MANAGING IMPACTS OF DEEP SEA RESOURCE EXPLOITATION

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MIDAS

MANAGING IMPACTS OF DEEP SEA RESOURCE EXPLOITATION

Integrative habitat mapping technologies for identification of different deep-sea habitats and their spatial coverage

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1. Introduction

Knowledge of the spatial distribution, quality and quantity of seafloor habitats is fundamental to both the understanding and management of marine ecosystems. Habitat maps have thus become a major tool in the assessment and monitoring of marine ecosystems, spatial planning and resource assessment (Cogan *et al.*, 2009; Kenny *et al.*, 2003). Our knowledge of the extent and geographical range of benthic habitats is however extremely poor due to limitation posed by conventional seabed survey methods and it is estimated that only 5-10% of the seafloor is mapped with a resolution of similar studies on land (Brown *et al.*, 2011; Wright and Heyman, 2008).

Two strategies have traditionally been followed to produce habitat classification and maps of the seafloor. The bottom-up strategy involves discrete sampling or observation of environmental and biological parameters to decipher biophysical patterns and processes. These methods provide detailed information on the small area they sample but due to sampling difficulties, it is often very difficult to derive accurate representation of the broader spatial configuration of seafloor biophysical characteristics without extensive and prohibitively expensive survey designs (Brown *et al.*, 2011). The top-down strategy aggregates and cluster environmental data that are hypothesized to govern biological patterns to infer habitat distribution. These methods produce large continuous maps that can be useful for the identification of biogeographic provinces or broad physiographic features but tend to be poor predictors of species patterns. Integrative habitat mapping is a combination of both strategies and can be defined as the use of spatially continuous data sets and biological ground-thruthing to represent and predict biological patterns on the seafloor (modified from Brown *et al.*, 2011).

Integrative habitat mapping have been growing with the development of acoustic technologies providing high-resolution bathymetry and acoustic backscatter of the seafloor (Kenny *et al.*, 2003). These two features and a number of derivatives (e.g. slope, aspect, terrain variability, hardness, roughness,…) form the base map and provide the physical structure of the seabed. Acoustic remote sensing technologies and data processing are introduced in section 2. Oceanographic parameters have an equally important influence on seafloor biologic characteristics although spatial data have a much coarser resolution than geological and morphological characteristics of the seabed. Habitat mapping studies incorporating oceanographic parameters thus tend to be conducted at much broader scales. New sensors and *in situ* analytical methods are however developed, which may provide high-resolution spatial data for key physic-chemical factors of the water column. These methods are described in section 3. Biological or ground-thruthing data can be acquired through a variety of ways including cores, grabs, dredges or trawls but most development in recent years focused on imagery, particularly in the deep sea. Video or photographic surveys may allow to bridge in gap in resolution between acoustic mapping and discrete sampling of the seafloor as the methodology spans from the footprint of a single image to a mosaic of thousands of images. The ongoing developments in data acquisition and data processing of optical imagery are described in section 4.

Acoustic and optic imagery of the seafloor generates huge volumes of data that needs to be managed and visualized before they are combined to produce habitat maps. Statistical methods of increasing complexity are being developed to integrate geological, oceanographic and biological data into habitats, which will be briefly introduced in section 5.

2. Acoustic remote sensing of the seafloor

2.1 Acoustic seabed mapping technologies

Acoustic methods for bathymetry and backscatter mapping as well as imaging are able to map the seafloor at spatial resolutions from 100 m down to a few cm depending on the acoustic technologies and platforms used. The most commonly used and versatile systems are Multi-Beam Echo-Sounders (MBES) and Side Scan Sonar (SSS) (Kenny *et al.*, 2003). A number of recent publications provide extensive details on the implementation of these technologies and data processing (Blondel, 2009; Lurton, 2010; Lurton and Lamarche, 2015).

MBES produces high density geolocated depth measurements through digital processing techniques, and can be used to produce high-resolution shaded-relief topographic maps. Eco-strength data (reflectance) can also be extracted and presented as seabed backscatter maps. MBES thus provides three types of datasets: bathymetry, backscatter mosaic and backscatter angular response (Che Hasan *et al.*, 2014). Bathymetry is the data type MBES were originally designed to record. In addition, full-coverage bathymetry allows the extraction of seascape metrics that may be used to estimate variations in environmental complexity, such as slope, orientation, curvature, terrain variability (Brown *et al.*, 2011). The backscatter mosaic is a georeferenced grey-level image representing the acoustic intensity scattered by the seabed, with different seabed types usually showing different intensity levels. Since the acoustic intensity scattered by the seabed is varying with the angle of incidence of the acoustic signal at the seafloor at the time of data acquisition, a statistical normalization of this angular variation is required prior to forming the backscatter mosaic, so that the intensity variations in the image are due to geographical changes in seafloor-type only. This normalization process implies that the quantitative aspect of the intensity level is lost, so that any analysis of the resulting backscatter mosaic requires some form of qualitative interpretation or ground-truthing. Finally, the backscatter angular response is the acoustic intensity scattered by the seabed as a function of the angle of incidence of the acoustic signal at the seafloor. Since the angular response is not normalized like the backscatter mosaic, it potentially allows the extraction of quantitative seafloor characteristics. The spatial resolution however is considerably coarser compared to that achieved in the backscatter mosaic format. As a consequence, approaches based on exploiting features describing the backscatter angular response curves have remained relatively scarce to date in comparison to those exploiting the backscatter mosaic format (Brown *et al.*, 2011). However there has been a renewed interest in this type of analysis recently (Che Hasan *et al.*, 2014).

SSS has been defined as an acoustic imaging device used to provide wide-area, high-resolution pictures of the seabed (Kenny *et al.*, 2003). Modern high (dual) frequency digital SSS devices offer high-resolution images of the seabed on which objects on the order of tens of cm may be detected. A major advantage is that under optimal conditions, SSS can generate an almost photo-realistic picture of the seabed. Once several swaths have been mosaiced, geological and sedimentological features are easily recognisable and their interpretation provides a valuable qualitative insight into the dynamics of the seabed. The recently developed synthetic aperture sonars (SAS) provide even higher-resolution sonar images at greater range. This system emits more energy by generating longer-duration and wide-bandwidth pulses, with the resolution of the sonar depending on the bandwidth and not the pulse length, as is the case with traditional SSS. Additionally SSS and SAS can collect interferometric bathymetry, providing co-collected acoustic reflectivity image and bathymetric depths.

2.2 Data acquisition

MBES can be deployed from either a vessel, an ROV or an AUV. The choice will be guided by the area to be mapped and the resolution to be achieved. Table 1 provides an example of two scenario of seafloor mapping from a vessel at 2000 m depth and an AUV at 50 m altitude. A ship survey is commonly run at a speed of 10 knots and would allow mapping about 100 km² per hour while the AUV survey carried out at 3 knots would allow mapping less than 1 km² per hour. The maximum resolution that can be achieved is given by the footprint of the centre beam and ranges from 35 to 70 m for a ship survey and 1 to 2 m for an AUV survey.

Table 1 - Example of areas mapped and resolution achieved according the MBES specifications for a ship survey at 2000 m depth and an AUV survey at 50m altitude.

Settings	**2000m to seafloor**	**50m to seafloor**
beam angle 2x2 deg, 120deg swath angle		
footprint centre beam (m)	69.8	1.75
footprint outer most beam (m)	279.5	6.99
max slant range (m)	4000	100
total swath width at flat seafloor (m)	6928	173
beam angle 1x1 deg, 120deg swath angle		
footprint centre beam (m)	34.9	0.87
footprint outer most beam (m)	139.6	3.49
max slant range (m)	4000	100
total swath width at flat seafloor (m)	6928	173
Distance between pings (single ping MBES)		
at 3kn (m)	9.05	0.23
at 10kn (m)	30.2	0.75
Area covered per h		
at 3kn (km^2) with 20% overlap (=80% of swath width)	30.79	0.77
at 10kn (km^2) with 20% overlap (=80% of swath width)	102.65	2.56

Contrary to MBES, SSS or SAS need to be close to the seafloor at an altitude usually not exceeding 50-100 m and thus deployed from either a towed system, ROV or an AUV. SSS and SAS are however best deployed from AUV assets given the stability of the platform and potentially large areal coverage. Moreover AUV surveys can be significantly improved by active and adaptive dive planning. New algorithms are being developed that allows the AUV to adapt its route in real time according to the environmental characteristics observed in the data itself (Hollinger *et al.*, 2013; Williams, 2012). At 50 m altitude, a SSS typically allows mapping an area of 3.5 km² per hour at maximum resolution of 0.5 to 1 m. The SAS can achieve a coverage of 1 km² per hour without a gap-filling multibeam and just over 2 km² per hour with a gap-filling multibeam. The sonar image produced has a theoretical resolution of 3x3 cm (4x4 cm practical limit) and bathymetric resolution of 9x9 cm. When using the gap-filling sonar, the sonar image will be in non-overlapping strips, but the bathymetry product will be consistent across the entire area (full swath width of ~500 m at a vehicle height of 30-50 m).

2.3 Data processing

2.3.1 Backscatter analysis approaches

The acoustic backscatter signal from SSS, and now increasingly from MBES, is used by geologists to segment the seafloor into geological classes (i.e. surficial sediment types), and a close association is reported between acoustic backscatter strength and geotechnical properties of the seafloor. Using the mosaicked imagery, segmentation of the backscatter data has conventionally been done by expert interpretation, whereby the imagery is divided into regions of similar texture or backscatter strength "by eye". More recently, automated methods of segmenting backscatter data have been explored, driven largely by the advantages of using objective classification algorithms applied to the backscatter data, thus eliminating the subjectivity of the expert segmentation process.

Automated segmentation methods can be broadly divided into two types; 1) image-based segmentation based on the division of a backscatter image into regions of similar backscatter characteristics (e.g. surface features, backscatter intensity, textural features etc.); 2) Signal-based segmentation where changes in the backscatter intensity with increasing grazing angle from nadir are analyzed to classify the data in some way. Several image-based segmentation approaches have been utilized for SSS data in the context of benthic habitat studies, for example; segmentation methods using textural analysis based on grey level co-occurrence matrices (Cochrane and Lafferty, 2002; Huvenne *et al.*, 2002); unsupervised classification techniques using combinations of backscatter (Allen *et al.*, 2005; Brown and Collier, 2008; Lucieer, 2007); supervised classification techniques linking habitat characteristics from ground-truth stations to distinctive acoustic signatures (Allen *et al.*, 2005); and segmentation methods using principal components analysis of multiple backscatter image-based attributes. In the context of seafloor habitat mapping, segmentation approaches for MBES backscatter data are broadly analogous to segmentation methods for SSS although signal-based methods have also been used to extract quantitative information from the returning MBES backscatter signal (Fonseca *et al.*, 2009; Lamarche *et al.*, 2011). The variation of the backscatter strength with the angle of incidence is an intrinsic property of the seafloor, which can be used as a robust method for acoustic seafloor characterization. Although multi-beam sonars acquire backscatter over a wide range of incidence angles, the angular information is lost during standard backscatter processing and mosaicking. Signal-based classification works by extracting several parameters from stacks of consecutive sonar pings. The average angular response is then compared to formal mathematical models that link acoustic backscatter observations to seafloor properties. The inversion of the model can be used to produce estimates of various seafloor geotechnical properties, which can be used to predict the substratum properties of the seabed (Fonseca *et al.*, 2009; Lamarche *et al.*, 2011). This general approach shows a great deal of promise for seafloor habitat mapping applications.

2.3.2 Bathymetric analysis approaches

Benthic species show preferences for certain depths and topographic conditions, and therefore bathymetry can be used to segment an area into regions which reflect distinctive biological characteristics. This type of segmentation is often referred to as "morphometric analysis", and has been used to map benthic habitats from a range of marine systems including deeper water environments (Buhl-Mortensen *et al.*, 2009; J *et al.*, 2009; Wilson *et al.*, 2007). Within these studies, a number of secondary-derived bathymetric layers have been used to help segment the seafloor into biologically-relevant units (e.g. slope, orientation, curvature and terrain variability). A number of these bathymetric parameters (e.g. terrain variability) can be calculated in different ways and at different spatial scales, which have important implications for what the map layers show and how they relate to the distribution of the benthic organisms (DC and PN, 2009). As GIS tools are developed for this type of analysis we are starting to witness an exploration of the different methods to relate bathymetric data for benthic habitat characterization. Recent studies have also started to explore ways to objectively combine both backscatter and bathymetry segmented data layers for habitat mapping, with some promising outcomes (Rattray *et al.*, 2009).

3. Physico-chemical imaging of the water column

Benthic ecosystems are not only influenced by the geomorphology and sedimentology of the seafloor, but are strongly affected by the overlying water column conditions. The exploitation of deep-sea resources is also expected to potentially affect the physico-chemical properties of the water column through the release of particle plumes (mineral mining) or gas (hydrate exploitation). Oceanographic parameters used to predict the distribution of benthic habitats are usually gathered from large data bases or models at a much coarser resolution than seafloor parameters measurable using acoustic methods (Brown *et al.*, 2011). However, with the development of *in situ* sensors on AUVs and ROVs, physico-chemical mapping at high resolution is increasingly used (Hofmann *et al.*, 2013; Prien, 2007).

As for seafloor mapping, acoustic technics are now used for imaging the water column. Acoustic returns from the water column have been used to locate and map cold seeps (Schneider von Deimling *et al.*, 2007) and hydrothermal vents (Kumagai *et al.*, 2010) using MBES and SSS, respectively.

Hydrographic surveys can be carried out using and Acoustic Doppler current profilers (ADCP) and Conductivity Temperature Depth probes (CTD). ADCP and CTD are standard component on AUVs and ROVs, though the ADCP is configured as a Doppler velocity log (DVL) to form part of the navigation system. The ADCP and its mandatory CTD have been successfully used to measure fields of ocean currents (Odegaard, 2004; Stansfield *et al.*, 2001) and, in the context of habitat mapping, to characterize bottom currents over cold-water coral mounds (Correa *et al.*, 2012) or to investigate hydrothermal plumes(Thomson *et al.*, 1989).

Beyond conductivity, temperature and depth, the development of physical- and chemical-based sensors now allows to also routinely measure oxygen, pH, carbon dioxide, turbidity, chlorophyll a, rhodamine, ammonia and nitrate *in situ* (Mills and Fones, 2012).

In recent years, another approach to achieving in situ measurements has been the miniaturisation of existing analytical methods, such as colorimetric and spectroscopic methods. Colorimetric methods rely on flow-injection analysis (FIA). A number of systems have been developed to measure nutrients (e.g. nitrate, phosphate, silicate), metals (iron, copper, manganese) or dissolved gas (hydrogen sulfide, methane). Spectroscopic- and spectrometric-based in situ devices have also been developed for use in marine applications for measuring dissolved gases, nutrients, organic chemicals and trace metals. A range of optical detectors can be used and include: absorbance, reflectance, luminescence, fluorescence, refractive index and light scattering (Prien, 2007).

The last developments in *in situ* characterization of water column parameters involve the use of biosensors (Farré *et al.*, 2009). Biosensors are devices that integrate a biological recognition element with a transducer that converts changes associated with an interaction between the receptor and the target compound into an output signal that can be measured quantitatively. A fluorescence-based fibre optic biosensor has for example been developed for determining *in situ* real-time concentrations of trace metals (copper and zinc) in sea water (Zeng *et al.*, 2003).

In most cases physic-chemical *in situ* measurements remain discrete. Interpolation or modeling needs to be developed to integrate physic-chemical measurements with either or both acoustic and optical imagery at relevant spatial scales. A main application for in-situ measurements to date have been plume detection of for example, hydrothermal vents (Box 1).

Box 1 - Combination of optical seafloor surveys with auxiliary Sensors for hydrothermal plume detection

Physicochemical measurements are needed to understand deep-sea environments and processes. However, to fully characterize habitat characteristics and their spatial variability it is essential to precisely locate and visualize the distribution of these properties and to combine them with visual information. Physicochemical monitoring and imaging with the Ocean Floor Observation system (OFOS) was used for the exploration of the Southwest Indian Ridge in 2013 (cruise PS81 of the German Research Icebreaker POLARSTERN) and the search for the Aurora vents on the Gakkel Ridge in the following year (cruise PS86). In standard configuration the OFOS system of the Alfred Wegener Institute in Bremerhaven, Germany (AWI) hosts equipment for imaging (HD video and Megapixel still camera, floodlights, flashlights, and point lasers for image scaling) and precise navigation (Posidonia pinger, altimeter). Transfer of power and data takes place via a hybrid optical/electrical cable connecting the system to the ship (see Meyer *et al.*, 2013) for a more detailed description). Ethernet communication further allows to transmit data from auxiliary sensors that are added to the system. For the investigations of the high latitude ridge systems during PS81 and 86, OFOS was used in combination with a set of fast-response micro-sensors (De Beer *et al.*, 2006). During the deployments the micro-sensors monitored water column properties such as temperature, redox potential, pH, as well as concentrations of hydrogen sulfide and oxygen in real-time. Online access to micro-sensor data allowed for fast decision making, giving OFOS operators the opportunity to react upon sudden variations in the parameters, e.g., by change in the direction of the survey. This proved especially beneficial when hunting for hydrothermal vent sites, where large gradients are expected over small distances within the hydrothermal plume. Furthermore, by merging the physic-chemical data with the acoustic navigation data of the OFOS, it is possible to visualize the along-track distribution of the different parameters (Figure 1 and Schlindwein, 2014). This information may then be combined with additional data obtained by the OFOS itself or by other instruments (e.g., visual observations in the water column or at the seafloor, bathymetries, subsurface heat flow measurements, CTD data, etc.). The resulting multidisciplinary and georeferenced data sets provide the holistic view on marine habitats that is needed to characterize different habitats and their spatial coverage and to predict the distribution of marine organisms.

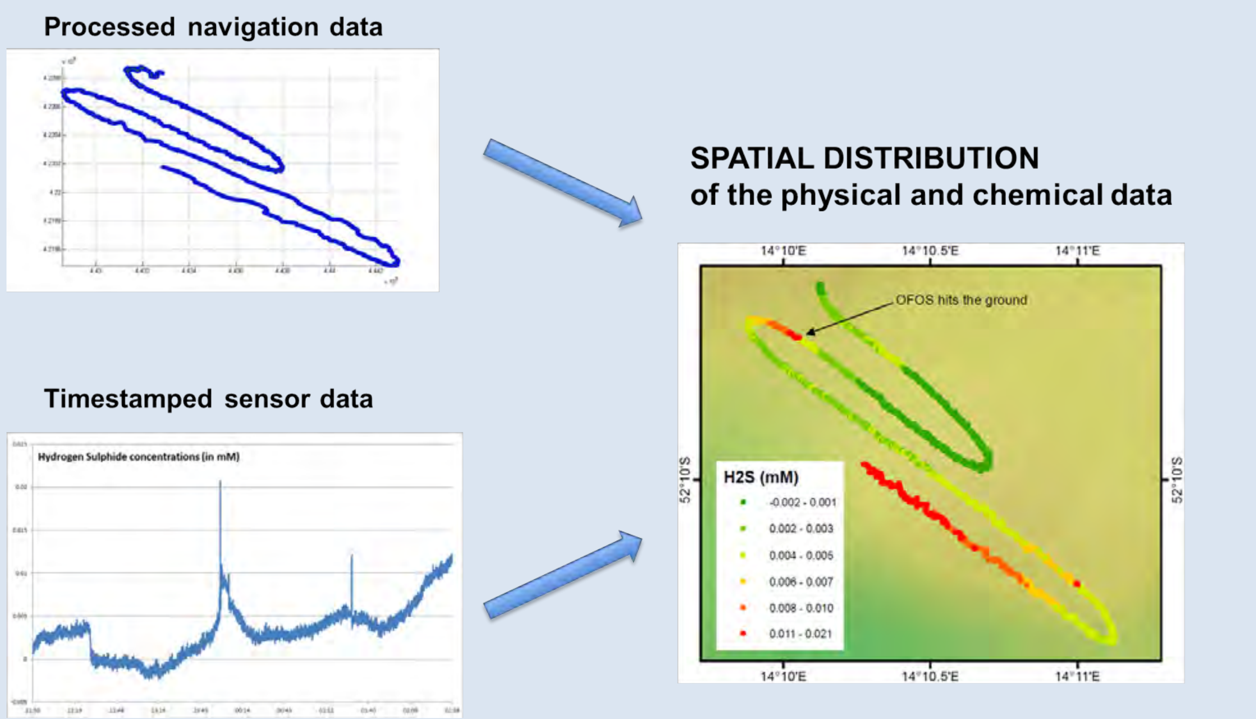

Figure 1 - Combination of the acoustic underwater navigation with data from the micro-sensors to image the spatial variations of the hydrogen sulfide concentrations in the bottom water at the Southwest Indian Ridge during cruise PS81 with the Research Icebreaker POLARSTERN (see also Schlindwein, 2014)

4. Optical imaging of the seafloor

4.1 Data acquisition

Optical images are an essential source of information for the analysis of the deep underwater environment which is not accessible for human intervention. Biodiversity, habitat mapping, description of ecosystems, related impacts and geophysical investigation are the major topics in this area.

The production of optical data requires specific sensor modules, integrated on remote or autonomous underwater vehicles (ROV and AUV) or towed systems. These modules or payloads consist of high sensitivity video or still cameras although a recent approach to imaging the seafloor optically is by utilizing lasers (Box 2). The camera is integrated into pressure resistant housing provided with glass portholes with optical quality handling the change of optical index. The imagery payloads also require lighting devices with HMI, Quartz-Ion, or LED sources that compose the appropriate color spectrum and homogeneous field of lighting.

The choice of the platform for optical imaging will depend on the objective of the survey, the ecosystem targeted as well as the size of the ship and berth availability. A towed camera is the lighter system, requiring a small ship and a limited number of operators (usually 3 for 24h/day operation). Underwater positioning however is not as accurate as with ROV/AUV and continuous image or video mosaicking over large area is not possible. Most AUVs do not require large ship either and usually 4 operators but they must sail at a safe distance to the seafloor, from 8 to 10 m, and at a minimum speed of about 3 knots. At these distances and speed, only the largest megafauna can be recognized on images. An ROV such as Victor 6000 or Kiel 6000 is less versatile than the other systems; it requires a larger ship and usually 8 to 9 operators. Although an ROV can be used for larger scale surveys, just as an AUV, it is best suited for detailed surveys, at a speed of 0.3 m/s and an altitude of 1 to 3 m. Table 2 provides example of the resolution and mapped area that can be achieved with various platforms. An AUV such as Abyss is able to map a large area at the expanse of image resolution as it provides less than 3 pixels to image the smaller range size of the megafauna.

Table 2 - Examples of image resolution, image size and area mapped with various platforms for optical imagery surveys.

Platform	Pixel/cm	m²/image	m²/hour
Towed camera (e.g. OFOS)	17.5	3	470
AUV, 20 m wide image (e.g. ABYSS)	2.4	222	795000
AUV, 2 m wide image (e.g. AutoSub)	16.3	2.25	11112
ROV, 2 m wide	_	_	5010

The quality of the optical images in the seawater medium is limited. Indeed, image quality is not only a function of the technical aspects like sensor and lighting performances as well as the geometry of installation of devices on the vehicle. The major limitation lies in the optical properties of the underwater environment, which do not allow capture of quality color images at more than a few meters of range.

Encountering disturbances such as attenuation, backscattering, marine snow, inhomogeneous illumination, underwater optical imaging possesses at present limited performances for a quantitative scientific exploitation. Such exploitation includes among others, images mosaicking.

Box 2 – Application of lasers in optical imaging approaches

A recent approach to imaging the seafloor optically is by utilizing lasers, as near monochromatic lights sources with good depth of penetration, and in combination with laser receptors for computing distances to surface features.

Lasers have been used in marine optical imaging for a number of years as calibration systems for collected data: commonly a pair, trio or quad of lasers are mounted on a vehicle, with the parallel laser beams showing up on a surface as a set of points. The spacing of the mounted lasers is known and therefore the collected image can be sized. The narrow beam and high penetration in seawater of the focused laser light has been a primary drive in their use.

Laser based imaging systems are based around the principle of firing very narrow, distinct wavelengths of light and recording the returning pulses. Several designs are possible, all of which offer imaging over greater distances than is possible with reasonably powered traditional light sources, and at higher resolution. This narrow, penetrating beam has a drawback in use however, with only a point of surface (or seafloor, marine feature) imaged by the system at a time. Because of this the laser imaging system must physically alter its orientation to collect information adjacent to the point of initial imaging: A scanning laser imaging system is required.

Laser Range-Gating (LRG) systems scan the region around a vehicle (or seafloor installation) in a 'pan and tilt' fashion with a laser utilizing a specific frequency. By timing the laser pulses and using a 'time gating' ICCD system to collect the returning pulses and filter out scatter, a 3D image of the surrounding area is produced. Such a system is mounted on the latest iteration of the Jacobs University Bremen / ROBEX deep sea crawler 'Wally II' (Schwendner *et al.*, submitted), and will be deployed to image a methane seep site this autumn in Pacific Canada.

Laser Line Scan (LLS) systems operate in a similar way to the LRG systems, are applicable for vehicle mounting only and collect a linear swathe of data perpendicularly to the movement of a vehicle. As the vehicle moves within the water column, the region below is imaged by collecting the swathes of laser point returns, with these later (or potentially in real-time) being plotted to produce a mapped surface. Figure 2 shows a seafloor microtopography obtained by a custom built laser scanning approach at sub-mm accuracy to assess bioturbation activity in the Black Sea as a function of environmental stressors, in this case bottom water oxygenation (Lichtschlag et al., submitted). A description of the laser scanning approach is found in (Cook *et al.*, 2007).

Further details of the operation, strengths and weaknesses of laser based systems for optical imaging are given in Bonin *et al.* (2011).

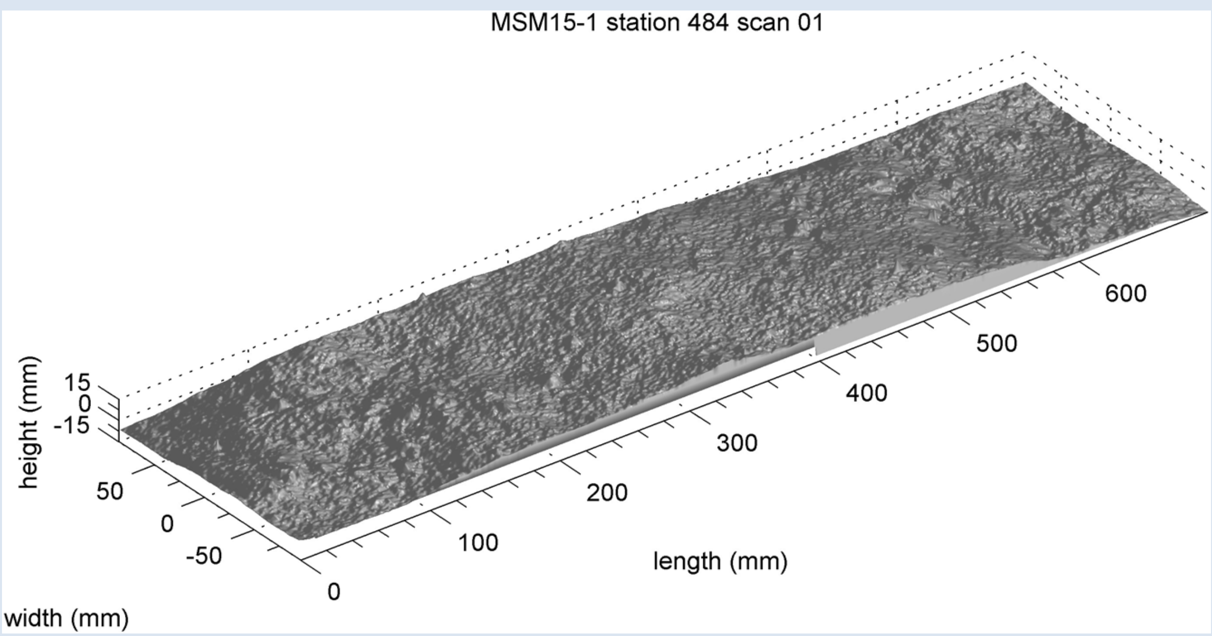

Figure 2 - Shaded 3D surface of a Laser Line Scanning-based micro-topography measurement obtained at 104 m water depth at the Black Sea Crimean Shelf.

4.2 Data processing

4.2.1 Image pre-processing

The first problem that arises when optical measurements are done in deep water comes from the illumination. Light is highly attenuated in water, so that sunlight intensity is low at only a few tens of meters deep. Moreover this attenuation depends on the considered wavelength and beyond 5 meters from the lighting source the scene contains essentially blue tones. Artificial lighting sources are thus needed for optical seafloor surveys.

However, with artificial light, a uniform illumination of the scene is hard to obtain. This image presents strong variations of intensity due to the non-uniform illumination (Figure 3). Before any processing, it is highly recommended to correct this effect in order to improve all further steps applied for mosaicking.

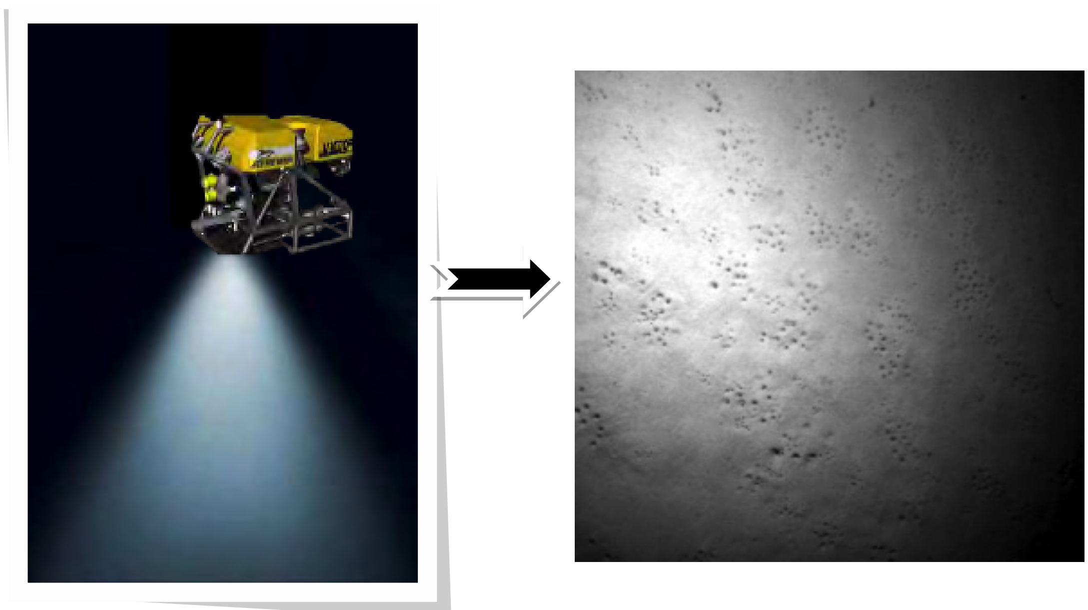

Figure 3 : Consequences of the use of a non-uniform illumination for optical seafloor survey. The image on the right has been acquired by Ifremer's ROV (Victor 6000).

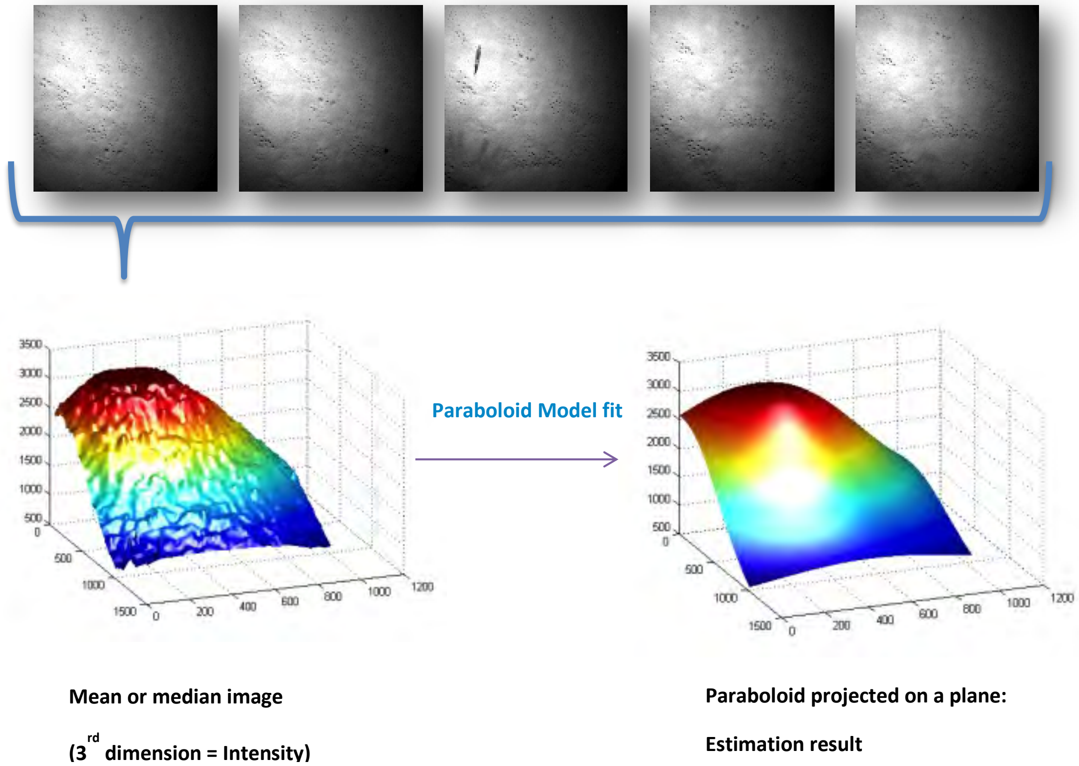

Figure 4 - The top of the Figure illustrate the sliding mean or median used to keep only the illumination pattern. The estimated pattern, at the bottom left is quite noisy due to remaining seafloor information. The next step is the model fit to reduce this noise.

Correction method is based on the idea that successive images are acquired in quite the same illumination conditions and hence only information from the seafloor is changing along the different acquisitions. To remove information from the seafloor and only keep the illumination pattern, a sliding mean or median is applied. This process as illustrated on the Figure 4 produces a noisy. The “noise” corresponds to the fact that some information from the seafloor is remaining. Most of the algorithms from the literature use this noisy pattern to restore images as if they were uniformly illuminated. Pattern estimation can however be improved by using a fit to a model in order to reduce noise influence. Finally, the image is corrected using the estimated illumination pattern as presented on the Figure 5. As it can be seen on this Figure, this methodology removed almost completely the intensity variations and helped to preserve and enhance all details. This procedure is now considered as a systematic pre-processing and is applied before any mosaicking technique.

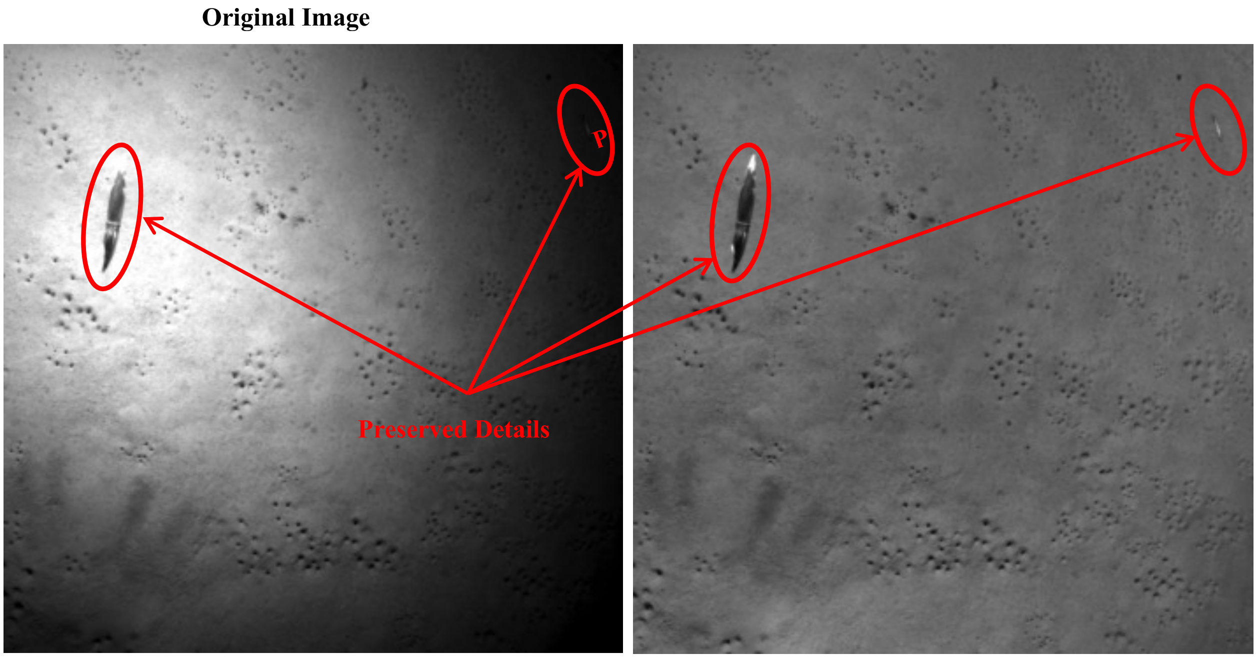

Figure 5 - This Figure illustrates the results obtained using illumination pattern removal process. High resolution details are preserved and enhanced.

4.2.2 Mosaicking techniques

Due to the high attenuation of light in water, the maximum altitude that can be used in an optical survey is limited to a few meters and the footprint on the seafloor can be quite small. A larger view of the sea-floor scene is only possible with the construction of a mosaic of multiple images.

The exploitation of each survey hence relies on the good puzzling of optical data, what mosaicking is supposed to do. Every mosaicking technique uses the redundancy in the successive images or within a video flux to put all pieces together and build the global view.

Geo-referencing is a mandatory requirement and hence the navigation data have to be merged to the map in order to make a real cartography.

Features detection and matching

The first mosaicking step consists in features detection. This detection has to be accurate and selective enough, so that different features cannot be confused and so that corresponding ones can be matched. The most widely used is the SIFT (Scale Invariant feature transform) algorithm, justified by its strong robustness and accuracy. The algorithm has been implemented on GPU (Graphical processing unit) parallel architecture for fast processing. With this software architecture and a modern GPU, a 10 Megapixels image can be processed in less than a second. An example of SIFT features detection is given in Figure 6 for two successive images. One can note that features have been detected in high contrast areas which consist here in holes made by prawns.

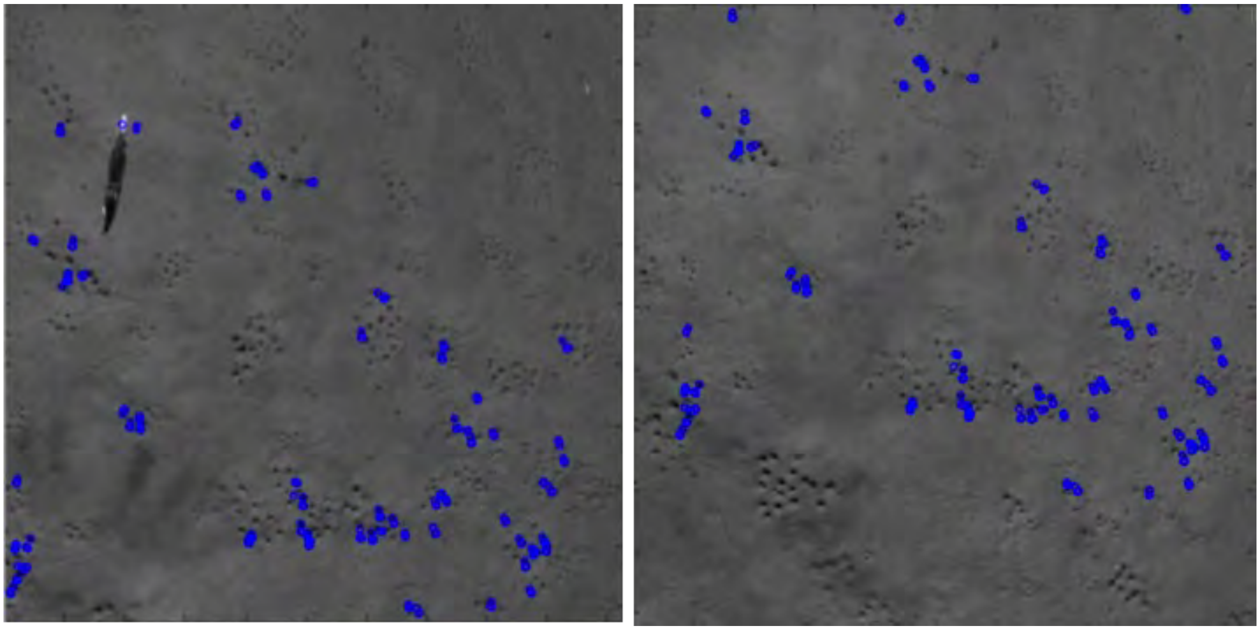

Figure 6 - This Figure presents the results of the features detection using the SIFT algorithm on two successive images. The blue circles indicate the location of the SIFT features

Once the detection is done, corresponding features of the different images have to be matched. A pre-match is done with the method proposed by the SIFT algorithm. However, the presence of false matches (outliers) cannot be avoided at this stage of the algorithm, where only individual points have been paired using a local image subset. The global consistency of the complete set of matched points (bundle adjustment) is improved in the next step by removing outliers. This is accomplished with the RANSAC (RANdom SAmple Consensus) robust estimation method. The result is illustrated in Figure 7.

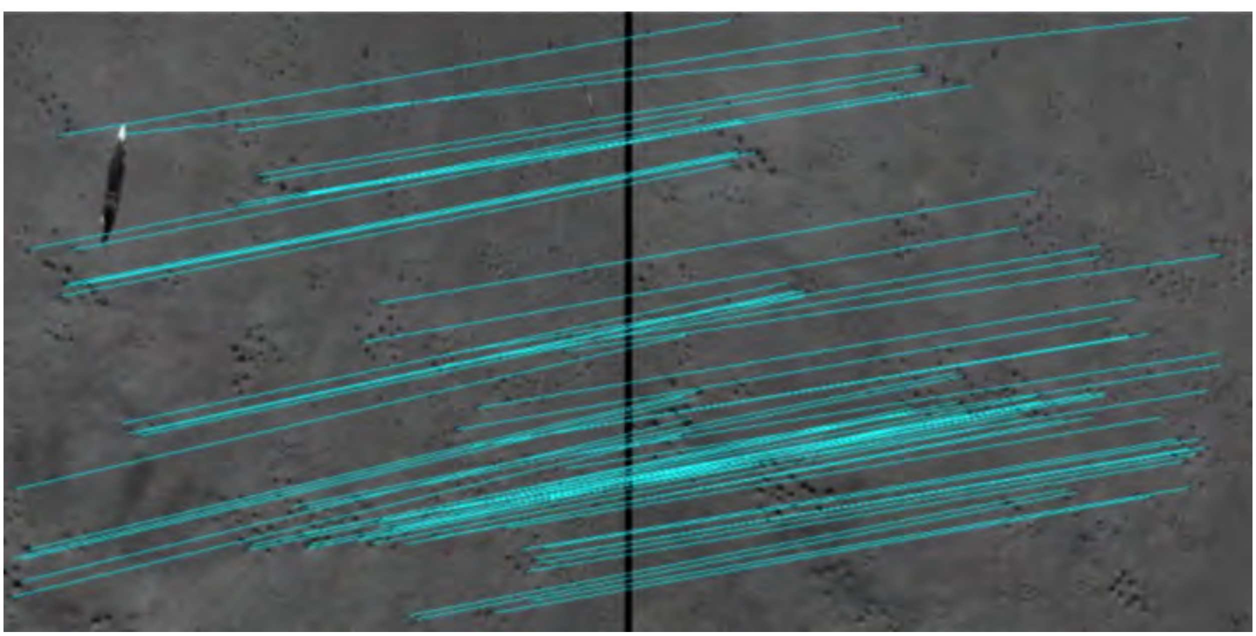

Figure 7 - Matching result for two successive images. The blue line link the corresponding features together. One can see that in this case the movement between the two images is essentially a translation.

Transformation in the mosaicking plane and optimization

Each acquired image has its own geometry and the final mosaicking step consist in warping each image into the mosaicking plane geometry. A first solution can be given by the RANSAC method, which in the same time, removes outliers and also estimates a transformation between the two images. The Homography model offers the most complete transformation that can be found between two planes and hence the higher number of degrees of freedom in the case of 2D mosaicking assumption. The result obtained using this approach is illustrated on two images in Figure 8 with and without illumination compensation.

With acquired images **With corrected images**

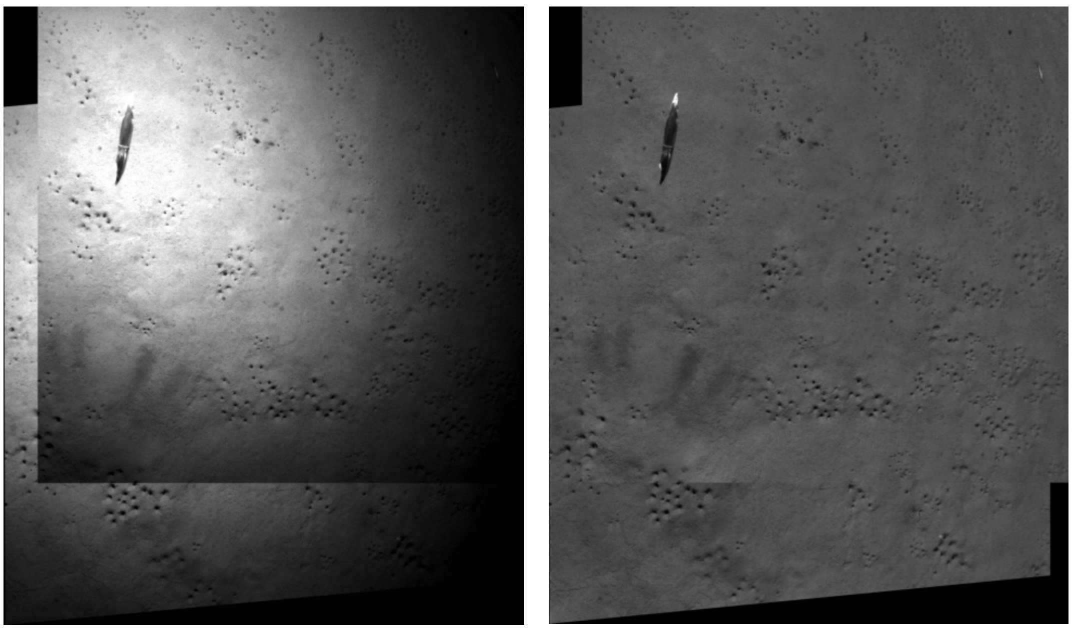

Figure 8 - On the left the mosaicking of two images is done without illumination correction while on the right this effect is corrected. One can see a good enhancement even without any blending technique.

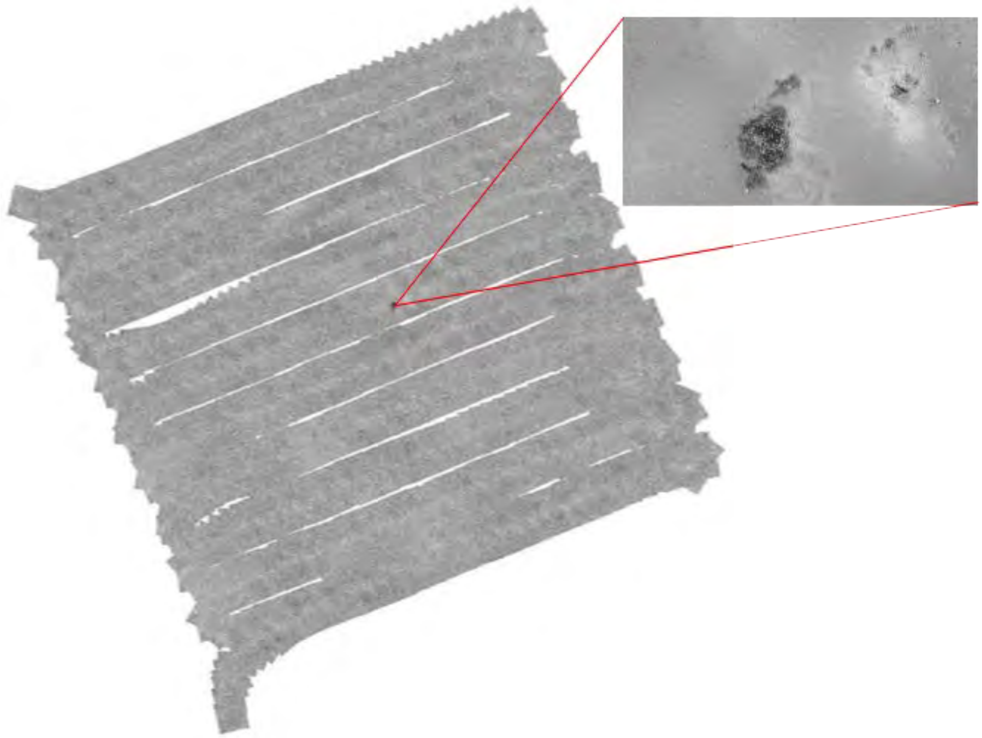

Figure 9 - A 100x100m mosaic, acquired by Victor 6000 ROV. This mosaic benefits from the illumination correction, exposure compensation and blending methods.

The illumination compensation improves image registration and reduces the need for a more 'cosmetic' post-mosaïck blending technique. If this simple approach was extended to recursive pairwise processing of a big number of images, a drift of the image trajectory would appear in the mosaic. To avoid this issue, a further step is added, which optimizes a global consistency of the set of image positions with the trajectory (vehicle navigation and orientation). This allows precise geo-referencing and scaling of the mosaic at image level, moving from mere image mosaicking to visual mapping or cartography. The final mosaic file is a standard GeoTiff image which can be imported in any GIS software for measurements (Figure 9)

Post-processing mosaicking

The previously presented algorithms have been first applied to a post-processing mosaicking approach, for which the processing time is not the major constraint. Post-processing also allows taking into account a complete data set (images and vehicle navigation) for given period of time. The mosaicking algorithm benefits from the global optimization step, which enable to merge mosaic and navigation data to obtain a precisely geo-referenced mosaic. The global optimization approach can only be applied once the complete data set is available. Even if this is not a real-time approach, the processing time is sufficiently short to use it to create mosaics in less than an hour in the work-flow of an ROV dive.

Real time mosaicking

The performance gain brought by the GPU implementation enabled to envisage real time mosaicking with state-of-the-art algorithms. Real-time mosaicking has already been explored at IFREMER with the MATISSE software operating with RMR (Robust Multi-Resolution) method. The RMR algorithms main drawback is that it needs a very high overlap between two successive images, reserving its use to video flux with a high sampling rate (~5Hz). This constraint has been removed with state-of-the-art SIFT algorithm on GPU architecture. This algorithm is able to mosaic still photo sequences or HD video sources with lower frequency sampling in real-time. The overlapping area is only 30%, which enables the vehicle to move at (relatively) higher speed and reduce the survey time. The implementation uses the same libraries as the post-processing approach, except that no global optimization is accomplished. Every mosaic 'tile' is thus geo-referenced at its reference starting point.

4.2.3 3D Reconstruction

Using the same optical images and videos as for the 2D mosaicking techniques, the feasibility of 3D reconstruction has been evaluated. This topic has been extensively studied in the absence of the water medium and many techniques exist in the literature. The technique evaluated at Ifremer belongs to "structure from motion" techniques, which, based on multi-view geometry and images matching, reconstruct the 3D points of the scene and the positions of the camera during the acquisition up to a given scale factor. This section presents some of the results obtained using this type of technique for underwater scene reconstruction.

Sparse 3D reconstruction

The first step for 3D reconstruction consists in the estimation of the camera positions corresponding to each image relative to the first camera and up to a given scaling factor. During this step only a few number of 3D points are estimated which is why this step is called "sparse" reconstruction. A high overlapping is needed between the successive images (more than 50%). The algorithm benefits from the multiple views of the same scene for the reconstruction and hence the best acquisition scenario is the one presented on the Figure 10 which consists in rotating around the scene to be reconstructed. This scenario is often not possible in underwater mapping for which the scene is only seen from the top as on Figure 11.

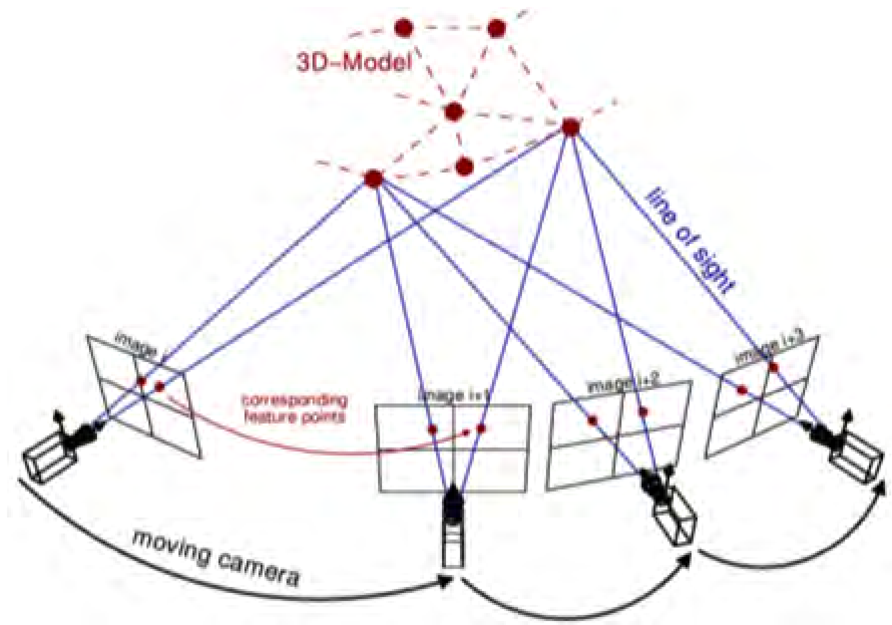

Figure10 - Acquisition scenario for 3D reconstruction. In this scenario, the camera rotates all around the scene which facilitates the reconstruction as each part of the scene is seen through numerous different angles.

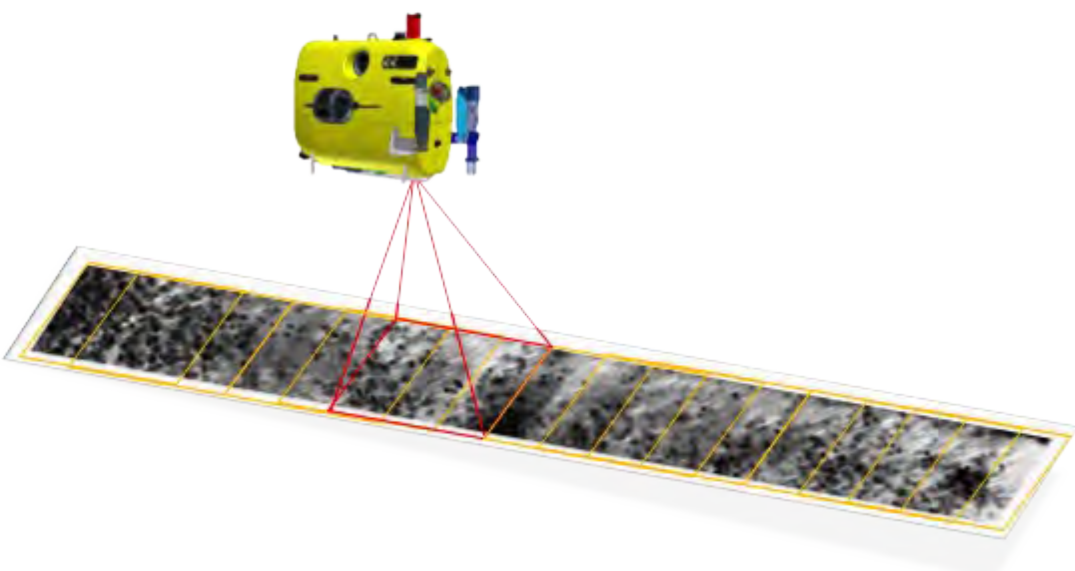

Figure 11 - The most common scenario for underwater optical survey is the one presented above, where scene is seen from the top. In this scenario the acquisition angle is almost constant and only the camera baseline is changing.

As for 2D mosaicking, the sparse reconstruction is based on the sift detection and matching. Then using the robust RANSAC method, the matrix F that links the overlapping camera (called the fundamental matrix) is estimated. This is done for a first couple of overlapping cameras, and then an initial position of the two cameras is obtained from the decomposition of the F matrix. Once the positions are retrieved, it is possible to triangulate the 2D images points to obtain a first cloud of sparse 3D points.

Finally, an optical distortion model is added to account for image deformations due to the camera lens (critical issue for 3D reconstruction) and all parameters are globally. The cost function used for the optimization account for the error between the reprojection of the 3D cloud of points to the planes of the two cameras and the measured position of those points. A third camera is added to the reconstruction and all steps are iterated. The reconstruction ends when all cameras have been added to the model and hence all possible points have been reconstructed. The complete description and bibliography can be found in the Ph.D dissertation of Noah Snavely.

This reconstruction can lead to some aberrant points and hence some filtering operations that won't be detailed here are needed. A sparse reconstruction example is presented in Figure 12 with real underwater images acquired by OTUS camera from the Victor 6000 ROV.

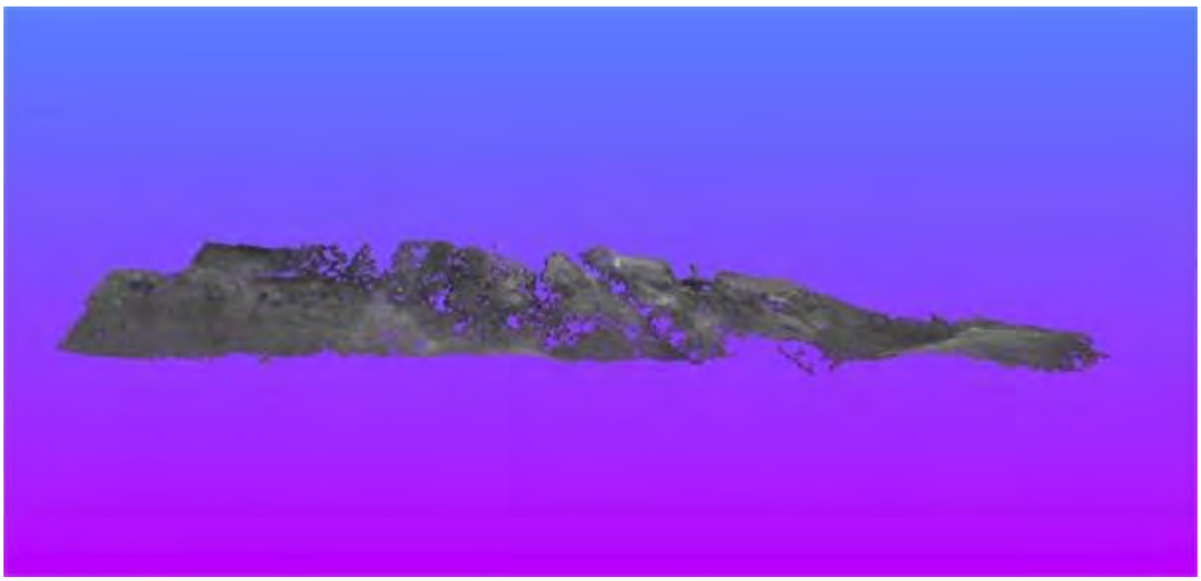

Figure 12 - Sparse reconstruction of 3D points and cameras.

Dense 3D reconstruction

The reconstruction presented in the previous section only generate 3D points were sift features have been detected. This means that for low contrast images the 3D cloud will not be dense as the sift is based on intensity gradient and hence no contrast means no features. To overcome this problem, the dense matching method can be used. This method supposes that a few features points have been detected (using Harris corners or Sift) and that the position of the cameras are known (this has been estimated using the sparse reconstruction method). Then 3D features are locally approximated by plane patches and hence are characterized by a center and a normal. The center corresponds to the 3D localization of the point. The matching is done using criteria based on correlation and enables to increase the number of points to be matched. That's the reason why this method is called "dense". At the end of this step the 3D cloud is dense and each point is affected a normal perpendicular to the surface passing through those points. An application to 3D sparse technique for seafloor reconstruction is illustrated in Box 3.

Box 3 - Application of sparse 3D technique for seafloor reconstruction and change detection in a methane pockmark area

"Sparse" reconstruction of regions of seafloor can be particularly effective in regions of high physical heterogeneity and when it is possible to collect image data from a series of stable viewpoints. During the last three years a deep sea crawler developed and deployed by Jacobs University Bremen (Bremen, Germany; Figure 13) has imaged a methane pockmark of approx. 10m diameter that is situated at ~890m depth in the Barkley Canyon, Pacific Canada.

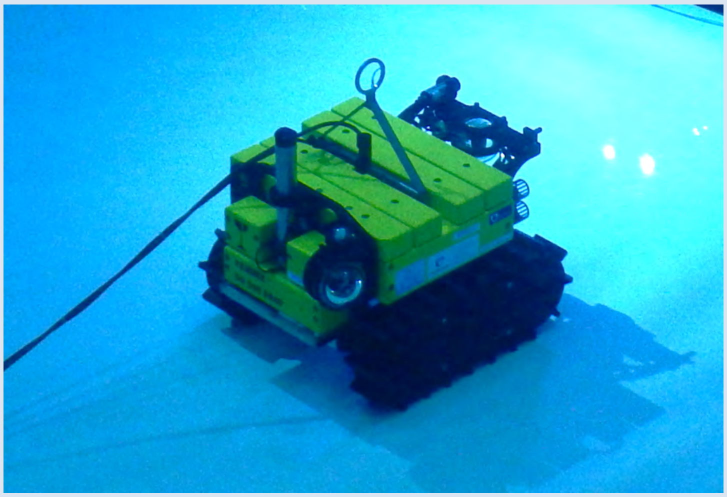

Figure 13 - Jacobs University Bremen deep sea crawler. Side-mounted cameras are visible on the rear of the vehicle.

The crawler has been mounted with two camera systems, one on the front of the vehicle for navigation, seafloor inspection etc. and one on the side of the camera, capable of filming or taking still images in HD perpendicular to the direction of vehicle movement. This camera has been used to capture images of the methane pockmark using the method illustrated in Figure 11. An overlap of ~80% was maintained between images of the image set. These images were then used to produce 3D models of the seep pockmark (Figure 14).

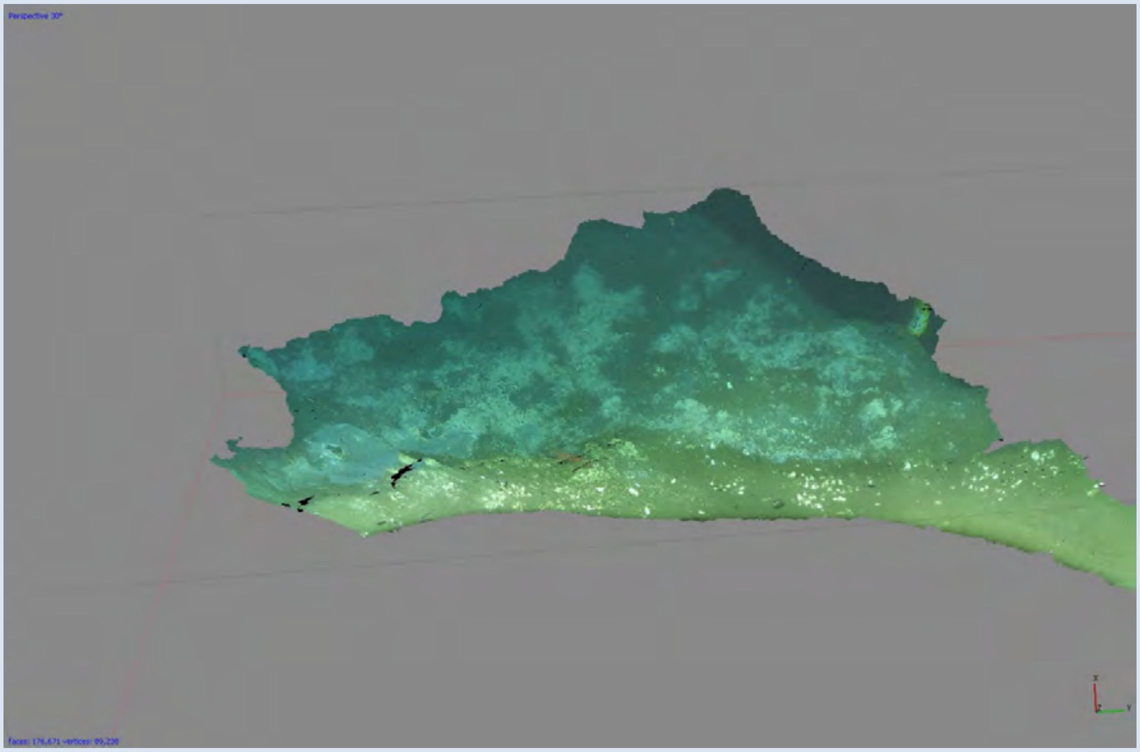

Figure 14 - One flank of the Barkley Canyon pockmark, as rendered into 3D via 'Sparse 3D reconstruction'

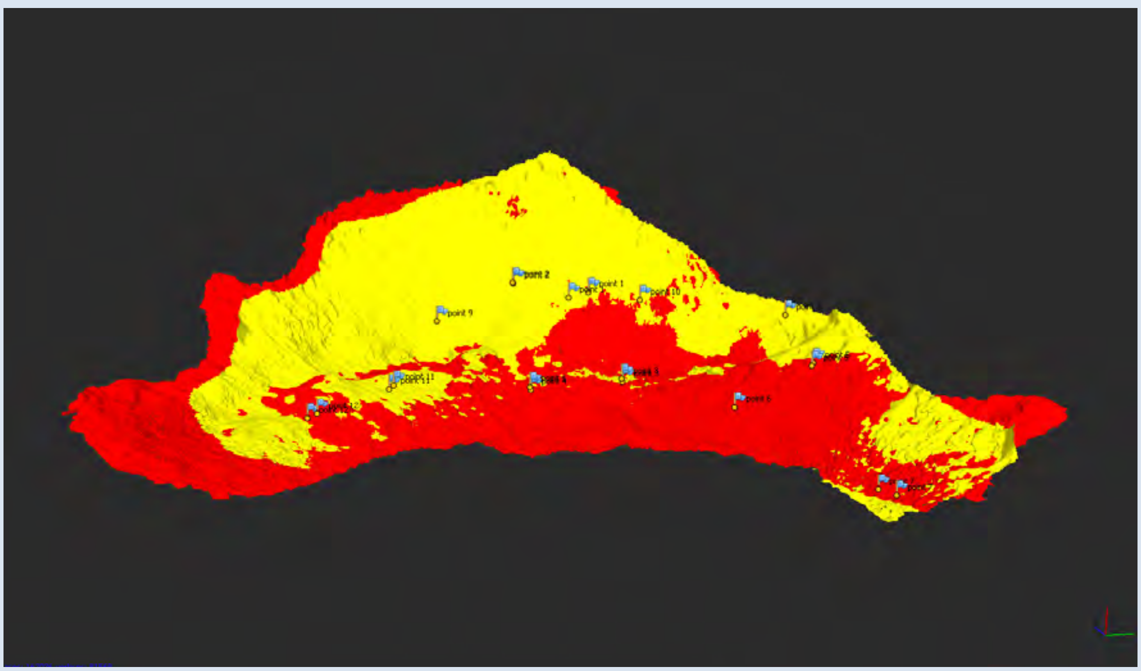

Figure 15 - Temporal evolution in methane pockmark form. Comparison of two 'Sparse 3D reconstructions' made from image sets collected 6 months apart. Clear indicator points visible in both sets of images (such as carbonate outcrops) were fixed in the two image sets. Yellow indicates areas of the mound uplifted during the 6 month period, red indicates areas of slumping

By repeatedly recording HD images with the same camera parameters (e.g., illumination, focal length) it is possible to detect temporal changes in pockmark structure. In Figure 15 regions of the pockmark which have been subjected to uplift are indicated in yellow, while areas of slumping shown in red. Such 3D monitoring can be used to detect natural changes in a range of seafloor regions, such as the rapidly changing mid-oceanic ridge regions and other seismically active areas. In the context of marine resource exploitation the same methods may be used to detect subtle changes in seafloor habitat structure that may happen as a consequence of mining activities (e.g., gas hydrate extraction)

3D Reconstruction scaling and georeferencing

Following sparse 3D reconstruction, the cameras position and the dense cloud of points have been estimated up to a given scale and with a position and orientation relative to the first camera. In order to geo-reference those data and make measurements, the absolute position and scale have to be estimated. In the underwater environment, the vehicle which makes the acquisitions is most of the time equipped with a navigation system. Consequently, the position of the camera has been measure for each image. This position is also estimated up to a given scale using the structure from motion 3D reconstruction. Therefore, the scale factor, the absolute position and rotation can be estimated by fitting the structure from motion cameras position to the ones measured by the navigation system in a least square sense. The camera position and 3D points are then transformed according to the estimated transformation. After this step, the 3D reconstruction is metric and georeferenced, as illustrated by Figure 16.

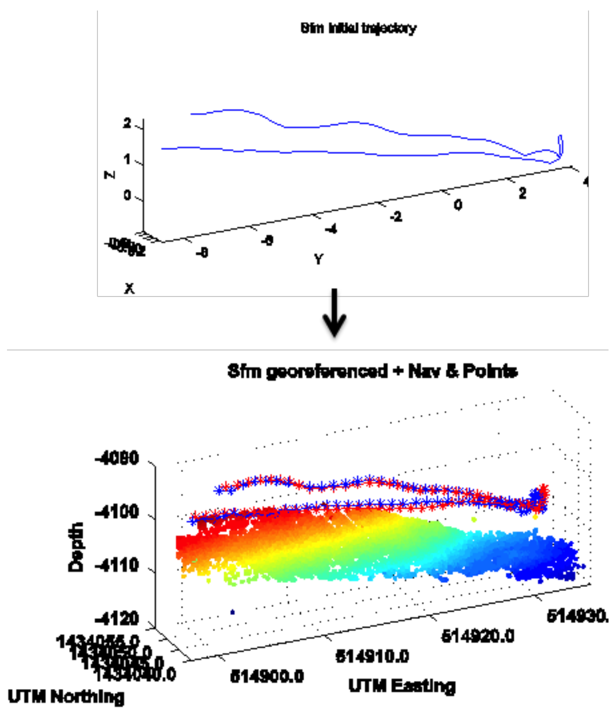

Figure 16 - The top represents the initial structure from motion trajectory which is not scale and hence not metric. The bottom shows the navigation trajectory (in blue) and structure from motion trajectory (in red) after scaling and georeferencing with the associated points. The depth and UTM coordinates can be directly read on the Figure.

Surface reconstruction from 3D cloud

It can be useful to reconstruct a surface from the 3D cloud of points, for each application that needs a continuous 3D curve. This can help to project a texture on the 3D structure and hence to make an orthophoto of the scene. A solution used to solve this problem is the poisson surface reconstruction algorithm. This algorithm needs a 3D cloud of points and its associated normal as obtained from the dense matching. The algorithm search for a surface passing through the 3D points with the corresponding normal in a least square sense.

4.3 Pictures and video annotations

4.3.1 Manual annotation

The most basic form of image annotation is done via human observation and classification. A series of software packages for manual annotation of underwater imagery have been developed in the last two decades to assist in underwater surveys. These range from stand-alone players, to GUIs that run within complex environments, such as Integrated Real-Time Logging Systems or even interacting with relational databases. Underwater image annotation softwares (UIAS) for annotation are basically GUIs that facilitate transposing visual objects and events displayed in a still image or video sequence to the semantic level. For this purpose UIAS provide image display environments (e.g., video player or image browser) with a customizable interface that allows logging textual records in a time-stamped and/or geo-referenced manner. Time is most often used as the key field to relate the image content to the image recording platform position (latitude, longitude), depth, sensors in situ, etc.. This represents the main difference from similar software, and by allowing to geo-reference seafloor occurrences, it provides base data for quantitative analyses and habitat mapping methodologies.

A number of different UIAS have been developed worldwide by large state-funded research institutes and private companies, and are either used exclusively in-house or made freely or commercially available. With the earlier developments devoted to annotate still images from shallow coastal tropical reefs (e.g., ‘Coral Point Count with Excel extensions (CPCe), Kohler and Gill, 2006), software packages have evolved to allow annotating video and still image content for technical operations, geology (including seafloor groundtruthing), and biology. Currently, there are over two dozens of softwares’ under use by different research institutes, which have contributed to over 500 papers worldwide.

Three main features determine the overall of functioning of UIAS: a) the capacity to operate during data collection (e.g., onboard vessels), b) the ability to complete annotation and post processing of imagery and associated data after data collection, and c) the capacity to interact with relational databases for archiving, querying and exporting annotation outputs. Most software packages were developed for either or both of the first two, and may or may not interact with a database (Gomes-Pereira, Submitted). The interaction with a database allows the automatic integration of annotations from different surveys, repeated annotation and collaborative annotation of shared datasets, browsing and querying of data (see section 5.1 on data management and visualization)

Generalist and specialized packages (e.g., dedicated to specific platforms, such as 3D cameras) have been developed worldwide. Image acquisition for seafloor mapping is normally done with moving platforms. UIAS for manual annotation that work with video data allow annotating both continuous and discrete events. Sub-sampling of video segments, or extraction of still images towards a random-based analysis of seafloor imagery is often used for the purpose of quantitative analysis and habitat mapping and can be done prior to video annotation (reducing the amount of video to annotate), or posteriorly by using the annotated output. Several packages allow extracting video frames at a specified distance or time interval (e.g. OFOP Huetten and Greinert, 2008), which can then be used for annotation and analysis. Pictures / still image analysis can be assisted by several dedicated software packages (CPCe; photoQuad, Trygonis and Sini, 2012; Seascape, Teixidó *et al.*, 2011). Common tools include measurements of length, area, image segmentation, point count, etc. Expected future developments include improvements in terms of functionality for visual, graphical and contextual review of annotations, as well as database interactions. Also the integration of image-processing tools (e.g., image filtering for photomosaic), or event detection will greatly alleviate the processing burden. Current automated annotation solutions still require expert-based knowledge, as explained using BIIGLE (Box 3).

The annotation of seafloor features is normally done using reference classification systems. UIAS commonly allow uploading a list of descriptors (knowledge base) to be added in the annotation window/interface (e.g., txt file). A number of schemes defining different types of seafloor features have been developed, including a classification scheme for deep seafloor habitats in the United States (Greene *et al.*, 1999), the national marine habitat classification for Britain and Ireland (Connor *et al.*, 2003), the Australian classification scheme for scoring marine biota and substrata in underwater imagery (Althaus *et al.*, 2013), or a recent cold-water coral biota classification scheme for ecosystem based management of the deep sea (Davies *et al.*, Submitted).

This approach allows for coherence in the annotation between different experts, promoting consistency and a more rapid selection of commonly used descriptors. Studies on inter-observer agreement on analysis of standard samples of physical and/or image-based specimens (species identification and abundance) is only around 50% (Schoening *et al.*, 2012). A quality assessment protocol should be followed, as recently proposed by Howell *et al.* (2014). Data analysis should include the creation of image-based species catalogue for the analyzed dataset prior to the onset of any observations. To improve parity between observers it is suggest that, prior to full analysis of the dataset, a fixed percentage (e.g., 10%) of images/video is selected at random for initial independent analysis by all observers and by an experienced senior observer. The results of this analysis should be reviewed and discussed by all observers before the full dataset is analyzed. After full analysis of the dataset, a random percentage of data should again be selected for inter-observer comparison to obtain a robust measure of agreement (Howell *et al.*, 2014).

Box 3 - The image annotation environment BIIGLE

For many applications, including marine science, the utilization of a web interface to access and annotate these large datasets greatly increases their usefulness. For still image annotation and labeling, the ‘Bielefeld Image Graphical Labeller and Explorer’ (BIIGLE) is a currently used application to collaborate on detection and identification of specific features in underwater images. The system allows a user to spatially identify regions or points within an image as belonging to a particular class of objects, such as ‘coral’, ‘muddy seafloor’ or ‘marine litter’. BIIGLE users can be situated anywhere in the world and simply sign onto a webpage to annotate images held in a repository in Bielefeld, Germany. A typical interface window is shown in Figure 17. After selecting areas or points within the image, users choose the most appropriate label from a large range at the right of the window. While this approach makes sure that common terms are used by all users, new labels can always be added if new features are identified.

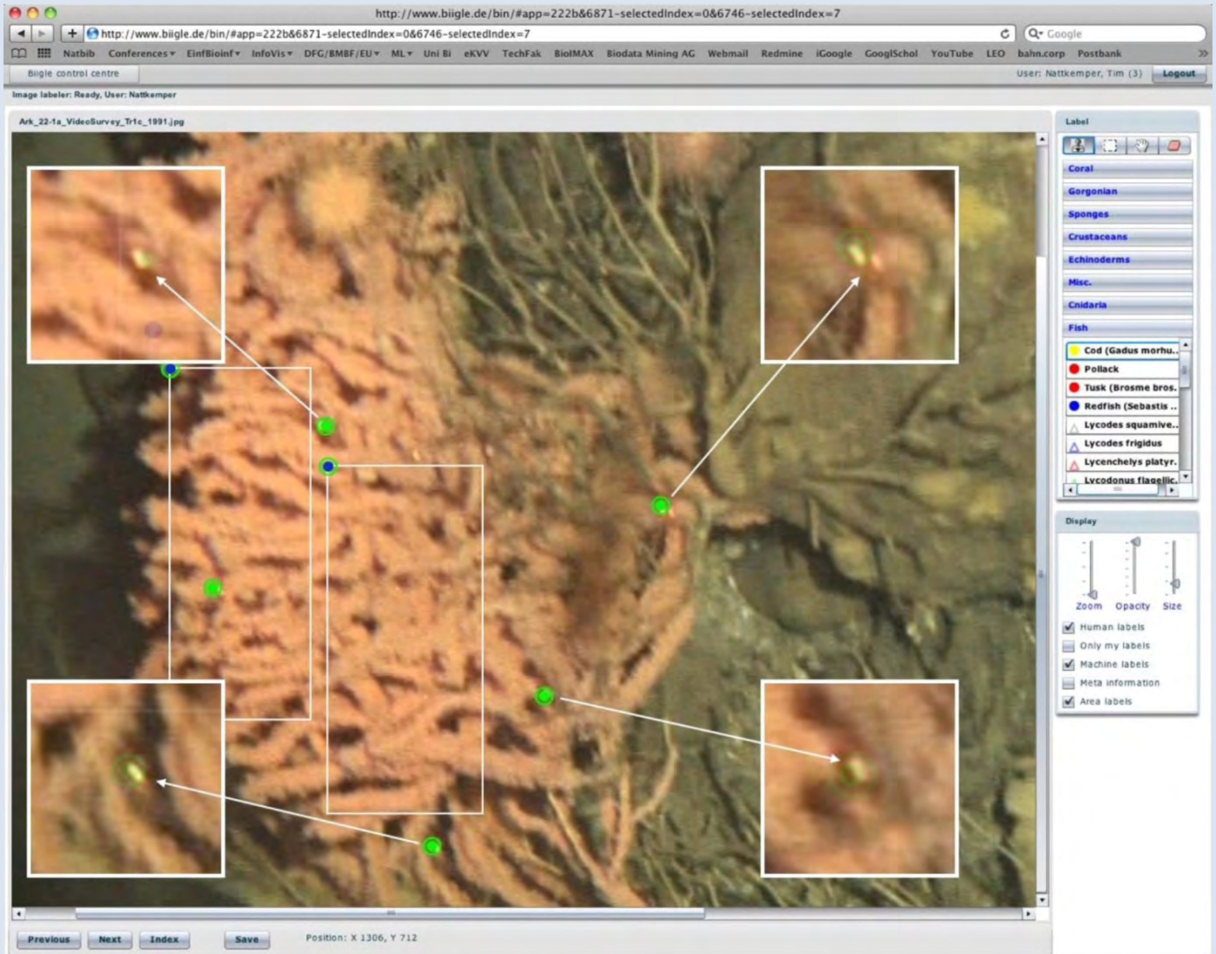

Figure 17 - An image of a Norwegian Shelf cold water coral reef as displayed in the BIIGLE system. Two large boxes of orange coral are indicated, while smaller point features (shrimp resting on the coral structure as shown in the four close-ups) are being logged as well. To the right of the screen the possible label options are shown.

The web based nature of such systems allows experts from around the world (such as taxonomists, geologists, environmental surveyors) to readily access images as well as annotations assigned so far. As current generation digital stills and video cameras capture images of considerable size and render the transport of these data to the relevant experts a difficult task it is more efficient to provide the experts with virtual means to 'travel' to the data via the PC.

In addition to providing data on the contents of the images, these labels can be combined with georeferencing data (if available) to provide quantitative data on, e.g., seafloor type, abundance and spatial distribution of fauna and other seafloor features (e.g. Purser *et al.*, 2013), and for input into automated annotation and identification systems (see section 4.3.2).

4.3.2 (semi-)Automated recognition on images

Methods for automatic detection

Scientists have developed various ways to count and keep track of species, but most of the methods require human analysis of many hours of video. Hence, an important need is to provide automatic assistance for species detection in the videos. Ifremer evaluated the potential of state of the art of techniques for automatic detection of events in underwater videos. This work will give the possibility in the future to automatically annotate videos with metadata describing important portions of videos, in order to help the scientists to replay their data and videos more efficiently after the cruise. The underwater environment presents a lot of disturbance for image detection, such as low light conditions and particles in suspension. Two methods were implemented in the scope of this work:

- Cascade classifier. Haar and LBP Feature-based Cascade Classifier defines the shapes of interest using basic classifiers combined with learning techniques that efficiently combines those basic classifiers for detection. This cascade classifier has been initially proposed by (Viola and Jones, 2001) and improved by (Lienhart and Maydt, 2002).
- Multi-scale saliency model (from MBARI). The saliency-based detection is a visual attention system, inspired by the behavior and the neuronal architecture of the early primate visual system. Multiscale image features are combined into a single topographical saliency map where potential areas of interest could be easily segmented. This detection system is coming from the MBARI's AVED project, and has been initially published by Itti (Itti *et al.*, 1998).

Those algorithms have been implemented in a testing tool with a video annotation function (called VideoNote, see Figure 18), which can manually extract images (and metadata) from video clips. VideoNote helped to build images database for the training phase of the classification method.

Figure 18 - Video note has been used to extract images of fauna in order to create a database for training.

Adopting machine learning algorithms to train the automated annotation systems

A critical issue in automatic detection is to train the algorithm. A guided learning approach can be used for the automated recognition of fauna, seafloor structures and features from image data that utilizes a pool of expert knowledge to train an automated system.

The image annotation platform BIIGLE (Box 3) is able to employ machine-learning algorithms to learn from expert notations in order to automatically distinguish particular organisms or other features within images. Of the many different dimensions or characteristics that can be used by learning algorithms, BIIGLE initially focused on the analysis of texture. The system algorithm converts data from the digital image into a 2D hierarchically growing hyperbolic self-organizing map (H2SOM). In images with expert labels, the system learns to identify which areas of an image (and therefore areas of the H2SOM map) best represent a particular feature, and how distinct such features are from other labeled areas. The higher the number of training images, the more successful will be the learning process. After consideration of the expert labeled areas the system can be fed with further unlabeled images for auto-analysis. The process is outlined in Figure 19 and Purser *et al.* (2013).

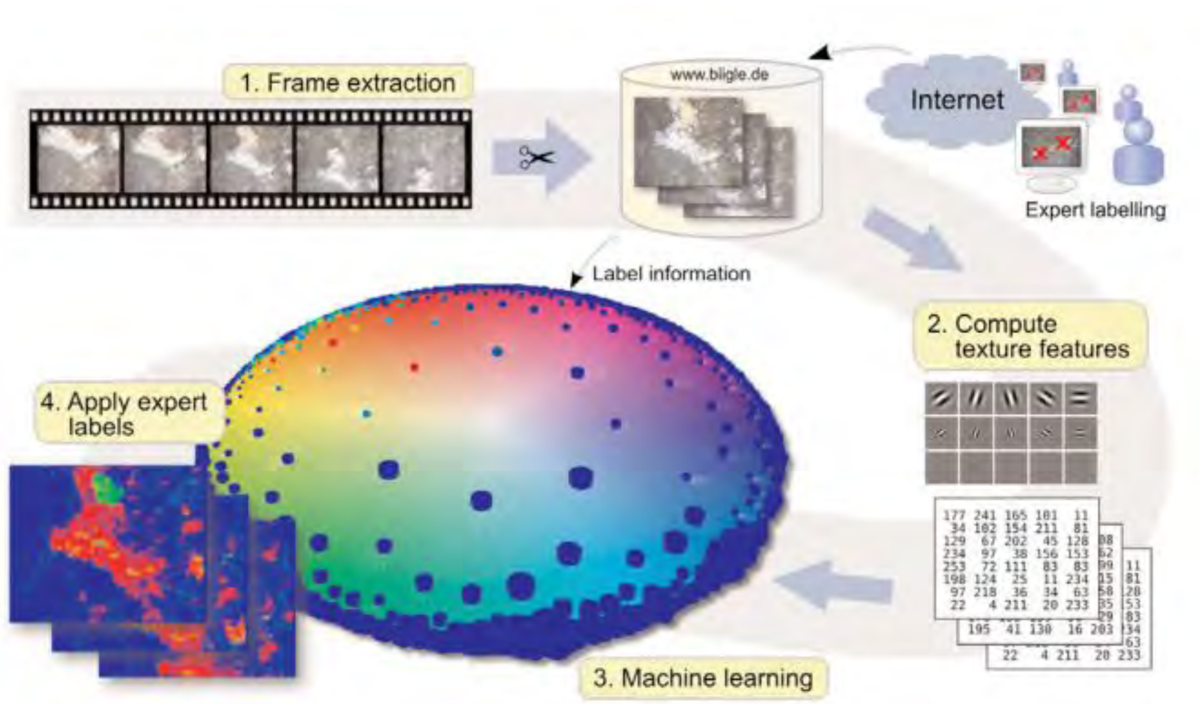

Figure 19 - Processing stages in automated learning with the BIIGLE system. For more information see Purser et al. (2009).

In ecosystems with very different textures in evidence, such as in the broken coral reefs of the Norwegian Skagerrak, machine learning can be useful and very accurate in automatically assessing seafloor coverage or composition. Figure 20 shows the accurate identification of cold water corals based on a training set of several hundred images. The degree to which the automated output matches more traditional methods for determining coverage quantification in images was tested by also running 15-point, 100-point and image mapping analyses on a subset of the analyzed frames (Figure 21). As the figure shows, the auto analysis method (black bars) is in almost all cases the closest in comparison to the very labor intensive image mapping methodology (white bars).

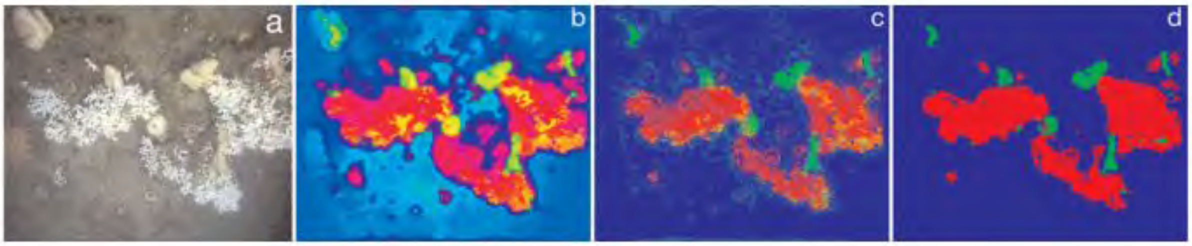

Figure 20 - Sequence of result images from the auto analysis processing pipeline. (a) The original video frame. (b) The cluster colours the neural network has learned from the texture data. Note that this image is generated without any expert labels (unsupervised training process only). For preparation of (c), expert labels were applied to the neural network. Depending on the number of coral or sponge labels within the clusters on the map, regions of the image are coloured red or green, respectively. (d) The final categorised frame from which the coverage estimations are produced by counting the coloured pixels.

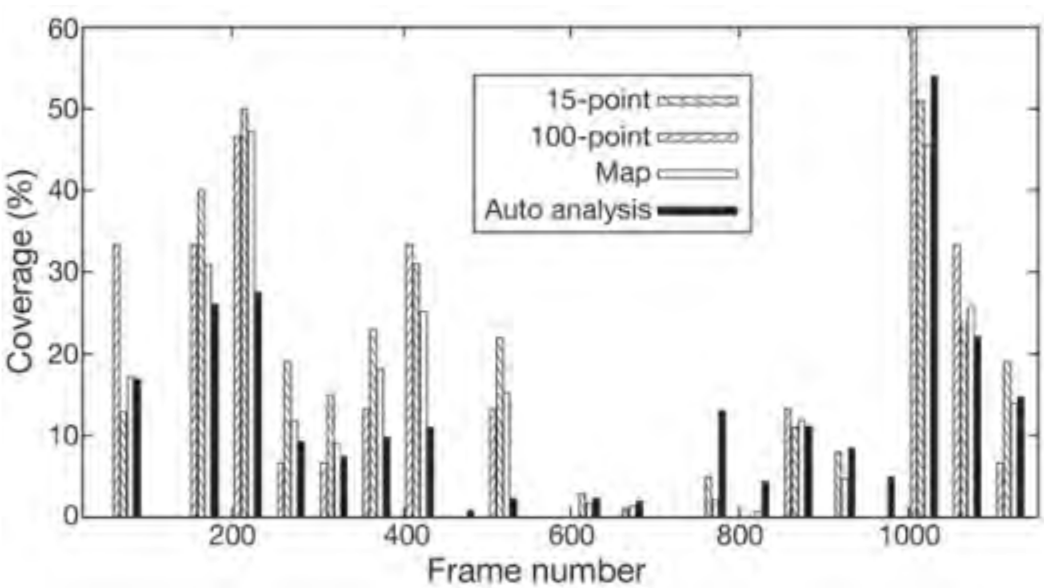

Figure 21 - Comparison of different methods for the determination of the spatial coverage of the cold water coral Lophelia pertusa.

Further analysis of the method revealed that the robustness of the method may differ for features of different optical characteristics. For example it turned out that sponges are less distinct from the seafloor than the corals. Although the human eye can still differentiate the difference, the auto analysis system did not perform as well as in the case of the corals. More details on this study are found in Purser *et al.* (2013). Apart from the ability to detect and distinct feature characteristics in the images the success of semi-automated trained system approaches also depends on both the quality of the images (resolution, illumination) and the expert labels (agreement between experts and the approaches used for data entry, Schoening *et al.*, 2012). In situations where auto analysis is shown to be quite efficient, the auto analysis output frames maybe georeferenced and imported into GIS, or returned to a video stream to play alongside the raw collected data (an example video from Purser *et al.*, 2013 paper is found at www.int-res.com/articles/suppl/m397p241_app/). This approach allows errors caused by camera distance, light vignetting etc. to be rapidly identified.

Automated image acquisition systems in combination with automated feature recognition have a strong potential for the application in deep sea monitoring. As long as images of high and consistent quality can be obtained, repeated surveys of the same region may be analyzed with only little efforts. In the case of seafloor disturbances, such as coral reef breakage or deep sea nodule removal, the change in distribution of the distinct seafloor features would be readily apparent.

5. Data integration: Producing and visualizing the habitat maps

5.1 Data management and visualization

Data management is a major issue in deep-sea habitat mapping, where workflows integrate multiple types of digital data including large image / video files. Management starts during data collection, where different sensors collect and stream data to software packages at the surface. Software packages can simply record information, allow online visualization, or be used to interact with sensors assisting the deployment operations. Common types of data include date, time, SHIP position, deployment platform (e.g., SUB, ROV, AUV) position, depth, heading, speed, etc.; CTD data (temperature, pressure, salinity), manual annotations and the video or digital photographs. Data input normally occurs via customizable COM ports, requiring a video capture card and updated video codecs. There is an ongoing trend for software packages to allow receiving a larger number and types of data during at sea operations. Visualization of data from the sensors during collection at sea (acoustic, optical, etc.) can be streamed throughout the ship via intranet (including wireless streaming to portable platforms such as smartphones, tablets, etc). Intranet connections on-board the ship can also allow multiple annotators to record events to a single output file. Output files format is mainly comma separated value files, text files or, less frequently, web or web-GIS enabled formats such as HTML, KMZ, etc. These features facilitate the set-up of data workflows, data compilation and analysis, survey reports, and posterior integration with databases. More information on software capabilities can be found in (Gomes-Pereira, Submitted).

It is now possible to broadcast sensors data and communicate in real time via the worldwide web during operations at sea. This emerging concept entitled telepresence requires advanced broadband satellite communication, with elevated costs associated to host the uplink and downlink from the ship/deployment station and the amount of data stream (Leslie *et al.*, submitted), allowing to combine expert knowledge from a geographically spread community, and being a great environmental awareness product.

Datasets provide the basis for post-processing via manual, semi-automated and automated analysis. Also, within the present context of increasing data load and international orientations for data sharing to promote marine spatial planning, data is now expected to be easily integrated into in-house databases and to be shared with the international community (e.g., EMODnet). In-house databases usually include a reference to the source data file in a video library and can, in some cases, interact with other metadatabases such as OBIS (Grassle, 2000) or GBIF (Edwards *et al.*, 2000). Software packages normally interact with a database at-shore via intranet or the internet.

Institutes worldwide have developed databases to assist deep-sea habitat mapping with different structures and architectures (e.g., Biocean, Fabri *et al.*, 2006; NICAMS ; VARS, Schlining and Jacobsen-Stout, 2006; VIDLIB, see Box 4, VirtualVan, Lerner and Maffei, 2002). The main programming language used are MySQL, Microsoft Office Database, and less frequently in Matlab, PostGIS, among others (Gomes-Pereira, Submitted). Web-based solutions, such as BIIGLE allow for data access from a common web-browser anywhere in the world (Box 3).

Box 4 - The VIDLIB Deep-Sea Video Database

The VIDLIB Deep-Sea Video Database is a storage database for marine video data sharing, visualization and analysis. It is a joint development of MARUM at Bremen University, the Max Planck Institute for Marine Microbiology in Bremen, the Alfred Wegener Institute in Bremerhaven, Germany together with Interworks in Bitola Macedonia. The database can be accessed through a web-based portal interface available at http://vidlib.marum.de. Through the main database portal, registered users can, depending on their access rights, upload, visualize, and annotate video data. The VIDLIB database is aimed at providing scientists with an easy way to share and analyze video data. Scientists can share expert knowledge for the video analysis, for instance for species identification, without the need to send video files around. Using the portal functionalities specialists can access and annotate the same videos from anywhere, thus making the analysis process faster.

When uploading a video file, users need to provide meta-information including the latitude and longitude where the data was acquired as well as the exact date and time of the start of the video file. This information will then be used to timestamp all annotations on the video file. Optionally, a watermark logo can also be provided that is later superimposed on the video to deal with copyright issues. Upon successful uploading onto the database, the new video files are automatically re-encoded in a suitable format in order to permit rapid and high-quality (including HD) streaming of the video file. Users can then freely stream and scroll through the videos until the desired part of the file (Figure 22). While visualizing the videos, users with annotator rights can additionally access the annotation interface. This interface provides tools to mark and comment all observations on the video image itself. Annotation comments can contain either free text or selectable keywords. The list of keywords can be customized for the different video files depending on the needs. Annotations are classified into different categories (e.g., marine geology, marine biology, etc.) in order to allow viewers to turn on and off the different types of annotations while visualizing a video file. If switched on, annotations will appear on the video when their starting timestamp is reached and then disappear as the annotation duration ends.

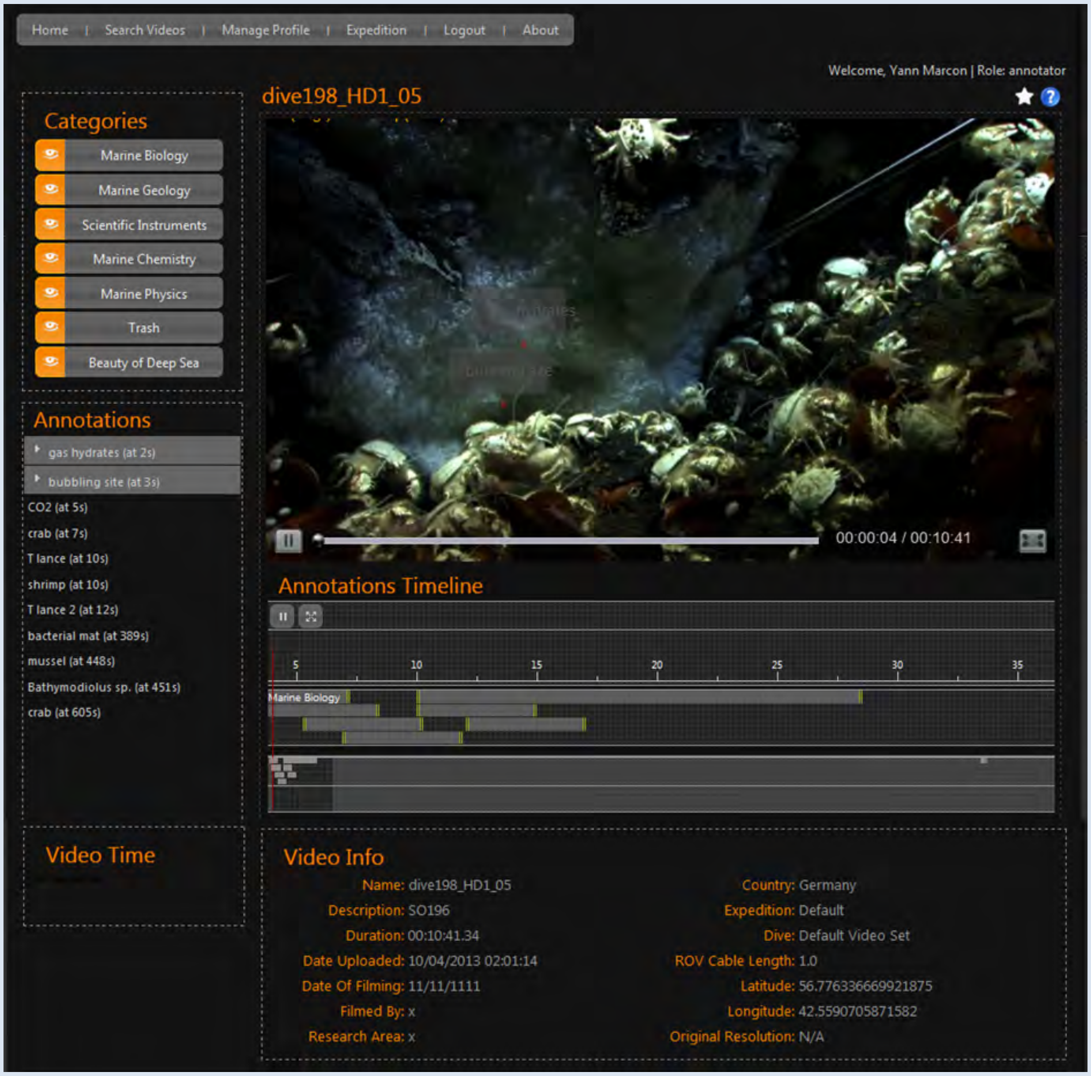

Figure 22 - Video streaming interface of the VIDLIB Deep-Sea Video Database. The 'Annotation Timeline' field showed the time-location of the comments while the video is being played.

Analysis results can be exported into text and Excel files. Exported annotations include additional information, such as the name of the annotator, the position of the annotation in the image frame, and the absolute date and time of the video frame related to the annotation. The main value of time-stamping every single annotation is to permit the later merging of the video analysis results with the underwater navigation data in order to geo-reference and display the spatial distribution of all observations. Currently, the VIDLIB database is being used to analyze the distribution of benthic megafauna using video data acquired with a towed camera system (OFOS) during recent cruises to the Southwest Indian Ridge (cruise PS81, 2013) and the Aurora vents on the Gakkel Ridge (cruise PS86, 2014). Similar video data bases are expected to represent powerful tools for the distribution, visualization and annotation of large amounts of video material as they will be obtained in the context of mining operations and associated environmental monitoring.

5.2 Integrative habitat mapping

Seafloor habitat mapping is the process of depicting and predicting biological patterns according to environmental data. The basic assumptions behind habitat mapping are that the spatial distribution of species or assemblages of species within a community is mainly governed by abotic factors and these factors or proxies for these factors can be accurately mapped. However, information relating to species–environment interactions is often lacking, which makes it difficult to select and determine which environmental data are relevant and how they should be analyzed. Moreover, for the purpose of environmental management, it may be useful to define bounded habitat units, which distribution and extent can be mapped and quantified. The distribution of species or communities in nature is however often continuous rather discrete and boundaries may be difficult to define (Brown *et al.*, 2011).

The integration of environmental and biological data layers thus requires some form of statistical analyses to define homogeneous discrete entities within environmental and biological data layers and/or to identify correlations between environmental data and the distribution of species. A number of methods have been developed to produce habitats, which can be divided into broadly two categories (Brown *et al.*, 2011):

- Unsupervised classification takes a top-down approach, whereby the environmental data and in situ biological/geological data are organized before they are combined (an unsupervised classification strategy). This involves the segmentation of the environmental data into spatial units, using either expert interpretation by eye or an objective based approach (see section 2.3). This strategy can be used to produce single species maps, community maps, or maps of generalized habitat classes based on observed geological/biological seafloor characteristics using a benthic habitat classification scheme. In the case of single species habitat mapping, a focal species is selected and its presence/absence is then modeled against the segmented environmental data. The modeling usually takes the form of simple statistical assessment of the correlation between the data sets. Species presence can then be extrapolated based on the segmented environmental data where there is geographical concurrence between the data sets. Community mapping is done in a comparable way, where the biological data are usually organized into classes using (multivariate) statistical methods. Similarly, the *in situ* biological (and geological) data may be classified using expert judgment or statistical methods based on an existing habitat classification scheme. The community or habitat (biotope) classes are then compared against the segmented environmental data set in a comparable way to the single species example. In this way the classes can be extrapolated on the basis of the segmented environmental data. In the deep-sea, this strategy has been successfully used to map deep-sea coral habitats (Savini *et al.*, 2014), hydrothermal vent macrohabitats (Durand *et al.*, 2006), cold seep (Wagner *et al.*, 2013) or megafaunal assemblages on large and topographically complex geomorphological features such as seamount (Davies *et al.*, 2015) and rise (Anderson *et al.*, 2011).
- Supervised classification adopts a bottom up approach whereby the biological data are used to inform the organization and segmentation of the environmental data, and can be applied from a single species or a community stand point. From a single species perspective, the presence of the chosen focal species is modeled as a function of the environmental predictors, thereby generating a predicted species distribution map. It is also theoretically possible to generate community maps using this approach by producing single species habitat maps one at a time, and then combine the resulting stack of species distribution maps to produce a community distribution map. This is a fairly new approach, and whilst examples of this strategy are emerging from terrestrial systems (Peppler-Lisbach and Schröder, 2004), as yet it has not been tested with marine data sets. More commonly, community maps are generated by first organizing the in situ data into classes using

(multivariate) statistical methods, or by classifying the data using expert judgment or statistical methods based on an existing habitat classification scheme. These classes are then used to perform some form of supervised classification on the environmental data sets to segment the continuous coverage variables. In the deep sea, species distribution modeling is increasingly used but mainly to predict the distribution of Cold Water Corals (CWC) (Vierod, Guinotte et al. 2014). The resolution of the environmental datasets however is a major restriction to the reliability and applicability of cold water coral SDMs (Rengstorf, Grehan et al. 2012). The first global scale models to be developed had a resolution of about 100 km (Davies, Wisshak et al. 2008, Tittensor, Baco et al. 2009). The best predictors for CWC occurrences were temperatures, oxygen, aragonite saturation state and enhanced primary productivity thus providing a global envelope for potential environmental niches. Regional to local scale models now have a resolution on the order of 10 m or even less. In these models, bathymetric terrain attributes have shown good potential as environmental predictors as they act as proxies indicating areas of enhanced currents and food supply for suspension-feeding corals (Rengstorf, Grehan et al. 2012, Vierod, Guinotte et al. 2014), narrowing down the footprint of the potential niche. Species and community modeling have also been used to compare continental margins with low and high environmental complexity although at a broad regional scale (Compton *et al.*, 2013).

To date, habitat mapping in the deep sea has mainly integrated the topography and texture of the seafloor with biological data, focusing on i) species for which the distribution is known to be highly constrained by topography and substrate (i.e. cold water corals) and/or species associated with high backscatter signal (e.g. mussel beds and bushes of tube worms in chemosynthetic ecosystems and ii) benthic communities on complex topographic features such as seamounts or rises. In the framework of the environmental management of resource exploitation in the deep sea, integrative habitat mapping thus seems to be particularly well fitted for ecosystems dominated by hard substrates such as those associated with massive sulfide and cobalt crusts as well as cold-seep ecosystems potentially associated with gas hydrate. Habitat mapping of soft-bottom communities over large areas of the continental slopes or abyssal plains may prove more difficult to produce because environmental drivers for species distribution are not as well constrained. Mangenese nodule coverage however can be quantified from MBES or SSS imagery (Chunhui *et al.*, 2013) and is known to influence biodiversity patterns (Bluhm *et al.*, 1995; Miljutina *et al.*, 2010) thus offering potentialities for integrative habitat mapping in ecosystem associated with this mineral resource.

Oceanographic data have been used in distribution models at broad, global to regional, spatial scales but there is no example of integration of geological, physic-chemical and biological datasets at high spatial resolution. For most parameters, technologies for measuring and mapping physic-chemical properties of the benthic boundary layer are still under development and provide discrete measurements that need to be interpolated or modeled at habitat scale. These physic-chemical variables are also highly dynamic at frequencies ranging from days to years and would require an integration of both mapping and monitoring strategies.

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