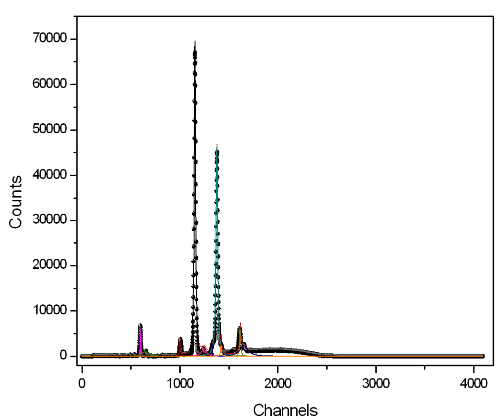

Figure 9: Least-squares fitted X-ray fluorescence spectrum using genetic algorithms and Lorentzian line shapes. This measurement was performed using a X-123 PIN-Diode radiation detector from Amptek and a miniaturized X-Ray tube (mini-X also from Amptek) equipped with Tungsten target. The sample is a Pb-bearing calibration target.

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