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Textural analyses of multibeam sonar imagery from Stanton Banks, Northern Ireland continental shelf

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ABSTRACT

The mapping of marine habitats mainly relies on acoustic techniques and there is a clear need for reliable classification methods supplementing the interpreter with as much quantitative information as possible. This article presents textural analyses of multibeam sonar imagery from Stanton Banks, on the continental shelf off Northern Ireland. TexAn, originally developed for the textural analysis of sidescan sonar imagery, was tested over an area of ~72 km^2 surveyed in 2005 by the European MESH project. The multibeam imagery is affected by several artefacts, including strong uncorrected angular variations in some tracks, and the acquisition of some tracks with very different aspects. The results from unsupervised classification of the imagery, using K-Means, match well the interpretations that can be made using concurrent bathymetric data and visual observations acquired in a later cruise. Textural analyses successfully detect faint trawlmarks and distinguish between the different types of seafloor, including variations within sediments, rocky outcrops and gullied terrains.

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1. Rationale

Large-scale acoustic mapping of marine habitats began in earnest about a decade ago, with the collaborative research efforts of North American institutions to create national marine sanctuaries like Stellwagen Bank (e.g. [1]). It has now become a full-blown field of study, with many successful applications throughout the world (e.g. [2–5]). Habitat mapping aims at integrating biological and geological studies with sonar imaging of the seabed and overlying features. Although each mapping system has its own advantages and limitations (e.g. coverage vs. resolution), multibeam sounders have proved the most versatile and complete instrument, providing background topography and showing seabed features in relatively high detail (e.g. [6]). For most modern surveys, repeatability and time evolution have become key factors (e.g. [7]). Owing to the amount of data collected in a typical survey, and the subtle variations in acoustic responses of some seabed features, visual interpretation of sonar records is no longer an option. Acoustic classification systems must provide quantitative data in a reasonable time, and supplement the interpreter with as much information as possible.

There are many approaches to acoustic seabed classification, and end-users from different fields aim for different objectives. To conciliate the different aims, a workshop was organised in 2006 to bring together both providers of acoustic classification systems and users of sonar imagery and (potentially) classified maps [8]. This workshop was held at the University of Ulster, Coleraine, Northern Ireland, within the framework of the Interreg IIIB project MESH ("*Mapping European Seabed Habitats*") [9]. A common dataset of multibeam bathymetry and imagery was issued to all participants before the meeting, for treatment with different approaches. These included reprocessing of the raw acoustic measurements as well as processing with acoustic classification systems, and the results are presented in companion papers in this issue. The present article focuses on the analysis of the multibeam imagery with *TexAn*, a proprietary software from the University of Bath originally designed for textural analyses of sidescan sonar imagery [10,11]. Section 2 describes the general method used to analyse acoustic textures of sonar images with TexAn. Section 3 shows its application to the multibeam imagery from the common MESH dataset. Section 4 discusses the results, comparing them with those from other studies and with available ground-truth. It also makes recommendations for improving the processing of the input multibeam imagery. Finally, Section 5 provides a synthesis and guidelines for further uses of the textural analyses of multibeam imagery.

2. Method

2.1. Acoustic textures – TexAn software

Images, whatever their origin, are intuitively mapped on the basis of their tonal and textural properties. In the case of sonar

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images, whether acquired with a sidescan or a multibeam, tonal information is directly related to the amount of acoustic energy backscattered, generally represented as grey levels. Different statistical indices (e.g. extrema and median values) can be used to quantify local information. These first-order statistics quantify the distribution of the grey levels, but do not take into account their positions relative to each other (i.e. the acoustic textures). These textures, however, account for most of the information in acoustic images, as countless studies have shown (e.g. [7,10–21]). The local textural properties can be summarised as rough or smooth, varied or homogeneous, repetitive or random, and hence can help in distinguishing between different areas and features in the images. Quantitative textural measurements (second-order statistics) can be extracted from the image with various techniques, the most efficient being stochastic [12]. This original theoretical work was supplemented with practical applications to sonar imagery by [10,13–16] and others, showing that Grey-Level Co-occurrence Matrices (GLCMs) are optimally adapted. GLCMs address the average spatial relationships between pixels of a small region. Experiments on human vision (Julesz, 1973, *in* [10]) demonstrated that the eye could not distinguish between textures with different second-order statistics, proving GLCMs could be used to go further than traditional, visual interpretation alone.

The University of Bath software *TexAn* uses the indices derived from GLCMs calculated for each pixel in the images and clusters relevant textural indices into appropriate groups, related to specific acoustic processes and structures on/in the seabed. This software has been validated on sidescan sonar imagery in a variety of environments (e.g. [10,11,15,17,18]), and recent developments [19,20] showed its promise with multibeam sonar imagery.

To quantify the textures, *TexAn* calculates GLCMs $\{P_D(i,j)\}$ over the entire image, within moving windows of a set size. Each element $P_D(i,j)$ expresses the relative frequency of occurrence, within the window, of two pixels with the respective grey levels i and j at $D(SZ,\theta)$ (Euclidian distance SZ and angle θ) from one another. If the image is quantified with NG grey levels, the GLCMs will be NG $\times$ NG arrays. The distance $D(SZ,\theta)$ is very sensitive to the orientation θ. This is particularly true for sonar images, in which the insonification angle can vary both along and across track. In order to avoid changes in the textural indices of a feature with non-isotropic texture, insonified at different angles, the GLCMs are calculated for the angles $\theta = 0°$, 45°, 90° and 135° and then averaged, following Refs. [13] and [10]. Hence the only remaining computational parameters are the inter-pixel displacement *SZ*, the number of grey levels (*NG*) and the size of the computational window (*WS*). The matrices resulting from the calculations described above, however, cannot be interpreted directly in an easy way (as can be seen from the examples in Fig. 1). Therefore, their information is summarised in a set of statistical measures, called 'indices'. More than 25 different textural indices have been described in the literature (e.g. [10,13]), but a detailed evaluation of their performance has shown that the combination of two indices (entropy and homogeneity) seems sufficient to explain nearly all the textural variability in sidescan sonar images [10,14]. The entropy index measures the lack of spatial organisation within the computational window, and hence is a measure of the local amount of 'chaos'. It will be higher for rough textures, and lower for organised heterogeneities such as ripples. Textural homogeneity is a measure of the amount of local similarities within the window. The index is similar to the 'inverse-difference moment' of [15] and will increase in windows with less contrast (fewer grey levels). An additional factor was introduced by [10] in the calculation of this index to ensure invariance during linear grey-level transformations (such as those caused by variations in TVG or AVG from one computation window to another). Fig. 1 shows how GLCMs can vary for even simple textures, and how entropy and homogeneity can clearly distinguish between even complex textures. The textural indices having been chosen, there is now a need to identify the best combination(s) of inter-pixel displacement *SZ*, number of grey levels *NG* and computation window size (*WS*) that maximise the difference between regions in the entropy/homogeneity space (also called feature space).

2.2. Optimisation of textural parameters

This optimisation is performed by choosing Training Zones representative of the acoustic facies encountered in the entire image and which one wants to distinguish. These Training Zones need to be square (to avoid over-emphasis on one direction in the image). They need to be large enough to be statistically significant for a large range of window sizes, WS, as their size influences the number of times independent values can be measured. For example, for a Training Zone of 100 $\times$ 100 pixels, choosing $WS = 90$ pixels can only yield 100 independent measurements of entropy and homogeneity, whereas choosing $WS = 10$ pixels can yield 8100 independent measurements. Conversely, Training Zones need to be small enough to encompass only one type of acoustic texture.

The first parameter to vary is the size *WS* of the computation window. It can in theory take any value smaller than the size of the Training Zones, but is in fact constrained by its physical significance. Smaller values (10 pixels or smaller) will increase the contributions of very close pixels and measure the high-frequency backscatter variations in the image (generally attributable to speckle, particularly in multibeam imagery). Larger values (close to the size of the Training Zones) will instead look at lower-frequency variations in the image, and will have a higher probability of mixing two texturally distinct regions or missing intrinsic textural characteristics. Finally, the difference in insonification angles from one edge of the computation window to the opposite edge will need to be taken into account, although it will be smaller for multibeam systems than for sidescan sonars.

The second textural parameter is the displacement size *SZ* within the window. It is intricately linked to its size *WS*. Values close to *WS* will emphasize variations of the same size as the computation window, whereas the smaller values will emphasize the noise within the window. Again, the influence of the variations in ensonification angle between pixels separated by *SZ* should be accounted for. If small-scale variations in large structures are to be detected, a small *SZ* should be associated to a large *WS*. However, if the structures to be observed are characterised by variations of a wavelength comparable to their dimensions, *SZ* should be slightly less than the size of the window. Based on practice with both sidescan and multibeam imagery, the optimal values of *SZ* usually lie close to *WS*/2.

Last but not least, the number of grey levels *NG* will affect both the speed of the computation and its accuracy. As *NG* decreases, there are less and less variations around the mean grey levels (smoothing of the dynamic range). For high values (as close to the full dynamic range as possible), the textures are more likely to appear rougher and more heterogeneous. Systematic tests show that, as *NG* decreases from 256 (8-bit dynamics) to 16 (4-bit dynamics), entropy will decrease linearly by 50% at most, and homogeneity by 30%. The overall computation time varies approximately as $o(NG^2)$. For 8-bit dynamic ranges, practice shows that optimal numbers are usually between 32 and 128, depending on the quality of the processing and the amount of noise in the image.

The combination(s) of optimal values are found by systematically varying *NG*, *WS* and *SZ* and calculating entropy and homogeneity at each point in the Training Zones. The separation between Training Zones is visualised in the feature space. It can be tested quantitatively, but it is very sensitive to the overlap of poorly defined (or complex) classes and a contextual assessment of the separation is preferred. For example, dunes will be seen either as "dunes" for large values of *WS* or as alternate "strips" for small values of *WS*. Similarly,

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