OIL POLLUTION USING SHIPBORNE LIF/LIDAR

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ABSTRACT

The use of real time data for oil pollution detection is very important for the monitoring of coastal waters. For this reason it is widely accepted the necessity of new technology and tools in order to improve the oil spill detection methods. In this paper we present the results of Laser Induced Fluorescence (LIF) technique and GIS tools for the monitoring of innocuous dyes spilled in the Ría de Vigo waters. This study was carried out in the framework of DEOSOM (AMPERA) project. The aim of this study was to explore a shipborne LIDAR-system recently designed by LDI Laser Diagnostic Instruments (Tallinn, Estonia). The device was used onboard different vessels for monitoring of coastal waters and detection of oil spills and organic pollutants. The field tests were carried out by University of Vigo and Galician Coast Guard. Several biological innocuous dyes were used to simulate an oil spill in the Ria de Vigo waters. The results were integrated into web-GIS-application for visualization purposes. The GIS-application in this work is based on open source Mapserver 5.x and Google Earth plug-in. The design of a web-based GIS-system would allow users to operate with geographical data without a GIS application installed on the local computer and would make possible to share the information and experience among a wide range of users and experts.

Keywords: marine pollution, lidar, laser-induced fluorescence, GIS

INTRODUCTION

It is well known that pollution is the most urgent question of the marine ecology. Increased consumption and transportation of oil products by ship worsen the situation of ocean pollution. Even the best regulation measures do not guarantee the prevention of the accidents leading to contamination. Every year about 20 accidents occur, with thousands of tons of oil being spilled into seas, and several accidents every week with tens or hundreds of tons spilled. According to the estimation of oil spill cleanup companies, the collection of 1 kg of oil in the open sea costs about 1 Euro, in coastal waters the price is about 10 times higher, and when oil reaches shore the oil collection costs increase up to 100 Euro per kg. Therefore, fast detection of oil spill accidents not only saves nature, but also reduces the accident elimination costs (1, 2).

There are different methods of remote sensing and delineation of oil spills and its derivatives on the water surface. Oil interacts with electromagnetic waves in different ways at different wavelengths. This makes it possible to use different kinds of sensors, which have their advantages and disadvantages, such as radar and microwave radiometers, and multispectral imagers in the UV, visible, or IR spectral range (3).

In this field, the sensor based on laser induced fluorescence has the unique capability to identify oil on backgrounds that include water, beaches, soil, ice and snow. The main advantage of fluorescence sensing is the possibility of obtaining of real-time, in-situ, low cost, non-contact and high sensitivity information of the target. If oils are irradiated by UV radiation, the light is absorbed and a

portion of its energy is emitted as fluorescence at longer wavelengths. Different oils yield different fluorescence spectra (4, 5), and, therefore, it is possible to discriminate between certain classes of oil. Some examples of fluorescence characteristics are shown in Figure 1. The analysis of spectra of fluorescence for various hydrocarbon products gives the evidence of clear difference in emission signals (6).

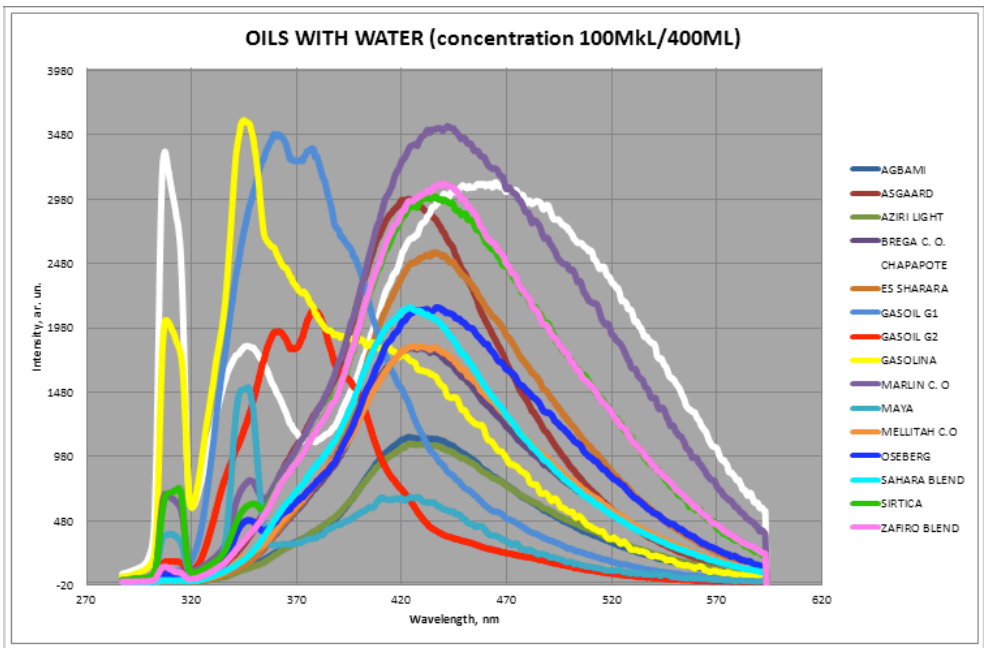

Figure 1.Spectra of Fluorescence of different hydrocarbons.

Several techniques also are based on high-resolution satellite images (ASAR). The satellite high-resolution images passing through neural network algorithms give us information about probable contamination (Figure 2). This information is a preliminary analysis that allows us to react correctly in compliance with the geographical situation, meteorological conditions or current speed.

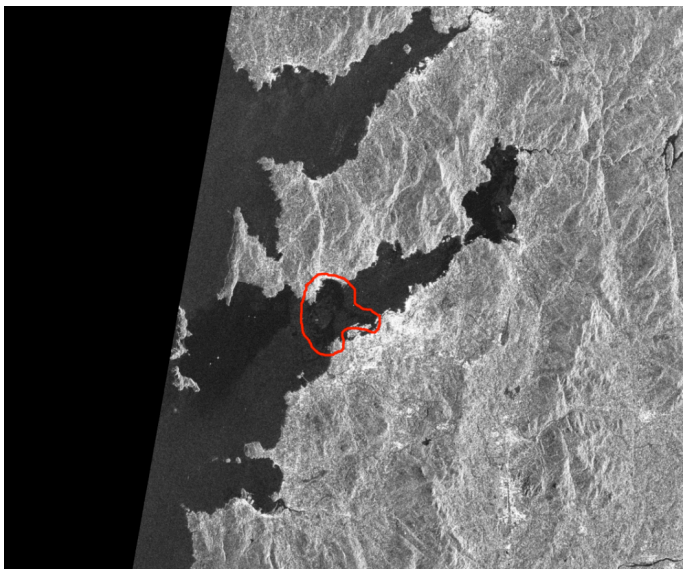

Figure 2.Possible contamination in the satellite ASAR image of high resolution.

Combining of these two kinds of data for quantitative mapping and analysis of oil slicks in the water is a potential measure for the efficient monitoring issue.

In this work the field and laboratory experiments made during five expeditions in March – September of the 2010 in the coastal waters of Galicia (Spain) with a prototype of LIF/LIDAR are observed.

METHODS

FLS®-SUV LiDAR Description

The FLS®-SUV (Figure 3, left) is a compact hyperspectral LiDAR (**Li**ght **D**etection **A**nd **R**anging system) based on Laser Induced Fluorescence (LIF) method (Figure 3, right). The device is used onboard of a vessel or stationary platform for observation of coastal waters and detection of oil and organic pollution. It is able to measure the concentration of oil in water from trace amount (part per million – ppm levels) on the water surface.

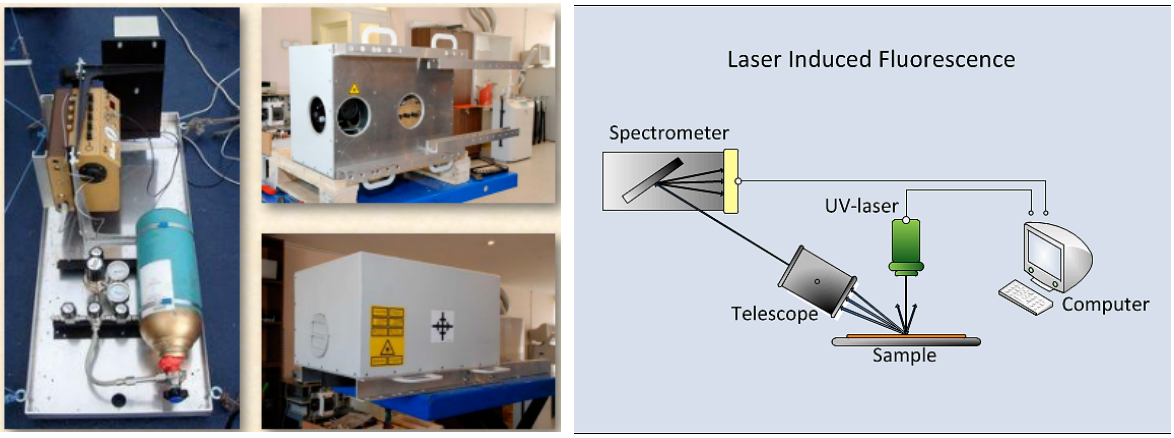

Figure 3. Left: LIF/LiDAR prototype; right: Laser Induced Fluorescence (LIF) technology for detection of oil spills in water.

The FLS®-SUV LiDAR is based on Ultra-Violet (excimer) laser and hyper-spectral detector. A pulsed laser beam senses the water body remotely. The resulting time-gated echo-signal is collected, spread into spectrum and recorded by detector. Read-out of comprehensive LIF spectrum per every laser pulse allows detailed analysis of its spectral shape by recognition of specific spectral patterns characteristic for oil and oil products and another chemicals in water.

LiDAR specifications are shown in the Table1 below.

Tests description

The focus of all operations was contaminant detection and pollution mapping over coastal zone in seawater. The monitoring was carried out during a few months. From March to September of 2010 were made 5 field experiments with LIF/LIDAR prototype in the Ria of Vigo (Atlantic Coast of Galicia, Spain) due to collaboration with a Coast Guard of Galicia. As artificial contaminants were used innocuous dyes (rhodamine and fluorescein, Figure 4, left) developed by CEDRE (Center of Documentation, Research and Experimentation on Accidental Water Pollution, France).

Table 1: LiDAR specifications.

Detection distance	up to 25 m
Conditions of operation	Day and Night
Mode of operation	Continuous, underway
Sensitivity for oil products: Min. concentration in water Min. oil thickness on water	 1 ppm 1 µm
Samplingrate	up to 90 Hz
Excimer laser	308 nm
Hyperspectral detector	256/512 channels
PC interface	LAN
Power consumption	200 W
Dimensions	70 x 50 x 40 cm
Weight	52 kg

During the operations the LIDAR was installed onboard of the coast guard vessel. The installation consisted of LIF/LIDAR Prototype itself, one portable computer as operator console connected by network cable with a LIDAR station and GPS. Figure 4 right shows how the system looks like onboard of the vessel.

Figure 4:.Left: Rhodamine (red) and Fluorescein (green) dyes; right: installation of LIF/LIDAR Prototype.

Conducted routes varied in each experiment, but in a whole have covered a wide area across the Ria de Vigo. All the operations were held in the morning, with weather conditions suitable for navigation. The maximum speed reached by the vessel during the measurements was 35 nautical knots or 64.82 km/h. The innocuous dyes were dissolved in water and formed spills with a diame-

ter approximately 5-10 meters. In addition were made a few measurements in the port of Vigo in the zone of docks.

Classification

The spectra concerned in the experiments were processed in laboratory with especially developed classifier (Figure 5) based on two different algorithms: Neural Network with a One-Class Support Vector Machine topology (OC SVM) and Minimum-Distance-to-Means (MINDIST).

First pretends to separate a multiple data received from LiDAR and to classify it in two classes only: water and anomaly. By means of OC SVM a classification model is trained using only normal data. As a result, each new sample not fitting the trained model will be considered an anomaly.

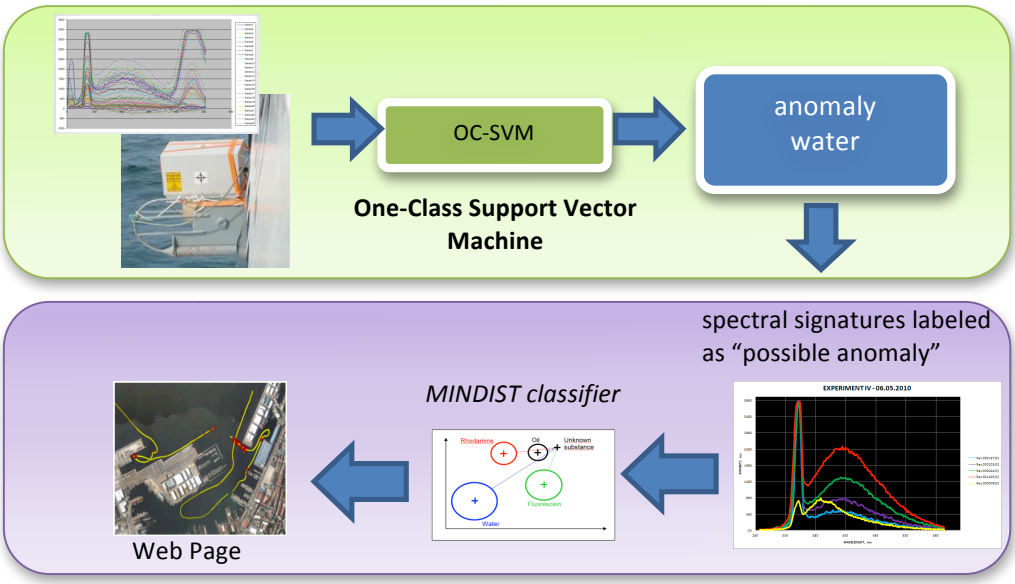

Figure 5: Classification Algorithm.

In the field campaigns five data sets were obtained. In each data set there are a lot of signatures labeled as "water" (normal data) and only a few spectral signatures labeled as "possible contamination" (possibly polluted, abnormal data). Two subsets were randomly selected from each data set: a *training* subset, composed only of data labeled as "water"; and a *test* subset, composed of data labeled "water" (different ones from those selected for the training subset) and a small fraction of data labeled as "possible anomaly". Table 2 specifies the exact composition of each data set.

Table 2: Data sets composition.

Subset	Label	Data sets				
		1st	2nd	3rd	4th	5th
Training	"water"	2713	3011	1543	1423	772
Test	"water"	3778	8530	3008	1980	1073
	"anomaly"	60	148	64	9	34

Figure 6 shows some examples of spectral signatures from the data sets. Two examples of “water” and two examples of “possible anomaly” are shown for data sets.

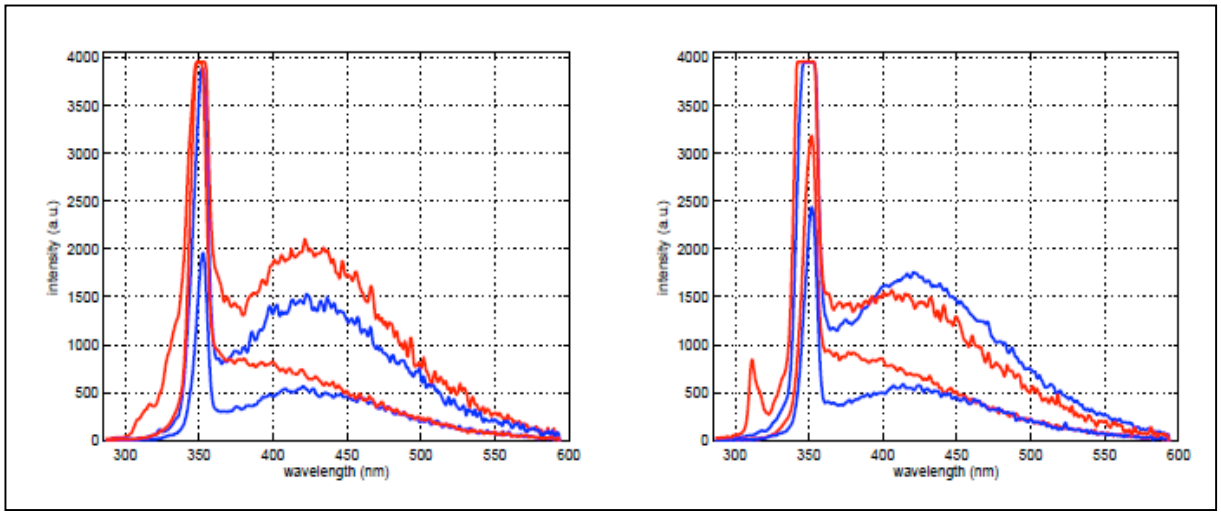

Figure 6. Examples of spectral signatures from the datasets. Spectral signatures in blue correspond with “water” labels, while spectral signatures in red correspond with “possible anomaly” labels.

Previously, a feature extraction step from the raw spectral signatures was performed. This encodes the information contained in the spectral signatures in order to make them more representative. Two techniques were tested, Principal Component Analysis (PCA) and Kernel-PCA; and different number of features were selected to represent the data. In this work, {6, 10, 20} PCA and K-PCA features were selected.

The classification rule classifies as anomalies (possibly pollution) those data that do not fit the model trained, and as normal data (clean water) those that fit the model. Furthermore the second algorithm (MINDIST) was applied in order to classify a previously detected anomaly.

MINDIST algorithm characterizes each class by its mean position on each band. In our case each spectrum is a point with coordinates in the 512 mathematical dimensions. To classify an unknown pixel, MINDIST examines the euclidean distance from an unknown point to each class and assigns it the identity of the nearest class. As each class could have the variability the developed algorithm calculates the minimum distance to each spectrum of the scope.

Data Interaction

The processing chain of LiDAR and classifier data is shown in Figure 7. A special web-interface was designed, based on open source technologies Google Earth engine, Open Layers java script and Map Server. The operator onboard of the vessel with installed LiDAR can interact with a page and receive the results of classified LiDAR data.

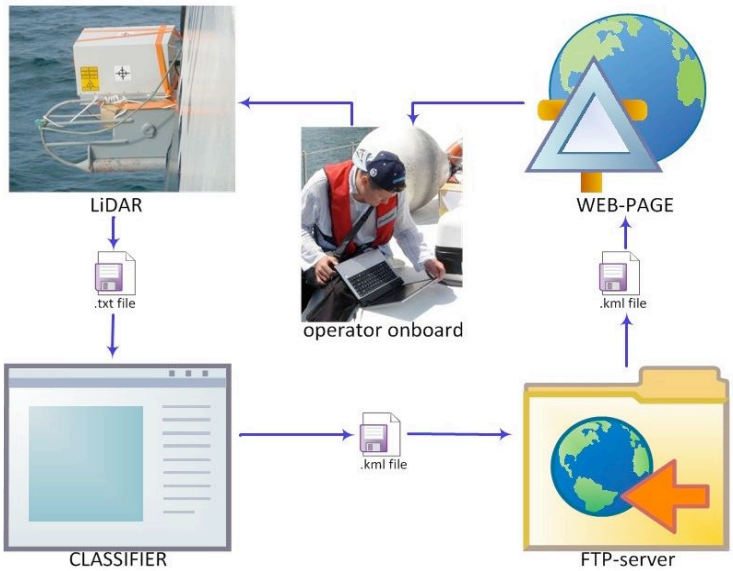

Figure 7. Data interaction scheme.

RESULTS

The important aim achieved in the study is obtaining and demonstration of results in the mode of real-time. The operator was able to detect exactly at the moment if the ship was passing through the dye spot or a real contamination, without any pre-processed analysis. Nevertheless after all experiments the whole data was processed again by different software. The artificial contaminants of rhodamine and fluorescein were accurately detected including after a few hours when the colorants are visually disappeared.

During one of the operations was made a test of depths with an organic (cotton) material. The measuring was interrupted because of the strong sea current. But the preliminary result gave us 4 meters of the depth for detection of dissolved contamination. The visualization was made by implementing the results into a web GIS application that was developed especially for this purpose using Open Source Software. Figure 8 shows a range of spectra typical of water, of rhodamine and fluorescein and also of real contamination registered by LIDAR in the Ria of Vigo.

The plots of data shown in the Figure 8 clearly demonstrate the variation of peaks between different materials dissolved in marine water. With the same excitation wavelength of laser (308 nm) the obtained signal emission wavelength for rhodamine was approximately 580 nm and for fluorescein 510 nm and for “real contamination” detected in the port 370 nm.

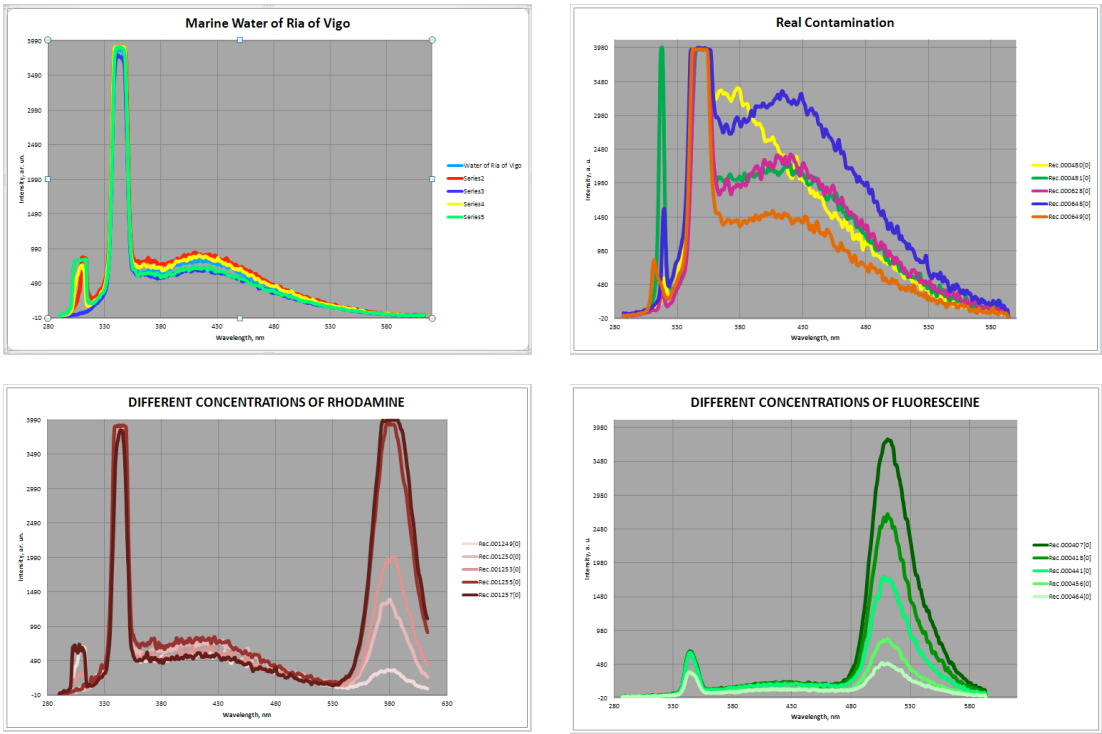

Figure 8. Detected in the experiments spectrum of: Top left: Marine Water in the Ria of Vigo; Top right: Real Contamination discovered in the port of Vigo; Bottom left: Rhodamine dye; Bottom right: Fluorescein dye.

Table 3 show results obtained by OC-SVM algorithm with each data set for the 20 features extracted. The first column indicates the feature extraction technique used, PCA_i or $K\text{-}PCA_i$, where the subindex *i* means the number of the features considered. The second column indicates the classification accuracy in the whole test subset.

Table 3: Results obtained by OC-SVM algorithm with data vectors of 20 features.

Feature extractor	Classification accuracy
Data Set 1	
PCA_{20}	3728/3838 (0.9713)
$KPCA_{20}$	3722/3838 (0.9698)
Data Set 2	
PCA_{20}	8373/8678 (0.9649)
$KPCA_{20}$	8372/8678 (0.9647)
Data Set 3	
PCA_{20}	2987/3072 (0.9723)
$KPCA_{20}$	2988/3072 (0.9727)
Data Set 4	
PCA_{20}	1926/1989 (0.9683)
$KPCA_{20}$	1920/1989 (0.9653)
Data Set 5	
PCA_{20}	1082/1107 (0.9774)
$KPCA_{20}$	1080/1107 (0.9756)

The results obtained with PCA did not differ much from those obtained with K-PCA. However, there are differences in computational complexity. PCA has less complexity than KPCA. Thus, PCA seems to be more suitable for a real-time implementation of the feature extraction and classification tasks.

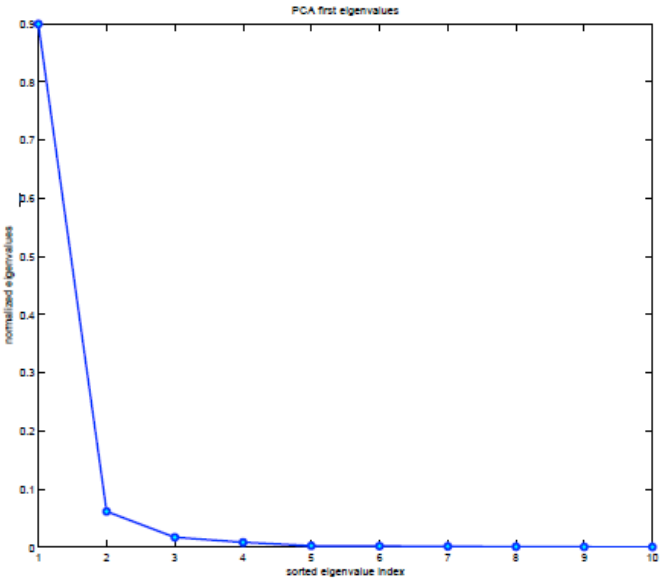

Figure 9: First ten normalized eigenvalues after applying PCA to training dataset.

Visualization

The developed web-page (http://www.tgis.uvigo.es/prueba12.html) aims at providing of collaboration and data-sharing between specialists. The user needs only to have a web browser and access to Internet. The final version permits exchange of different kinds of data, such as high-resolved ASAR pictures, LiDAR classified data and vector shapes, for relevant applications.

The figure 10 shows an implementation of the expedition results into a web GIS interface. Red/green marks of different size indicate the contamination spots with variable concentration.

CONCLUSIONS

The present study, carried out by Laboratory of Remote Sensing and GIS of University of Vigo due to collaboration with LDI (Laser Diagnostic Instruments), Tallinn – Estonia and Coast Guard of Galicia, convince that the LiDAR based on Laser Induced Fluorescence for shipboard application is ready to be implemented in operational use for remote sensing of marine targets. It has been clearly demonstrated the merits of the lidar-based remote sensing system that could be successfully employed for different environmental tasks.

A comparison analysis of different algorithms of classification for contamination data could be the next step in this investigation.

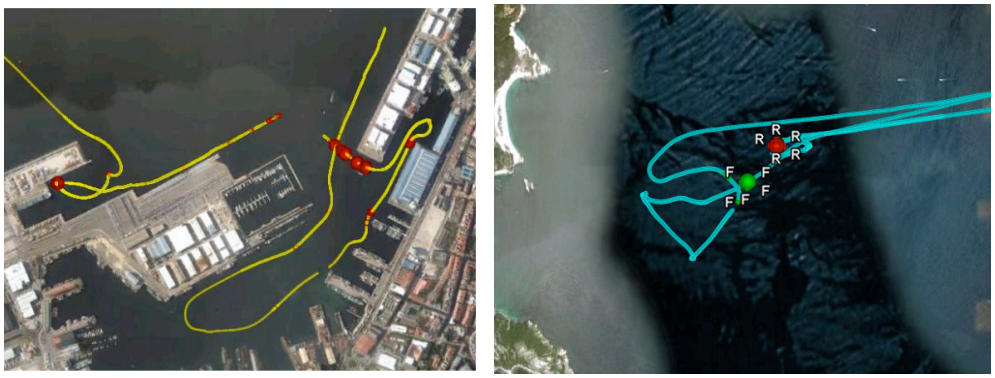

Figure 10.Distrubution of the contamination along the ship track. Left: in the port; right: in the sea with dyes.

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