COMPARING MANUAL AND SEMI-AUTOMATIC UNDERWATER IMAGERY ANALYSIS APPROACHES FOR HARD BOTTOM BENTHIC MACROFAUNA MONITORING AT OFFSHORE RENEWABLE ENERGY INSTALLATIONS

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Abstract

The construction of new offshore wind farms is one of the strategies to fulfill growing demands for "green" renewable energy. Underwater imagery is an important tool in the environmental monitoring of offshore renewable energy installations, especially in rocky benthic environment where traditional techniques, such as benthic grabs, are not applicable. Benthic features cover quantitative estimation from underwater imagery is a not easy task, especially when large amount of visual data must be processed in a short time. Underwater video from the high energy Norwegian Sea coast was used for this study. Traditional manual point-based benthic cover estimations from selected frames was tested against a semi-automatic color-based computer-assisted approach which involved making mosaic images from underwater videos. The study demonstrates that results of manual and semi-automatic benthic cover estimations are similar, although the manual analysis has a much larger spread in the variability of the data with many outliers due to the limited amount of points used in the analysis, compared to the semi-automatic analysis, where much larger proportion of the imagery is used. Although the number of benthic features that could be extracted by computer using color are fewer than those that can be detected with the human eye, the described semi-automatic method is less biased and less costly in terms of qualified staff. Implementation of the semi-automatic method does not reqiure any programing skills and has the ability to quickly and simply process larger amount of underwater imagery which would of decisive advantage to the industry.

Keywords: Underwater video, benthic cover estimation, features color, automatic image analysis, video mosaics

1. Introduction

By 2020 EU countries aim to derive 20% of their energy from renewable sources. European countries typically have high population densities and the corresponding need for larger amount of energy. Offshore wind power is one of the strategies to fulfill those needs that have received public and legislative support. Although Norway is not an EU country member, the Norwegian government was able to exercise significant influence on EU maritime policy development (Wedge, 2011). With a highly developed maritime industry (including oil and gas industry, fishing, aquaculture and shipping), Norway needed a strategy for sustainable use of these resources, which resulted in plans for an integrated ecosystem-based management developed specifically for the marine environment (Ottersen et al., 2011). Ecosystem-based management for offshore wind farms requires thorough planning and a well-developed environmental monitoring programs at all stages: baseline, construction, operation and decommissioning.

One of the solutions to the growing demand for offshore wind farm locations could be the siting of farms at shallow, high-energy rocky shores. Those areas are avoided by larger vessels due to high risk of navigation hazards, and only marginally used by local communities for small-scale fishery and kelp harvest, which limits the number of conflicting uses. There are a wide variety of traditional marine monitoring methods and legislation to regulate this monitoring in place for offshore wind farms sited at soft sea-beds (Magadana et al., 2012), and their use in national monitoring programs as well as for research purposes has resulted in large amounts of data being gathered about the impacts of offshore wind farms installations on soft sediments (Bergström et al., 2014). In contrast to traditional offshore wind farm sites on sandy substratum both, method guidelines and legislations are lacking at rocky, high energy areas (Dahlgren et al., 2014). Developing monitoring programs in such hydrological dynamic areas are challenging due to the difficulties in carrying out field sampling, the scarcity of knowledge about ecology of subtidal high-energy ecosystems, and the resulting lack of hypotheses of the possible impacts from wind farms developments (Shields et al., 2009, 2011; Dahlgren et al., 2014; but see Schläppy et al., 2014).

Technological advances in underwater imagery make any depths accessible and the quality and resolution of underwater imagery has constantly improved so that quantitative data can now be extracted from the images (Solan et al., 2003). However, visual data analysis remains challenging. Most common methods for quantitative benthic cover estimation are manual point-based approaches (Foster, 1991; Meese & Tomich, 1992; Leonard & Clark, 1993; Carleton & Done, 1995) and region based percentage estimation (Meese & Tomich, 1992; Garrabou et al., 1998, 2002; Teixidó et al., 2002, 2011; Pech et al., 2004; Guinda et al., 2013). Various software tools are exist to aid those analysis methods (Kohler & Gill, 2006; Teixidó et al., 2011; Trygonis & Sini, 2012, etc), but their application is still labor- intensive, forcing the analysis to be limited to only a subset of the imagery being used for the analysis. Those techniques are based on the analysis of selected frames only, not on complete video sequences. Tools and strategies for processing the entire images in order to obtain cover estimates from video streams, except simple but subjective visual census, are virtually non-existent.

A solution to replace the work-intensive point-estimate method (in which a large amount of the information contained in the image is not analysed) is to use automatic image segmentation. Those approaches are now a well-developed and applied to satellite and aerial images where various advanced techniques have been used (e.g. Jensen, 1996; Baatz & Schäpe, 2000; Burnett & Blaschke, 2003; Wang et al., 2004; Neubert et al., 2006). However, these methods have yet to find their way into the world of underwater imagery. The main difficulty in applying automatic image segmentation directly to an underwater image is the optical properties of the water that causes the water to strongly distort colors even at short distances (Duntley, 1963). This color distortion biases segmentation results when methods are used that originally have been developed for atmospheric conditions. To overcome this distortion problem, various approaches have been suggested, from the use of multispectral cameras that can make objects of interest more easily distinguishable (Gleason et al., 2007; Mortazavi et al., 2013), to the application of various image filters (Beuchel et al., 2010).

Due to the nature of *in situ* underwater imagery, accurate taxonomical identification to the species level is difficult and, in many cases, impossible because the practical resolution of modern underwater video equipment usually does not exceed the millimeter-scale (and in many cases centimeter-scale). Consequently, organisms may only be seen from one angle and cryptic organisms can be easily missed. However, identification to the species level is not always a necessity for monitoring programs (Somerfield & Clarke, 1995; Olsgard et al., 1998; Lampadariou et al., 2005; Bevilacqua et al., 2009) and in many cases higher rank taxon datasets have been successfully used to detect natural and anthropogenically-induced changes in the marine communities (Defeo & Lercari, 2004; Bevilacqua et al., 2009).

The aim of this study was to describe an underwater video analysis technique that is suitable for monitoring programs at offshore wind farms on high-energy rocky reefs. The described semi-automatic color-based benthic cover estimation method is compared with a manual point-based video image analysis method in terms of cost-effectiveness and consistency.

2. Materials and methods

2.1 Study area and video data collection

Video footage was collected in September 2010 and 2011 as part of a baseline study for a future assessment of the impact from a planned offshore wind farm called "Havsul", near the city of Ålesund, Norway. The wind farm site is to be situated at an open coast area with a rocky seafloor that is exposed to waves having one of the highest energy in the world (Golmen, 2007). A medium-class remotely operated vehicle (ROV) equipped with an HDTV video camera and powerful xenon lights (400 W in total) was used to collect video transects (Schläppy et al., 2014; Dahlgren et al., 2014). The camera faced down (90°) during the filming and the ROV pilot tried to keep the vehicle altitude as constant and as neutral as possible. This was a challenging task because the hydrological conditions at the site drastically affected the stability of the ROV. Additional inconsistencies in the video transects between the two years was introduced by variations in weather and the fact that the ROV pilots were different. Video was collected in 200 m transects of approximately ten minutes in duration at depths varying between 20 and 40 m. Four video transects (two collected in 2010 and two collected at the same locations in 2011) were used in this study. For the analysis, raw video footage was divided into 30 seconds video segments.

2.2 Video mosaicing

Video mosaicing is a process that converts a video stream into a single still image that contains overlapping video frames (Fig. 1).

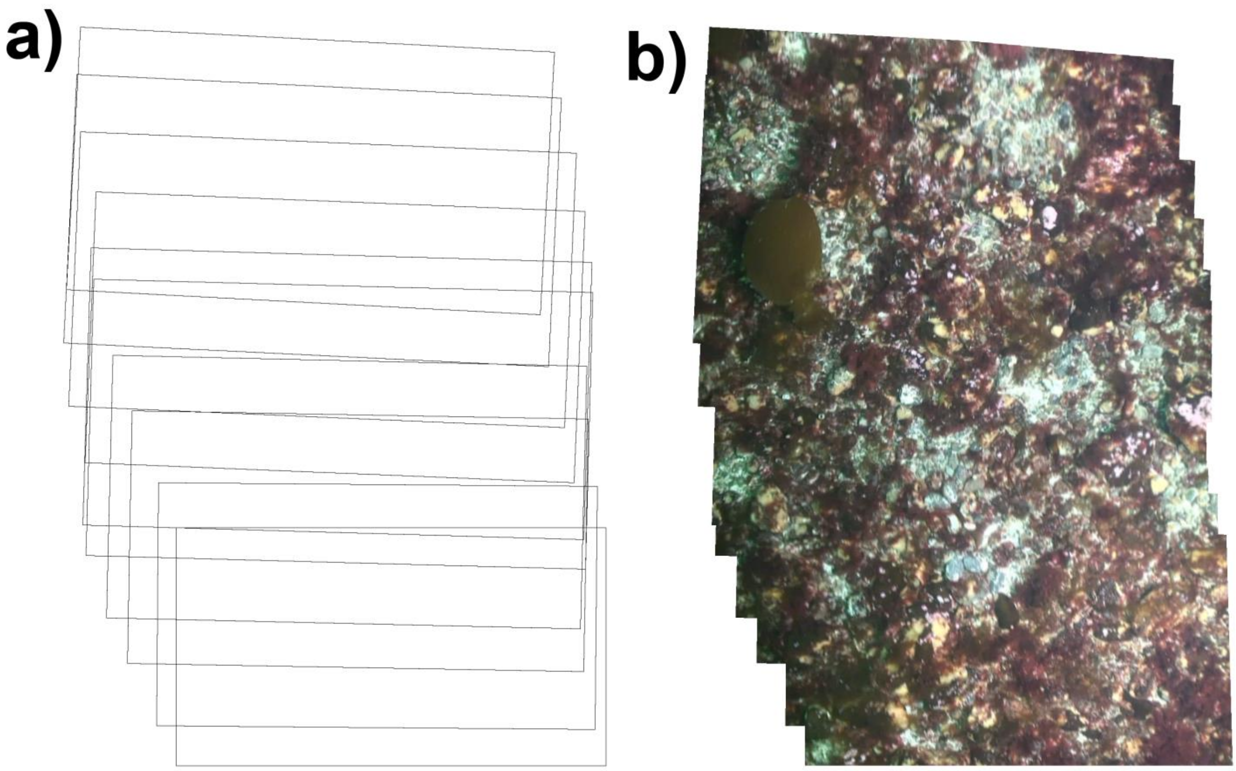

Figure 1. Example of overlapping frames outline (a) and resulting video mosaic (b).

The advantage of video mosaics is that practically all of the video data is used to construct the final mosaic image (i.e., frames that are omitted do not contain additional information that is not present in frames being used). In addition, each object appears on the mosaic only once, in contrast to raw video where each object appears several times on different overlapping frames. In this study, a video mosaic method that has been developed by the Center for Coastal and Ocean Mapping (CCOM), (Rzhanov et al., 2004) was used. The process of video mosaicing consists of several steps:

1. Raw video was divided into 30 s segments. This process also reduced the frame rate and frame size to eliminate interlace artifacts and to shorten computing time.
2. Video was compensated for the roll and pitch of the filming platform.
3. Each frame was enhanced using specific video-enhancing algorithms.
4. Automatic frame-to-frame pair-wise registration (a process used to calculate the overlap of neighboring frames) was performed to the enhanced video.
5. Video mosaics were built from non-enhanced video using pair-wise registration data from the previous step.

The success of automatic frame-to-frame pair-wise registration is directly dependent on the imagery quality. If details on the images are poorly recognizable (due to blur, insufficient lighting or other factors), the registration process is more likely to fail. In such case, neighboring frames can be registered manually. However, the failure in automatic registration does provide a proxy of image quality. If more than 10 pairs had failed to automatically register, then the video segment was considered of insufficient quality and no mosaic was built from it. This number had been chosen empirically: a single mosaic contains ~150 frames, therefore ten pairs (20 frames) makes more than 10% of the imagery, which was considered a significant proportion, too high for the segment to be of acceptable quality. The number of excluded video segments was different for 200 m transects, so a sample of 10 best-quality segments were chosen out of the 30 s segments from each video transect. In short, about 1/3 of the total imagery was used in the analysis. This subsampling strategy compensated for the sometimes sub-optimal data. Eighty mosaics (40 from 2010 survey and forty from a repeated 2011 survey) were ultimately used in this study.

2.3 Benthic cover estimation

2.3.1 Manual point-based benthic cover estimation

Percentage estimates of benthic cover were assessed using the point-count method modified from Miller and Müller (1999). The collected video transects were divided in 50 equal segments, making the average distance between the frames approximately 4 m. The video was stopped at each start of a segment and the screen that represents the segment start was used for benthic cover estimation. Five fixed sampling points were placed on the screen and each sample screen was analyzed using those 5 points. Percentage cover was estimated by identifying which benthic cover was directly underneath the 5 sampling points on each sample-screen of the paused clip (see Ohlhorst et al., 1988). The categories of benthic cover to which the sample point could be assigned were *Lithothamnion* spp., erect red algae, encrusting dark red algae (EDRA), sponges/bryozoans, sand, stone, bedrock, and kelp. The category *Lithothamnion* spp. represents a variety of crust-forming red algae of that genus. EDRA is a type of encrusting red algae that could not be identified either through the video only nor through the ground-truth samples collected during the campaign.

As the number of points used for frame analysis was limited, analysis results for individual frames sometimes were biased, especially for low-abundance features. Some features were underestimated (did not appear in the cover) and some features were substantially overestimated (each point gives 20% cover, even for benthic covers that were much smaller). A larger number of analyzed frames were used to try to reduce the bias introduced by individual frames, but still the bias was substantial.

Ideally, the optimal number of points to be analyzed on each sample screen should be the topic of a separate study; however, this was not possible for this study. Instead, we chose to use 5 points because this value was realistic in terms of manpower needed for the analysis and because this value was used by Miller and Müller (1999) and found appropriate to estimate benthic cover on a coral reef, an environment much more diverse than the rocky reef of Havsul.

The manual point-based benthic cover estimate procedure is:

1. Select 5 points on the screen where the user applies 5 empty squares which will serve to guide where to look for a benthic category. The squares are empty so that there is less confusion as to what category of benthos is under them. The squares stayed on the screen in the same location for all visual analyses.
2. Open the video.
3. Scroll to the desired video position, go frame-by-frame in order to select the frame that is of sufficient quality for the analysis (not blurred and with satisfactory colors, etc.).
4. Record the benthic category located in the exact middle of each of the 5 empty squares.
5. Repeat from step 2 once the first video is finished (the same squares on the screen are used for the next video).

2.3.2 Computer-aided color-based semi-automatic cover estimation

The video-derived images made highly heterogenic mosaics composed of small patches of sand, stones covered with encrusting and erect algae and sponges (Fig. 1). A computer-aided color-based approach similar to that reported in Beuchel et al. (2010) was used to estimate benthic cover. Pixels of similar colors that belonged to a certain benthic cover were extracted from the mosaic (Fig 2.) that yielded the proportion of the extracted pixels to the total pixels in the image as a quantitative estimation of benthic cover.

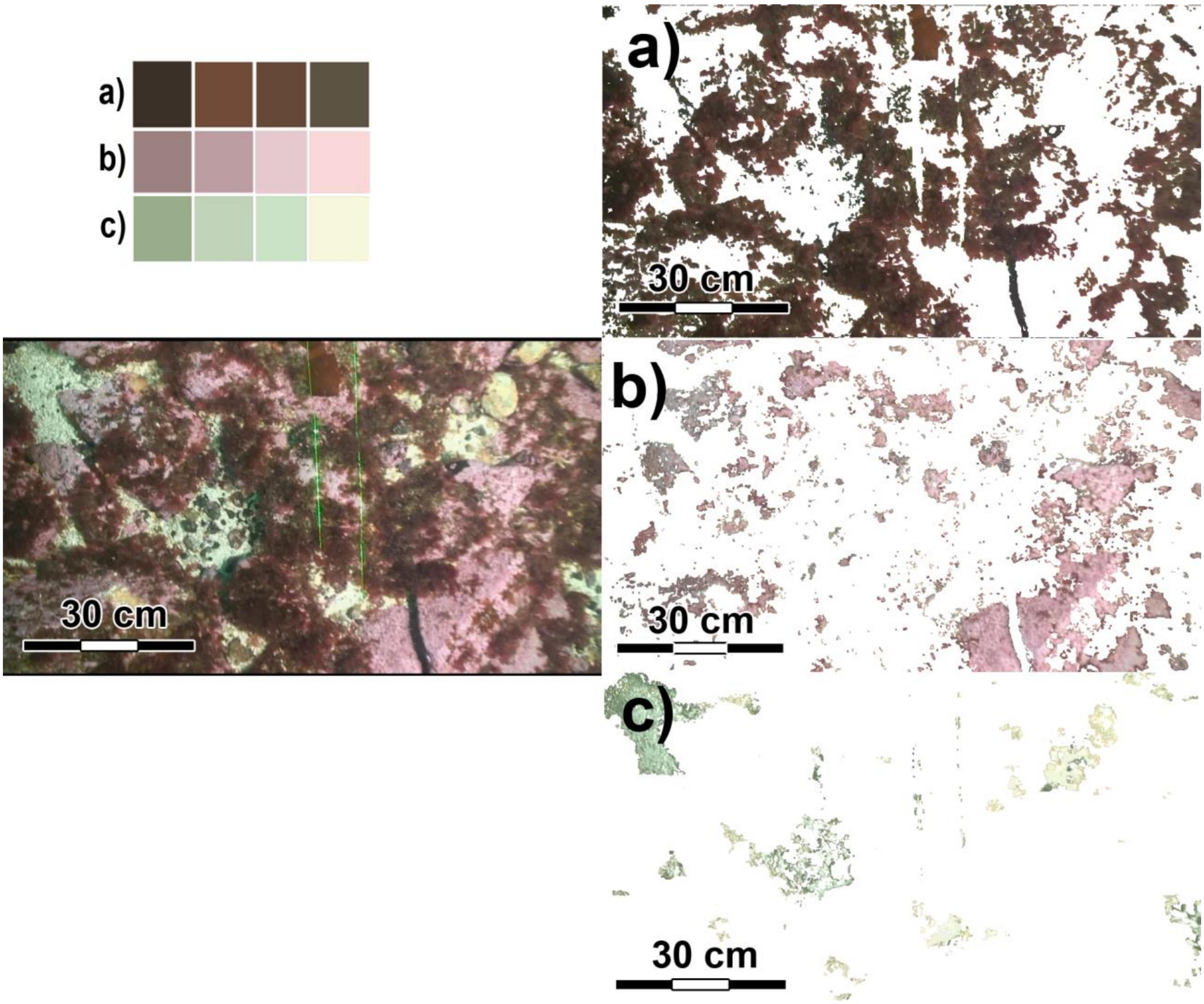

Figure 2. Benthic covers extracted by pixel colors. Frame showing raw video data in the middle left; a) extracted erect red algae layer; b) extracted *Lithothamnion* spp. layer; c) extracted sand layer. In the top left are simulated color palettes for appropriate benthic features.

Since the color of any one benthic cover type could vary according to the amount of illumination that it received from the ROV's lights (which in turn is a function of the ROV's height above the substratum), a range of colors (palette) were attributed to one benthic type, rather than only one color (Fig. 2). The number of colors belonging to a palette varied from 5 to 12 and all the colors belonging to this palette were hand-picked until the selection results on test mosaics were satisfactory. Each palette was attributed to one benthic cover type and there was no overlap in colors between other palettes. The procedure of identifying one type of benthic cover using the corresponding palette was done independently, not in the extraction of every pixel in the image. The colors corresponding to one benthic category type were extracted, for eg. erect red algae, as in Figure 2 a, then the color extraction was repeated with another palette for another benthic category.

A variety of graphic editing packages can be used to select and extract visual features by color and to provide the count of extracted pixels. We used the Adobe Photoshop (http://www.adobe.com) "magic wand" tool in non-contiguous mode for benthic covers selection and Reindeer Graphics (http://reindeergraphics.com/) WideHistogram Photoshop plug-in for counting pixels. To ensure consistency and repeatability, the "magic wand" settings were fixed (tolerance was set to 10) and the same benthic cover color palettes were used throughout the whole-imagery analysis. Additionally, the order that colors were picked was fixed, always from the darkest to the brightest. This procedure ensured repeatability of results and made the analysis completely operator-independent. Using Adobe Photoshop and WideHistogram plug-in, the full analysis procedure was as follows:

1. Open the mosaic in Adobe Photoshop.
2. Select the background color, invert the colors, open WideHistogram and record the mosaic pixel count.
3. Paste benthic cover color palettes into the open image.
4. Apply the color palettes in appropriate order for the first feature.
5. Open WideHistogram, check the number of selected pixels, and record the values.
6. Reset pixels selection, repeat step 4-5 for all remaining benthic covers.
7. Close the mosaic, repeat the procedure for the next one starting with step 1.

The human eye is a very powerful instrument in visual analyses and its performance exceeds by far the capacity of the computer-assisted color-based approach used in this study. Therefore, the number of benthic cover types that could be reliably distinguished with a color-based computer-assisted approach was substantially less than those distinguishable with the human eye. Even with very careful and precise tuning of the color selection tool and benthic cover color palettes, erect red algae, EDRA and kelp produced color overlaps. With slightly larger tolerances (that is necessary for the method to be applicable to a wide variety of video mosaics that contain color inconsistencies), stones and bedrock colors were selected that included a significant proportion of red algae. We encountered a similar problem with sand and sponge/bryozoanians. Considering this, benthic cover types suitable for semi-automatic estimations were chosen as:

1. Erect red and brown algae (ERBL). Cumulative value that contained the covers of red algae, EDRA and sometimes portions of kelp.
2. *Lithothamnion* spp. encrusting algae cover.
3. Sand cover. Cumulative value that contains sand and a significant proportion of the sponge/bryozoans cover.
4. Unidentified pixels: the difference between the sum of identified pixels and the total pixel count in the mosaic. Because benthic cover types were picked one-by-one, not every pixel in the mosaic was classified. The unidentified pixels count was used to evaluate the quality of the mosaic and of the analysis. A high positive count of unidentified indicated that those pixels were not classified by any of the benthic cover color palettes. The high positive pixel count usually indicated a high degree of inconsistency in the mosaic. To compensate for this inconsistency, the sum of identified pixels was used as the total pixel count and all further cover calculations were made with the total classified pixels count as 100%. Sometimes the unidentified pixel count was negative, which was an indication that some of the pixels were counted more than once (i.e. attributed to 2 different benthic cover type), which led to some benthic types being overestimated. Mosaics with more than 8% negative unidentified pixel counts were considered unreliable and discarded from the analysis.

Color selection results can be seen on a screen, and it makes human supervision instantaneous and easy; i.e., the operator could see immediately if the segmentation was acceptable or not.

For the comparison of the semi-automatic and manual point-based analysis results, features types used for manual analysis were reduced to match the semi-automatic analysis features.

2.3.3 Inconsistency in the data

Although all efforts were undertaken to make the video images as uniform as possible during filming, some variations were unavoidable because even small changes in the altitude of the ROV resulted into noticeable changes in the colors of benthic cover types. Such inconsistencies could substantially affect the performance of a color-based approach. Moreover, different pilots had different habits of flying the ROV, which resulted in systematic differences in the imagery between transects. To compensate for these differences, the video mosaics were visually divided into three colors classes: 31 mosaics were classified as colors class I, 44 mosaics were classified as colors class II and 5 as color class III (mosaic segments characteristic for each color class are shown at Fig. 3).

The differences between color classes were related to the mean color channels distribution. Color class I had mean color channels values (in the segment shown in Fig. 3) of Red/Green/Blue (later R/G/B) of 154/118/117 and represented approximately the natural colors (with artificial lights) of the substratum. Color class II with mean color channels R/G/B of 68/89/81 represented images filmed from greater ROV altitude, which resulted in the reduction of the all color channels, especially the Red channel which has the greatest absorption rate in water. Color class III with mean color channels values of R/G/B of 110/112/70 most probably represent images that were filmed with the ROV xenon bulbs not fully "warmed up", and therefore having different color temperature, with a reduced Blue channel.

Figure 3. Examples of the mosaic segments that belong to different color classes (from left to right: color class I, II and III). Independent benthic cover color palettes were created for each class.

Different benthic cover color palettes, derived from different mosaic color classes, were checked for overlap: so that one specific color could be assigned to the same benthic cover on different mosaic color classes. However, a unique color was not allowed to correspond to different benthic cover; e.g., a shade of red color could be used as the proxy for red algae on different classes of mosaics, but could not be the proxy for *Lithothamnion* spp. Although it is a time consuming and subjective process, in the end we were able to select appropriate color palettes for all benthic covers and mosaics color classes.

After reviewing of the preliminary results, mosaics that belonged to the color class III were discarded from the analysis. Colors degradation within this color class (the blue channel was significantly reduced), made the discrimination of *Lithothamnion* spp. from sand and/or erect red algae, in many cases, impossible.

For the final analysis, seven mosaics (six from 2010 and one from 2011) were excluded because they were of the color class III and five more (three from 2010 and two from 2011) were eliminated because of high negative unidentified pixels counts. Eventually, 31 mosaics from the 2010 season and 37 mosaics from the 2011 season remained. The number of mosaics per transect that remained in the analysis varied between 6 and 10 (Tab. 1).

Table 1. Number of mosaics used for semi-automatic analysis after rejection of inconsistent imagery (maximum possible count is 10, indicating that no mosaics were rejected in that transect).

	Transect			
Season	***5D***	***6E***	***8D***	***9D***
2010	6	8	10	7
2011	10	10	8	9

Regarding mosaic color classes, all mosaics that remained from 2010 season after the rejection process belonged to color class II. Only transect 9D (nine mosaics) from 2011 belonged to color class II whereas the remaining 28 mosaics from transects 5D, 6E and 8D belonged to color class I.

2.3.4 Different benthic cover color palettes

Although the sensitivity settings of the color picking tool and the order of the palette colors used to extract benthic cover could be easily standardized to completely eliminate operator bias, the benthic cover color palettes themselves were chosen manually, therefore some degree of bias during this process was unavoidable. To test an error inflicted by manually chosen color palettes, four randomly chosen video mosaics were analyzed using sets of independently prepared 32 color palettes for the ERBL and 32 color palettes for *Lithothamnion* spp. Benthic covers were calculated using each palette only once, hence, Mosaic 1 to Mosaic 4 were analyzed 7 times each, providing with sufficient amount of statistics.

3. Results

3.1 Different benthic cover color palettes

The comparison between the four randomly chosen video mosaics analyzed using different color palettes are shown in Fig. 4.

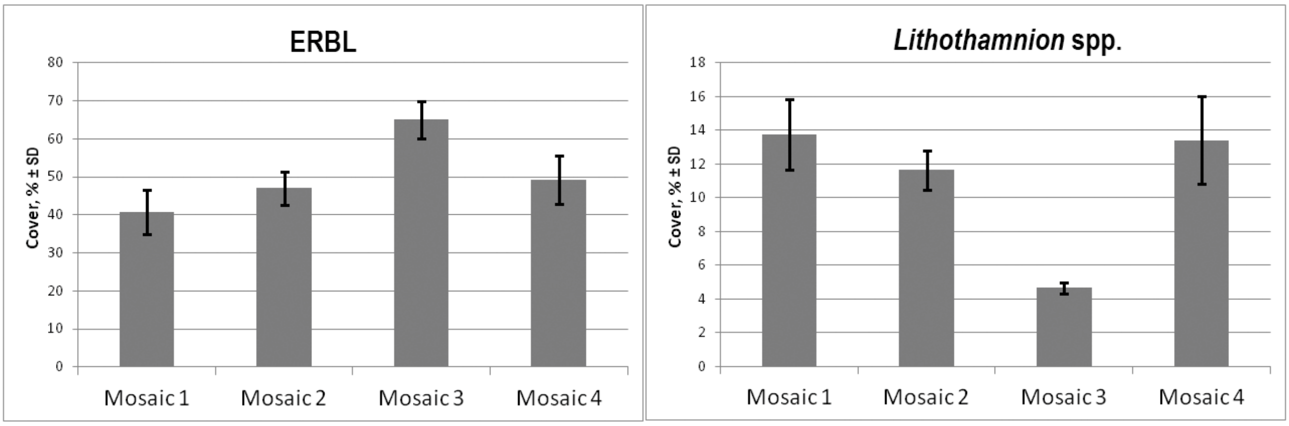

Figure 4. Average benthic cover estimations of *Lithothamnion* spp and ERBL with standard deviations, estimated from four randomly chosen mosaics using different color palettes.

For the *Lithothamnion* spp. coverage estimations, from the test mosaics the average coverarage was 10.8% with an average standard deviation of 1.5%, while for the erct red algae average cover was 50.5% with average standard deviation of 5.3%. Altrough general tendency is that standard deviation is greater for benthic covers having highier absolute values, variation still remains at an acceptable level. Most of the errors that added to the variations in average erect red algae and *Lithothamnion* spp. cover, appeared on the borders between different benthic cover types, were even manual classification (where to draw the line?) would be difficult and operator dependant.

3.2 Comparison of manual and computer-assisted cover estimations

The results from the semi-automated and manual analysis of benthic cover estimation were broadly congruent (Fig. 5 and Tab. 2). The most noticeable trend captured by both methods was an increase in red algae and corresponding decrease in *Lithothamnion* spp. cover for transects 8D and 9D in the 2011 season compared with the same transects in 2010 season. The biggest differences between the semi-automated and manual methods were between less abundant benthic cover types (sand in both seasons and *Lithothamnion* spp. cover in 2011 season), which were more affected by errors due to the limited amounts of sampling points used in the manual analysis. For more abundant (in our case, with absolute values bigger than approximately 30%) benthic cover types mean values for both methods were very close, although manual point-based analysis results have much higher variation.

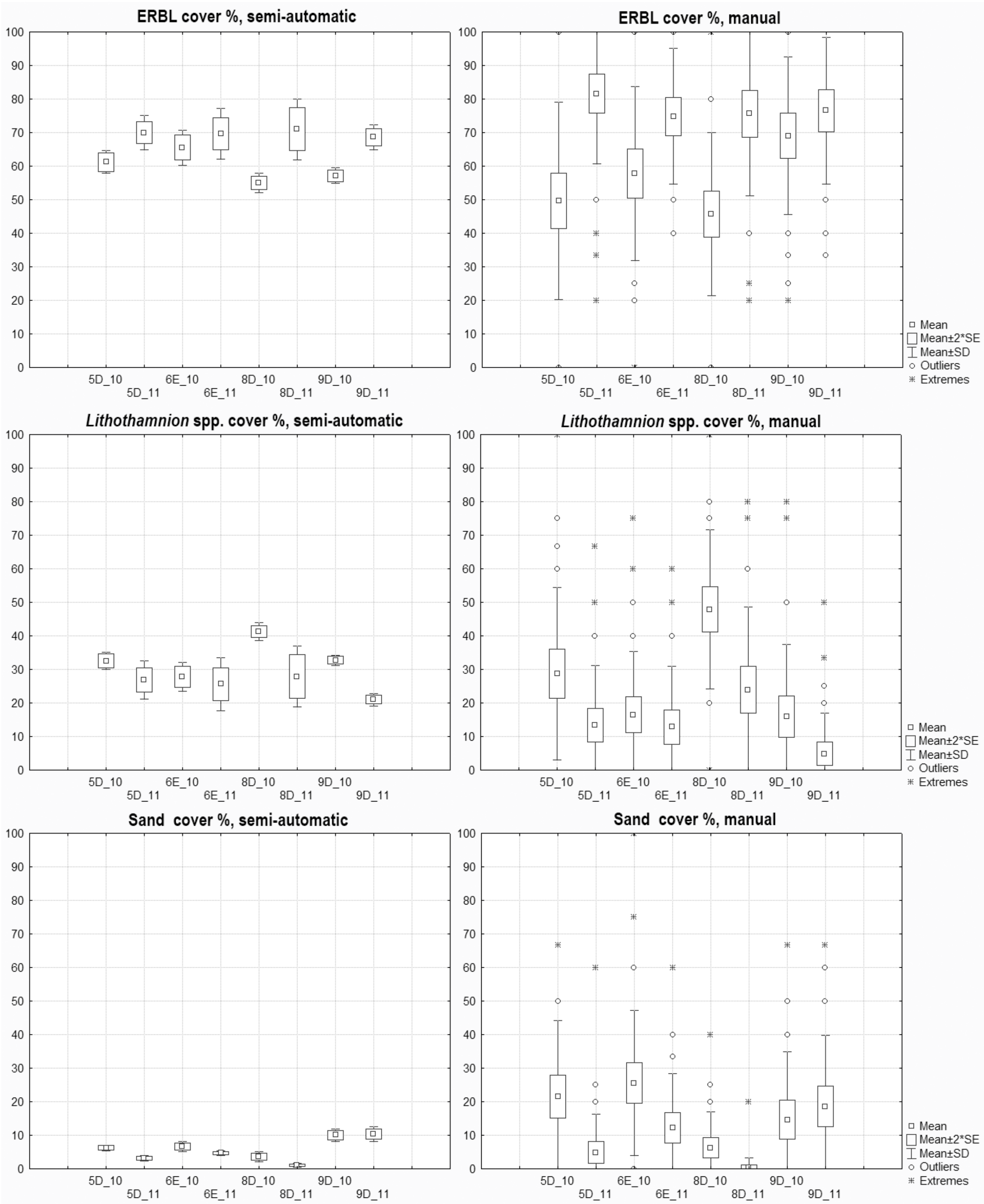

Figure 5. Computer-assisted cover estimations (on the left) compared to manual cover estimations (on the right). Labels on the X axis represent transect code (5D; 6E, etc) and season (10 for 2010 and 11 for 2011)

Table 2. Mean values and standard deviations of the benthic features covers estimated using manual point based and semi-automatic methods for 2010 and 2011 seasons.

	2010 season		2011 season	
	Manual	***Semi-automatic***	***Manual***	***Semi-automatic***
ERBL	55.6 ± 25.8	59.4 ± 3.9	77.2 ± 21.9	69.8 ± 6.0
***Lithothamnion* spp.**	27.3 ± 22.5	33.9 ± 3.0	13.8 ± 18.2	25.3 ± 5.8
Sand	17.0 ± 18.8	6.8 ± 1.5	9.0 ± 12.9	4.8 ± 1.0

3.3 Cost-effectiveness analysis

3.3.1 Semi-automatic computer-assisted color-based covers estimation

The computing time to create a mosaic from 30 seconds of raw video using the technique of Rzhanov et al. (2004) is approximately 15 minutes. Therefore, for the four video transects and 80 mosaics used in this study, the total computing time was 20 hours. However, the process could be easily parallelized using a modern computer with several processor cores and several copies of the software simultaneously running, without any performance loss. Such a computer would reduce the required computing time to 8 to10 hours. In addition, the creation of a mosaic using this technique does not require a solid scientific background, thereby reducing personnel costs. Results using this technique are operator independent so that using multiple operators will result in faster production of the mosaics.

3.3.2 Manual points-based video analysis

The initial preparation for the manual point-based analysis requires only features selection and naming, and in our case was accomplished in about 4 hours by an experienced researcher. After the features and the number of frames to be analyzed from transects are determined, a single frame analysis can be completed in approximately 5 minutes. The analysis of the test study data (4 transects, 200 frames) took about 16 hours. The entire analysis process should be performed by an experienced researcher and the process cannot be parallelized. Although it is possible to divide the data between several operators, the inter-calibration between each person and quality-control procedures are needed to ensure analysis uniformity.

Summary of the man-hours required to process our study data using semi-automatic and manual analyses is shown in the Tab. 3.

Table 3. Comparison of time, parallelization capabilities and operators qualifications for different steps of semi-automatic and manual imagery analyses

	Work hours	Parallelization	Technician	Researcher
Computer-assisted color-based semi-automatic analysis				
Mosaics creation	20	On same computer	Yes	Not required
Benthic cover color palettes	8	No	Not recommended	Recommended
Mosaics analysis	3	Different technicians	Yes	Not required
Total:	31			
Manual points-based analysis				
Features selection	4	No	Not recommended	Recommended
Frame analysis	16	Different researchers	Not recommended	Recommended
Total:	20			

Although semi-automatic analysis needed 9 more hours to be completed compared to a manual points-based analysis, the majority of this time (20 hours) was the computing time required to prepare mosaics. This process can be easily parallelized either on single computer or between computers and technicians. Furthermore, the majority of the tasks can be performed by moderately trained technicians, and researcher input is required only for 8 hours. As result, semi-automatic analysis can be performed faster and cheaper than manual analysis, which require researcher level operator on all stages of the process.

4. Discussion

The image analysis tools to parameterize feature coverage investigated in this study offer a robust method to assess environmental change at offshore wind farms and other offshore renewable energy projects sited at subtidal rocky substrates.

Although using manual point-based estimate techniques as “gold standard“ to assess other methods performance is arguable, any proposed new technique to determine cover estimates must have some level of similarity and show similar tendences to the manual-estimate technique, what was demonstrated during this study in the Fig. 5 and Tab. 2. Some outliers in the manual point-based benthic cover estimations are clearly artifacts due to relatively small number of points used in the frames; e.g., nowhere in the analyzed imagery was sand cover as high as 50% or more, which is the case in some of the frames analyzed manually, as scan be seen in the Fig. 5. Semi-automatic analysis uses a much greater number of pixels (the average number of identified pixels in single mosaics is 5.9 million, which corresponds to up to 60 million points per transect, comparing with only 200 points used in manual analysis), making such mistakes impossible.

The process of semi-automatic analysis could be fully automated, for example, with the use of scripting tools, but in this case human supervision on the extracted features is omitted and the quality of the analysis may suffer. Although a supervised analysis process cannot be parallelized on a single computer, using multiple technicians on the job will reduce the analysis time without impacting accuracy.

An alternative to the computer-assisted color-based semi-automatic or the manual point-based imagery analyses could be simple visual cover census that are simpler to implement and, in some cases, can be as accurate as point-based analysis (Deithier et al., 1993). However, simple visual cover census is subjective, and, in general, it uncertainty is difficult to predict and estimate. A point-based manual approach is more objective, but still is subject to significant errors in estimations within individual frames due to the limited amount of points that is practical to use. The semi-automatic benthic cover estimation from video mosaics approach have the potential to overcome the above difficulties. In projects were large amounts of imagery is needed to be analyzed, a semi-automatic approach is much faster and more efficient than any other analytical method, because, unlike manual methods, the most time consuming stage, the mosaics preparation is mainly computing time and could be easily parallelized as can be seen in the Tab. 3.

The biggest challenge with computer-assisted color-based cover estimations are inconsistencies in the real world underwater imagery due to inherent non-linearity of underwater imagery caused by the wavelength-dependent absorption (Duntley, 1963). This makes the proper compensation for the non-linearity a non-trivial task. The optical properties of sea water are dependent on many factors related to seasonal, geographical, hydrological differences. Different particles (biological and abiotic) also heavily affect the optical properties of seawater and it properties can rapidly change, especially in coastal areas. These changes make any modeling of water optical properties imprecise and probably inadequate for practical use. To properly compensate for water clarity, the optical properties of seawater need to be quantitatively measured during the filming. Although such measurements are fairly simple to do (Fonseca & Raimundo, 2007; Fu et al., 2014; Vecchi et al., 2014), this kind of equipment is rarely used during imagery collection and has yet to become a common tool in the benthologist inventory. As of today, information about the optical properties of seawater during filming is rarely available. Such uncertainties make the application of computer-vision algorithms for underwater video problematic because of the difficulties with colors and illumination add to the errors caused by the imperfections of the images-segmentation methods itself. The proposed approach allows the user to see the extracted features almost immediately so that quality control is fast and easy, thereby allowing for any inconsistencies in the extracted feature to be easily spotted, as well as the thoroughness of the selection.

Dividing video mosaics into different color classes can overcome some of the problems created by inconsistencies within the imagery. Subdividing the mosaics compromises analysis uniformity to some degree because separate benthic-cover color palettes are required for different mosaic color classes. However, our results shown in the Fig. 4 suggest that this compromise does not significantly affect the accuracy of the analyses. This conclusion is also supported by a comparison with a manual analysis (which is less affected by imagery inconsistency due to greater flexibility of the human eye) as shown in the Fig. 5. This is so even though the majority of the imagery from 2010 and 2011 had different colors and hence different color palettes that had to be used for features extraction (only one transect from 2011 was of the same color class as 2010 transects). Moreover, cover estimates for both seasons were in good agreement with manual point-based cover estimates. Human supervision of the extracted features indicated that the use of color palettes tuned to a specific color class can help with inconsistencies within the mosaics (e.g., when the ROV altitude changed for a short period of time that resulted in changes in the color in a small portion of the mosaic). Almost no pixels in such cases were extracted from areas that belong to different color classes, and instead they were added to the unidentified pixels count. Because only identified pixels were used to calculate total pixel count, any areas of different color class that were filled with unidentified pixels were effectively excluded from the analysis and did not biased the results.

There are ways to improve the results from automatic or semi-automatic underwater imagery analysis. Two improvements would be the use of more complicated and robust segmentation and/or imagery-preprocessing algorithms and improvements in the data collection procedures. While imagery processing methods development requires additional studies, implementation of stricter data-collection protocols is fairly simple. During this study, having more experience with data analysis after the 2010 season, we were able to reorganize data collection in 2011, which resulted into significant reduction in number of mosaics rejected during the computer-assisted color-based semi-automatic data analysis; nine were rejected from the 2010 dataset whereas only three were rejected from the 2011 data, as can be seen in the Tab. 1.

Although the technique used in the test study demonstrated good performance it has significant limitations. Not all of the benthic features were distinguished using colors alone, and we had to significantly reduce the number of features used in the semi-automatic analysis compared with the manual analysis. On another hand, the method does not require special programming skills, and a variety of image editing software can be used for benthic covers extraction by colors. Also, already produced mosaics can be used for other types of imagery analysis, such as count of visually distinguishable benthic organisms (e. g. sea stars or sea urchins). Comparing with the raw video, where only one of several overlapping frames can be seen at the time, and where zooming and scrolling through the imagery becomes more difficult, video mosaic can be easily scrolled in any direction and zoomed in and out, using most of image viewing software available, making imagery inspection from mosaics simpler and more flexible, thus less tiresome and probably more accurate.

The method can be adapted to imagery collected in different environments, containing different benthic features: all what is needed is to create color palettes for appropriate benthic features. For monitoring purposes, when data is repeatedly collected in the same environment, filming equipment and collection protocols are standardized, there is no need to change the imagery analysis procedures between the surveys and the same color palettes can be used over and over again, saving time and money.

Conclusion

As the need for offshore renewable energy increases, so does the need to find out whether installations have a deleterious effect on the marine environment. Methods of video data collection and analysis that reduce the cost of the impact assessments and environmental monitoring through the use of semi-automated video-analysis techniques would be of financial advantage to the companies operating offshore wind farms. Typically, impact studies need to be carried out before an impact exists, especially during the installation and then during the operations and finally after decommissioning of the installation. Ideally, the same areas should be repeatedly resampled in order to detect any changes in the benthic community. A semi-automated analysis of the video data collected on repeat surveys could be cost-effective and also reduce the bias caused by analyses performed by different personnel, as can be seen in the Tab. 3, that are expected to happen over the lifetime of an offshore wind farm. Of all the impact studies that need to be carried out (typically benthic fauna, marine birds, marine mammals and fish), the video analysis of benthic fauna has the largest potential for being automated. In the case of benthic cover, a semi-automated analysis is not only cheaper, but also allows to use much larger proportion of the imagery in the analysis comparing with manual methods, making it more robust to the random factors due to limited amount of sampling points. With proper equipment, sampling design and data collection protocols, virtually all the collected imagery can be used, rather than its subset, making the results more trust-worthy and the ability to detect change more reliable. The main constraint in a semi-automated analysis is the reduced number of features that can be extracted compared to a manual analysis. Future studies will have to assess whether the limited number of features that can be analyzed by a semi-automatic analysis are adequate to reflect the impact of offshore wind farms on the benthic community.

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References

Baatz, M., Schäpe, A. 2000. Multiresolution segmentation —an optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T., Griesebner, G. (eds) Angewandte Geographische Informations verarbeitung XII. Wichmann-Verlag, Heidelberg, pp. 12–23

Bergström, L., Kautsky, L., Malm, T., Rosenberg, R., Wahlberg, M., Åstrand capetillo, N., & Wilhelmsson, D. 2014. Effects of offshore wind farms on marine wildlife—a generalized impact assessment. Environmental Research Letters, 9(3), 034012. doi:10.1088/1748-9326/9/3/034012

Beuchel, F., Primicerio, R., Lønne, O. J., Gulliksen, B., Birkely, S-R. 2010. Counting and measuring epibenthic organisms from digital photographs: A semiautomated approach. Limnology and Oceanography: Methods 8, 2010, pp. 229–240

Burnett, C., Blaschke, T. 2003. A multi-scale segmentation/object relationship modeling methodology for landscape analysis. Landscape Theory and Landscape modeling 168, pp. 233–249

Bevilacqua, S., Fraschetti, A., Musco, L., Terlizzi, A. 2009. Taxonomic sufficiency in the detection of natural and human-induced changes in marine assemblages: A comparison of habitats and taxonomic groups. Marine Pollution Bulletin 58, pp. 1850–1859

Carleton, J.H., Done, T.J. 1995. Quantitative video sampling of coral reef benthos: large-scale application. Coral Reefs 14, pp. 35–46.

Dalghren, T. G., Schläppy, M-L., Šaškov, A., Andersson, M. H., Rzhanov, Y., Fer, I. 2014. Assessing the Impact of Windfarms in Subtidal, Exposed Marine Areas. In M. A. Shields, A. I. L. Payne (eds), Marine Renewable Energy Technology and Environmental Interactions, Humanity and the Sea, DOI 10.1007/978-94-017-8002-5_4, Springer Science+Business Media Dordrecht. pp. 39-48

Defeo, O., Lercari, D. 2004. Testing taxonomic resolution levels for ecological monitoring in sandy beach macrobenthic communities. Aquatic Conservation Marine and Freshwater Ecosystems 14, pp. 65–74.

Duntley, S. Q. 1963. Light in the sea. Journal of Optical Society of America 53, Issue 2, pp. 214-233

Dethier, M. N., Elizabeth S. Graham, T. S., Cohen, S., Tear, L. M. 1993. Visual versus random-point percent cover estimations: “objective” is not always better. Marine Ecology Progress Series. Vol. 96, pp. 93-100

Fonseca, A., Raimundo Jr., I. M. 2007. A simple method for water discrimination based on an light emitting diode (LED) photometer Analytica Chimica Acta 596, pp. 66–72

Foster, M.S., 1991. Point vs photo quadrat estimates of the cover of sessile marine organisms. Journal of Experimental Marine Biology and Ecology 146, pp. 193–203.

Fu, L-M., Ju, W-J., Liu, C-C., Yang, R-J., Wange, T-N. 2014. Integrated microfluidic array chip and LED photometer system for sulfur dioxide and methanol concentration detection. Chemical Engineering Journal 243, pp. 421–427

Garrabou, J., Riera, J., Zabala, M. 1998. Landscape pattern indices applied to Mediterranean subtidal rocky benthic communities. Landscape Ecology 13, pp. 225–247

Garrabou, J., Ballesteros, E., Zabala, M. 2002. Structure and dynamics of north-western Mediterranean rocky benthic communities along a depth gradient. Estuarian Coastal Shelf Science 55, 493–508

Gleason, A. C. R., Reid, R. P., Voss, K. J. 2007. Automated classification of underwater multispectral imagery for coral reef monitoring, Proceedings of MTS/IEEE Oceans 2007, 1-4 October, 2007.

Golmen, L.G., 2007. Potensiale for havenergiproduksjon i Møre og Romsdal, in: 04/2007, R.r.N. (Ed.), Runde miljøsenter/Energuide rapport om bølgje/tide energi i M&R. Runde miljøsenter. Norway. 53 pp.

Guinda, X., Gracia, A., Puente, A., Juanes, J. A., Rzhanov, Y., Mayer, L. 2013. Application of landscape mosaics for the assessment of subtidal macroalgae communities using the CFR index. Deep-Sea Research II (2013), http://dx.doi.org/10.1016/j.dsr2.2013.09.037i

Jensen J. R. 1996. Introductory digital image processing, 2nd edn. Prentice-Hall, Inc., Upper Saddle River, 379 pp.

Kohler, K.E., Gill, S.M. 2006. Coral Point Count with Excel extensions (CPCe): a visual basic program for the determination of coral and substrate coverage using random point count methodology. Computers & Geoscience 32, pp. 1259–1269.

Lampadariou, N., Karakassis, I., Pearson, T.H. 2005. Cost/benefit analysis of a benthic monitoring programme of organic benthic enrichment using different sampling and analysis methods. Marine Pollution Bulletin 50, pp. 1606–1618

Leonard, G.H., Clark, R.P. 1993. Point quadrat versus video transect estimates of the cover of benthic red algae. Marine Ecology Progres Series 101, pp. 203.

Magagna, D., Greaves, D., Conley, D., O’Hagan, A. M., Holmes, B., Witt, M., et al. 2012. How Experiences of the Offshore Wind Industry Can Aid Development of the Wave Energy Sector: Lessons Learnt from EIA Studies. Proceedings of the Twenty-second (2012) International Offshore and Polar Engineering Conference. Rhodes, Greece, June 17–22, 2012: pp. 644-651

Meese, R.J., Tomich, P.A. 1992. Dots on the rocks: a comparison of percent cover estimation methods. Journal of Experimental Marine Biology and Ecology 165, pp. 59–73.

Miller, I., Müller, R.1999. Validity and reproducibility of benthic cover estimates made during broad scale surveys of coral reefs by manta tow. Coral Reefs 18, pp. 353–356

Mortazavi, H., John P Oakley, J. P., Barkat, B. 2013.Mitigating the effect of optical back-scatter in multispectral underwater imaging Measurement Science and Technololy 24 074025 doi:10.1088/0957-0233/24/7/074025

Neubert, M., Herold, H., Meinel, G. 2006. Evaluation of remote sensing image segmentation quality—further results and concepts. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Salzburg

Ohlhorst, S. L., Liddell, W. D., Taylor, R. J., Taylor, J. M.1988. Evaluation of reef census techniques. In: Choat, J. H., Barnes, D., Borowitzka, M. A., Coll, J. C., Davies, P. J., Flood, P., Hatcher, B. G., Hopley, D., Hutchings, P. A., Kinsey, D., Orme, G. R., Pichon, M., Sale, P. F., Sammarco, P., Wallace, C. C., Wilkinson, C., Wolanski, E., Bellwood, O. (Eds.), Sixth International Coral Reef Symposium, Townsville, Australia, pp. 319–324.

Olsgard, F., Somerfield, P. J., Carr, M. R. 1998. Relationship between taxonomic resolution, macrobenthic community patterns and disturbance. Marine Ecology Progress Series 127, pp. 25–36.

Ottersen, G., Olsen, E., Meeren, G. I., Dommasnes, A., Loeng, H. 2011. The Norwegian plan for integrated ecosystem-based management of the marine environment in the Norwegian Sea. Marine Policy 35, pp. 389–398

Pech, D., Condal, A.R., Bourget, E., Ardisson, P.L. 2004. Abundance estimation of rocky shore invertebrates at small spatial scale by high-resolution digital photography and digital image analysis. Journal of Experimental Marine Biology and Ecology 299, pp. 185–199.

Rzhanov, Y., Mayer, L., Fornari, D. 2004. Deep-sea image processing. Proceedings of Oceans'04, Kobe, pp. 647–652

Schläppy, M-L., Šaškov, A., Dahlgren, T. G. 2014. Impact hypothesis for offshore windfarms: Explanatory models for species distribution at extremely exposed rocky areas. Continental Shelf Research 83, pp. 14-23 http://dx.doi.org/10.1016/j.csr.2013.11.018

Shields, M. A., Dillon, L. J., Woolf, D. K., Ford, A. T. 2009. Strategic priorities for assessing ecological impacts of marine renewable energy devices in the Pentland Firth (Scotland, UK). Marine Policy 33, pp. 635–642

Shields, M. A., Woolf, D. K., Grist, E. P. M., Kerr, S. A., Jackson, A. C., Harris, R. E., Bell, M. C., Beharie, R., Want, A., Osalusi, M., Stuart, W., Gibb, S. W., Side, J. 2011. Marine renewable energy: the ecological implications of altering the hydrodynamics of the marine environment. Ocean Coast Management 54, pp. 2–9

Solan, M., Germanob, J., Rhoadsc, D., Smithd, C., Michaude, E., Parryg, D., Wenzhoferh, F., Kennedyi, B., Henriquesa, C., Battlea, E., Careyj, D., Ioccok, L., Valentel, R., Watsonm, J., Rosenberg. R. 2003.Towards a greater understanding of pattern, scale and process in marine benthic systems: a picture is worth a thousand worms. Journal of Experimental Marine Biology and Ecology 285–286, pp. 313– 338

Somerfield, P. J., Clarke, K. R. 1995. Taxonomic levels, in marine community studines revisited. Marine Ecology Progress Series 127, pp. 113–119.

Teixidó, N., Garrabou, J., Arntz, W. E. 2002. Spatial pattern quantification of Antarctic benthic communities using landscape indices. Marine Ecology Progress Series. 242, pp. 1–14

Teixidó, N., Albajes-Eizagirre, A., Bolbo, D., Le Hir, E., Demestre, M., Garrabou, J., Guigues, L., Gili, J.M., Piera, J., Prelot, T., Soria-Frisch, A. 2011. Hierarchical segmentation-based software for cover classification analyses of seabed images (Seascape). Marine Ecology Progress Series 431, pp. 45–53.

Trygonis, V., Sini, M. 2012. photoQuad: A dedicated seabed image processing software, and a comparative error analysis of four photoquadrat methods. Journal of Experimental Marine Biology and Ecology 424–425, pp. 99–108.

Vecchi, R., Bernardoni, V., Paganelli, C., Valli, G. 2014. A filter-basedlight absorption measurement with polar photometer: Effects of sampling artefacts from organic carbon. Journal of Aerosol Science 70, pp. 15–25

Wang L., Sousa W. P., Gong P. 2004. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. International Journal of Remote Sensing 25: pp. 5655–5668

Wegge, N. 2011. Small state, maritime great power? Norway's strategies for influencing the maritime policy of the European Union. Marine Policy 35, pp. 335–342