

Techniques for Seabed Mapping using Underwater Hyperspectral Imaging : A Survey

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Abstract

High quality mapping of seafloor features has been receiving considerable interest over past few years. The traditional methods of seabed mapping are limited because of water depths and demands for considerable human interpretation. An Optical mapping method, underwater hyperspectral imaging (UHI) is found to leverage the above problems while providing us with a high quality seabed maps. We present the process of identifying/classifying a given object of interest (OOI) on the seabed using UHI. Influence of water layer on the reflectance spectra, being the primary challenge in UHI has been focused and a detailed survey on algorithms to eliminate its effect has been provided. A brief note on the classifiers for UHI and their limitations has been discussed. Possible scope of improvements at different stages of acquiring and processing the hyperspectral imagery in underwater platform has been concluded.

Key Words : Hyperspectral Imaging, Object of interest (OOI), optical fingerprints, Spectral library, Seabed mapping, Underwater

1 Introduction

Mapping of seabed provides information on bathymetry, biology, geology and environmental status of sea floors. It is a challenging task to create seabed mapping because of its complex, dynamic nature and huge variability in biogeochemical composition over space and time. Some of the traditional methods used for obtaining the seabed maps are Side Scan Sonars (SSS) which will not create a bathymetric data instead provides the information on sediment texture and topography, Multi-beam echo-sounders (MBES) [25] which performs better than SSS but cannot be used for smaller object detection, underwater photography and video towed by a boat which requires human assistance [1]. All these methods are limited spatially and demands for considerable human interpretation. The new technology for obtaining the seabed maps emerging in recent times is the use of Hyperspectral Imaging.

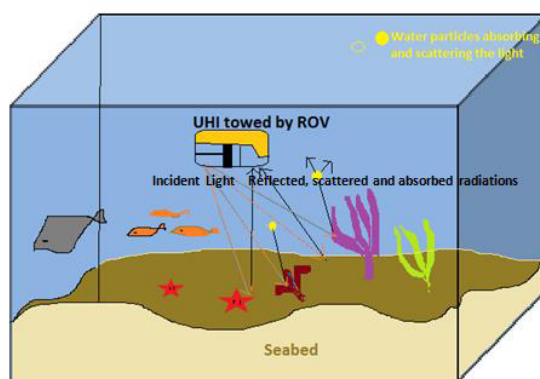
Over the past decade, hyperspectral imaging has been successfully used with the airborne vehicles for remote sensing application. This is possible because of unique spectral nature exhibited by different object of interests (OOI) like minerals, man-made materials, terrestrial vegetation etc. The absorption and reflection of visible spectrum varies uniquely with different objects resulting in their own optical fingerprints otherwise called spectral reflectance $R(\lambda)$. It is defined as the ratio of upwelling irradiance from the substrate

$$R(\lambda) = \frac{R_u(\lambda)}{R_d(\lambda)} \quad (1)$$

These unique optical fingerprints for different objects are collected to form the spectral library which can be then used for identification and classification of similar categories [2]. Several airborne sensors such as aviris, heperion have been effectively employed for identification and classification of objects both on land as well as in shallow waters [3, 4]. For underwater substrates, the collection

of optical fingerprints can be done either using lab measurements or spectrometers in field that are diver operated.

The application of hyperspectral imaging for underwater remote sensing is being developed only in the recent years. In [24], a study on potential usage of hyperspectral imager underwater was done as a part of seabed mapping program (MAREANO) in Norway. The primary objective of this work is to determine the marine sediments properties which could be identified/classified using the UHI and focuses only on carbonate sediments. But this was not carried out in-field instead evaluated in laboratory using prototype HI equipmentsoperated on samples submerged in water.



(a)

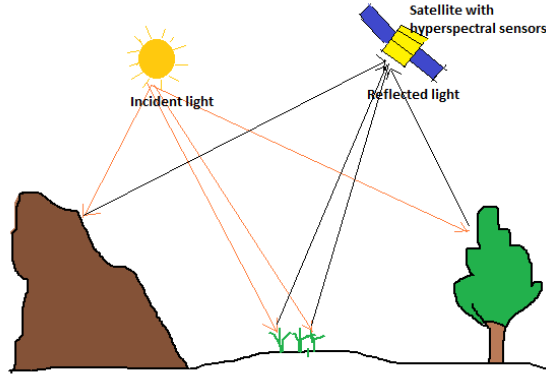


Fig.1. (a) Seabed mapping using UHI towed by ROV; (b) Terrestrial hyperspectral imaging using airborne vehicles.

This paper is organized as follows. In Section II, we discuss the challenges involved in underwater hyperspectral imaging. In Section III, we provide a detailed discussion on water column effects. A survey on different techniques for optical correction of UHI has been provided in Section IV and summarized in Section V.

2 Challenges in Underwater Hyperspectral Imaging

The usage of the hyperspectral imaging for the underwater objects is similar to that of terrestrial application except that the sensing is done at the bottom of the ocean bodies with the use of an artificial light source because of absence of sunlight under deep sea. Figure 1 illustrates the airborne and underwater remote sensing techniques. Figure 1(a) shows the seabed mapping using underwater hyperspectral imager (UHI). The UHI sensor is the push-broom scanner which is placed perpendicular to the line of scan along with an artificial light source. It is towed by remote operated vehicle (ROV) tethered from a ship or it can also be used with an autonomous underwater vehicle (AUV) [2].

In spite of having several advantages in using the UHI compared

to the traditional methods such as acoustic or optical techniques, there are few challenges associated with it. Some of them are addressed below.

2.1 Effect of Medium

The spectral reflectance of an OOI is captured using UHI which is deployed at some altitude above making it impossible to obtain the hyperspectral image without the influence of water column. This is discussed detailed in the following section. The existing water layer introduces the following effects on the acquired reflectance spectra.

Attenuation As the light propagates through the water, different part of visible light gets attenuated according to their wavelengths. The color of the ocean is decided by the deepest penetrating wavelength. In most of the cases, the less attenuated wavelength at the bottom will be blue or green making the water color to be the same.

Absorption and Scattering-Several particles and organisms present in the water column will absorb and scatter the light thereby attenuating it. They are water molecules which absorb the blue part and scatter the red part of the spectrum, phytoplanktons absorbing green light, colored dissolved organic matter (CDOM) absorbing UV and blue waves and total suspended matters like particulate organic and inorganic material (POM/PIM)[24].

2.2 Limited Spectrum Range

UHI can identify only the objects with reflectance spectrum that lies within the visible range. OOIs with absorption characteristics falling in infrared and ultraviolet range cannot be captured and identified as these wavelengths are strongly attenuated when propagating through the water.

2.3 Hazing Effect

The attenuation introduced by the water layer is wavelength dependent distorting the energy distribution of spectrum. This will attenuate the images acquired resulting in dull and hazy images.

Of the challenges discussed above, the primary one that ought to be focused is the effect of the medium introduced on the hyper-

spectral images. The attenuation, absorption and scattering errors added to the spectra should be corrected to arrive at the true reflectance of the object of interest. In the following sections of the paper, we consider only this key issue.

Figure 2 shows the flow chart of general remote sensing system using hyperspectral imaging. The block highlighted shows the additional processing required for the UHI compared to that of airborne systems. It shows the task of removing the added water effects to the spectra reflected from the seabed before they are processed for identification or classification units.

Algorithm for the flowchart shown in Figure 2 is given below.
Step 1: Hyperspectral images are acquired using the sensors which are mounted on the airborne vehicles for terrestrial applications or ROV/AUV for underwater applications.

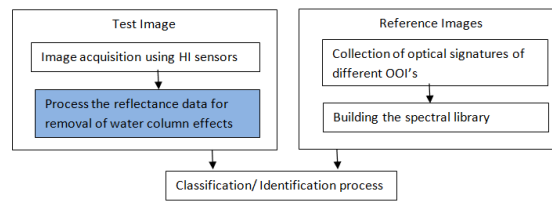


Fig. 2. Flow chart of general remote sensing system using Hyperspectral imaging

Step 2: In case of underwater remote sensing, the reflectance data is subjected to correction algorithms to remove the effects of water layer which is not required for terrestrial applications.

Step 3: The processed data can be then identified/classified using the spectral library consisting of optical finger prints of several materials. Spectral library is built using mapping techniques.

3 Effect of Water Column on Hyperspectral Imaging

The factor which makes the underwater hyperspectral imaging more complex from that of terrestrial hyperspectral imager used in airborne vehicles is the influence of water column on the images acquired. The reflected light from the substrate will be affected by the

intermediate water medium and its constituents thereby manipulating the reflectance spectra. These effects are found to be dependent on depth, bottom-type and wavelength. In this section, we present the optical properties of water column in relationship with the UHI and discuss some of the techniques for correcting them.

3.1 Optical Properties of water

The presence of water medium results in attenuation, absorption and scattering as discussed in Section II. These phenomena are related to the optical properties of water which are defined as Apparent and Inherent [24].

Commonly used apparent optical properties (AOPs) for remote sensing applications are diffuse attenuation coefficient and bottom reflectance. These are measured using passive optical sensors and are dependent on ambient light (sun) being light source. In contrast, the inherent optical properties (IOPs) are only medium dependent and are independent of ambient light source. In the context of underwater imaging spectrometers which is employed with active sensors, the IOPs are considered for analyzing the water layer attenuations.

Two commonly used IOPs for remote sensing and imaging are absorption coefficient and scattering coefficient which measures the fraction of absorbed and scattered light per unit distance within the medium respectively. Underwater constituents that are responsible for absorption of light include water molecules, phytoplankton pigments, particulate detritus etc. Each of them absorbs photons of different wavelengths in different regions of visible spectrum. Light scattering is because of water molecules, salts, organic and inorganic particles and bubbles [2].

3.2 Optical correction of UHI

Two common methods used for optical correction of water layer are:

- a. Use of reference target with a known reflectance properties situated at same depth as that of OOI.

- b. Modeling of reflectance from the bottom substrate using radiative transfer model.

In the first scenario, an object whose reflectance properties are known is placed within the sampled zone along with our object of interest. Generally, Spectralon which reflects light equally for all wavelengths will be used. Then correction to the sensed reflectance can be done by normalizing the radiance of each pixel with the measured light scattered from the known target [2, 6, 7, 8,]. The major drawback with this method is that it is difficult to place the reference target at same distance as that of OOI. Thus the idea is to keep the reference target at fixed distance from sensor and the response is numerically corrected assuming the water column is homogenous throughout.

The second approach is the widely used technique for correcting the water effects on image. In this, a model of true reflectance from the sea bed is built using the knowledge of IOPs i.e., absorption and scattering coefficients of water. Sensors can be used for measuring the water properties along with image acquisition task. The drawback is that the size of sensors for measuring the optical properties is large making difficult to employ them on the underwater vehicles [2].

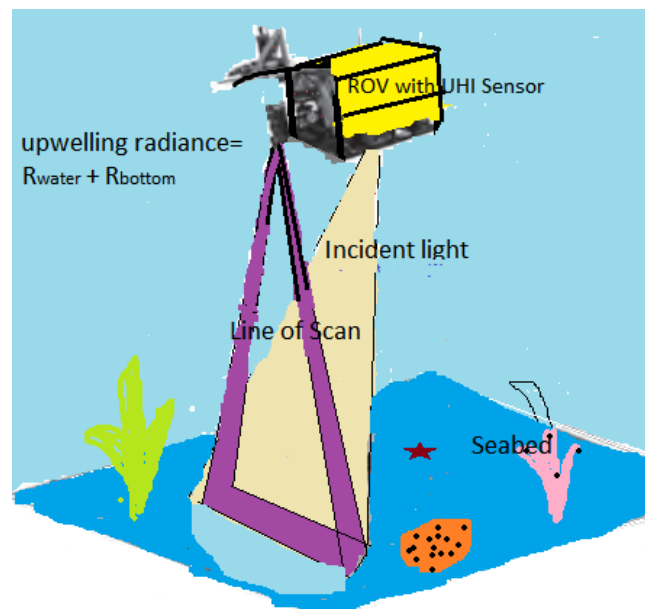


Fig. 3: Schematic showing imaging process for UHI mounted on ROV. The reflectance measured using the sensor will be because of water column and bottom.

3.3 Modeling of Remote Sensing Reflectance in underwater environments

The reflected radiance captured by the sensing device is not the true reflectance of the target in case of underwater systems. The reflectance measured at any point beneath the water surface will be contributed by the water column as well as the bottom as shown in Figure 3, where R_{water} is the upwelling radiance contributed by the water column and R_{bottom} is that of the bottom. Thus the reflected data has to be processed for removal of these effects. This problem is most widely being addressed for the past decade in literature in context of the remote sensing underwater using airborne sensors. For this type of systems, the objects under the shallow water can be sensed using the imaging spectrometers deployed on airplanes or satellites and then can be identified or classified.

Figure 4 depicts the remote sensing system for shallow water us-

ing airborne vehicles. For this type of system, the reflectance data seen at the sensor includes atmospheric effects, reflectance from the water surface, influence of water constituents and the desired bottom reflectance as shown in the figure 4. Hence, in order to obtain the true reflectance from the desired substrate, the obtained data has to be subjected for several pre-processing stages to remove the atmospheric, water surface and water constituents effects. Relating this to the systems where sensing done underwater, the affects of atmosphere and above water surface reflectance can be ignored whereas the techniques for removing the water layer attenuations can be explored for its application to the problem of interest.

For airborne systems used for shallow waters, in order to obtain the bottom reflectance above the water surface, we first arrive at the approximation to the subsurface reflectance i.e., the reflectance below the air-water surface which is given below [5],[26],[27]. Here, the first term corresponds to the water effects and the second related to the seabed bottom.

$$S_r \approx S_r^{dp} \{1 - C_0 \exp[-(K_d + K_u^c)H]\} + C_1 S_b \exp[-(K_d + K_u^B)H] \quad (2)$$

Where S_r^{dp} corresponds to subsurface reflectance for optically deep water, S_b is the reflected radiance from the bottom and K denotes the diffuse attenuation coefficient with subscript d corresponds to downwelling irradiance and u corresponding to upwelling radiance for water column and bottom (C and B superscripts respectively), H representing the depth of water layer, C_0 and C_1 are the constants.

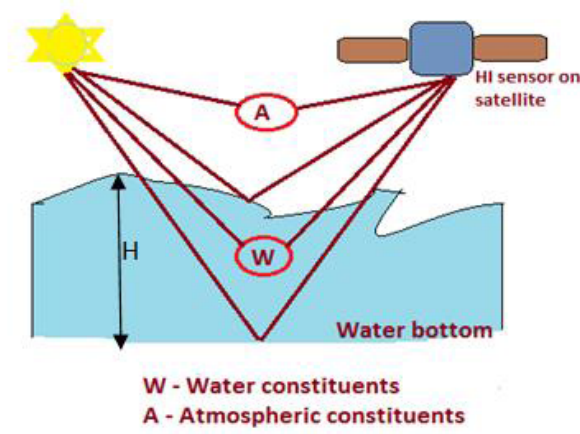


Fig. 4: Schematic diagram showing various effects on reflectance seen at airborne HI sensors

The diffuse attenuation coefficient is related to the inherent water properties: absorption and scattering coefficient as given in equation (3), with being the distribution function.

$$K = D(a + b_b) \quad (3)$$

The similarity between the airborne systems and UHI for identification of underwater targets is that the subsurface reflectance calculated at a point which is just below the air-water interface given in equation (2) for the former will become a point somewhere beneath the surface for the later. Also, the depth H indicates the depth of the shallow water region for the former system whereas for the later it will be the distance between the seabed and the imaging spectrometer as shown in figures 3 and 4. Usually the subsurface reflectance calculated will be the function of solar zenith angle which can be eliminated for underwater sensing systems.

4 Optimization based optical correction techniques

Several algorithms for deriving the water column properties for different underwater applications are found in literature. Most of the

techniques are based on optimization methods. We here presented some of them.

The modeling of reflectance spectrum using radiative transfer equation was first done by Lee et al. [9]. A semianalytical reflectance model is built using a set of absorption and scattering coefficients which is then compared with the measured reflectance. The coefficients are found by running a predictor-corrector program. Along with attenuation coefficients, it also derives bottom depth, albedo. An inversion method for the model was also developed and both were applied to synthetic and real data.

A comparison technique which measures the reflectance spectra of same substrate at the bottom and at air-water interface in order to estimate the intervening water effects for shallow water was proposed by Heather Holden [10]. A radiative transfer model with the inherent optical properties obtained using Haltrin was built to predict the reflectance spectra at the top of water layer. This requires reflectance of known substrate at the bottom. The classification of spectrum measured at both points are done and compared to estimate the effects of water intervention in classifying the underwater OOIs. The results show that the algorithm is restricted to maximum depth of 7.5m only which has been the major drawback.

Reflectance model given by Maritorena et al. [5] is a semianalytical model that is optimized using simulated annealing method. The global optimization technique, particle swarm optimization was used in [12] which is faster compared to traditional optimization techniques [21]. The objective function used here for optimizing the PSO routine is normalized root mean square error and absorption, scattering coefficients are measured at 440 and 555nm. This algorithm yields poor performance in terms of computational time and parameter choice sensitivity.

Goodman et al. [28] implemented a spectral unmixing technique for classifying the benthic composition and primarily focus on coral reefs identification. This algorithm uses both the forward and inversion model proposed by Lee [9, 29] and further integrates with a linear unmixing model. The detailed flow diagram for the image processing procedure using the semi-analytical model integrated with unmixing algorithm is given in [28]. A quantitative analysis made on accuracy of the proposed algorithm reveals that the results hold good for depth upto 3m and deteriorates further on.

Data fusion technique was adapted by Maria C. Torres-Madronero et al. [13, 14] which combines the high resolution optical signatures given by hyperspectral reflectance data with high spatially sampled lidar data to estimate the bottom reflectance. This algorithm considers the combined inversion model with unmixing at the bottom (CIUB) proposed by Castrodad et al [15] for which bathymetry information collected using Lidar is given as an additional input. The results were simulated for a synthetic data with varying substrate concentrations for depth upto 20m.

A Bathymetric model of subsurface reflectance based on one in Maritorena [5] was derived and inserted into matched filter for underwater target detection in [16]. The model considers the effects of three water constituents: phytoplankton, CDOM (color dissolved organic matter) and non algal particles and demands for a priori knowledge on water quality which is hard to determine in real scenarios. More robust model for unknown water qualities was developed in his other paper [17]. This algorithm fails to give appreciable results for larger depths.

A novel method estimating the seabed maps by eliminating the water effects based on spectral unmixing was addressed by Olivier Eches in [18]. Assuming the mixing to be linear, a bathymetric model given by Maritorena [5] is incorporated into it. For arriving at a solution, the authors had proposed an algorithm named triple NMF (Non negative Matrix Factorization) which can derive water attenuation, end members spectra and the abundances. In spite of having scaling issues, the algorithm performs better for high noise levels.

Most of the estimating methods assumes the water column homogeneity while arriving at a solution to the problem of seabed mapping which is not true for real scenarios. This was overcome in the algorithm presented by Guillaume et al in which the bottom reflectance and water properties are jointly estimated by modifying the likelihood function given in [19, 20]. For doing this, the unmixing algorithm, Tri- NMF [18] is combined with the ML model and then optimization is done for obtaining the bottom reflectance and water properties.

Table 1 shows the summary of the algorithms that can be used for finding the water properties. It is noted that the primary limiting factor is the depth which yields poor performance as increasing.

Most of the above presented algorithms were applicable for mapping of underwater habitats in case of shallow waters using airborne vehicles. A slight modification in them is demanded when deriving the optical properties for applications using UHIs. Here the light source being active, still the water attenuation property on the visible light remains same. Hence these algorithms can be effectively used for eliminating the water effects while dealing with seabed mapping using underwater hyperspectral techniques.

Several classifiers were developed for better classification of hyperspectral data. Classifiers to be solely used for underwater remote sensing applications are not exploited. To identify each class of objects, the current methods demand for precise variation in threshold which is not desirable [23]. Robust classifiers avoiding such issues can be developed. Support vector machine (SVMs) are widely used for classification or identification of objects. Recent developments reveal that Support Tensor machine (STM) can be used for the classification of remote sensed hyperspectral data and found to perform better than traditional SVMs [22].

5 Conclusion

The process and techniques involved in underwater hyperspectral imaging for remote sensing was presented in this paper. Various algorithms for eliminating the water column effects were discussed in detail. We can notice that all the algorithms can only minimize the water effects to some extent but not eliminate them and operates for only limited depths. Removal of water effects for deep ocean bodies is still an open issue and needs to be addressed. The survey reveals the fact that there is huge gap in various technologies like effective optical processing, building robust classifiers, spectral unmixing and sensor designing which has to be explored for developing an efficient UHI which can be used for mapping of sea floor and detecting its variable biogeochemical compositions as well as man-made materials for both civilian and military applications.

Table 1: Summary of water properties/bottom reflectance estimation techniques

Authors	Year	Algorithm	Depth	Pros	Cons
1 Zhongpin gLee, Kendall L.Carder, Curtis D.Mobley, Robert G.Steward, and Jennifer S.Patch	1999	Modeling the reflectance spectra using Predictor corrector scheme to determine water properties Compares the spectra of the substrate at bottom and air-water interface to find water coefficients	20-22m	Does not require in situ calibration measurements	Performs better with a priori knowledge on the spectral shapes of water constituents
2 Holden, Heather, and Ellsworth LeDrew	2002		Upto 7.5m	Simple and direct approach	Limited depth
3 WayneH. Slade, Habtom W.Ressom, Mohamad T.Musavi, Richard L.Miller	2004	Uses Particle Swarm Optimization for retrieving the water properties	No data	More accurate with less model error compared to genetic algorithm(GA) technique. Greater ability to quantify the distribution and coverage of benthic composition	More computational time and sensitive to parameter choice
4 Goodman, James, Susan L.Ustin	2007	Integration of Lees semianalytical model with a linear unmixing algorithm	Upto 3m		Requires information on benthic cover

5	Maria C. Torres-Madronero, Miguel Velez-Reyes, James A. Goodman	2009	Combines hyperspectral reflectance spectra with LiDAR spatial data using modified CIUB.	Upto 20m	Accurate estimation with less errors	Additional sensor (LiDAR) data is required.
6	Jay, Sylvain, Mireille Guillaume, and Jacques Blanc-Talon	2012	Model has the weighted sum of bottom and water column effects.	Detection upto 20 m	Doesnt require any a priori knowledge on water column	Performance decreases for turbid waters
7	Eches, Olivier, and Mireille Guillaume	2012	Spectral unmixing using Non negative matrix factorization	10-20m	Accurate estimation	Suffers from scaling issues
8	Guillaume, Mireille, Yves Michels, and Sylvain Jay	2015	A recursive Estimation unmixing (EU) algorithm is used	2.8m (estimated)	Estimates the water properties and sea bed reflectance for in homogeneous water layers	Assumes fixed water constituents concentrations

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