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Automatic mine detection by textural analysis of COTS sidescan sonar imagery

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Abstract. Sidescan sonar imagery of the sea floor is difficult to interpret visually, and classification techniques are now increasingly used to supplement the interpreter with reliable, quantitative results. Active high-resolution sonar has been shown to be the only sensor able to detect man-made objects and, in particular, mine-like objects on the sea bottom with a high probability of detection and an acceptably low false-alarm rate and a high area coverage rate. The actual distinction between the image of a mine and an object that physically resembles a mine is very complex, however, and relies on the recognition of subtle differences in shapes and textures. This study aimed to combine two different advances in sidescan sonar applications. Recent trials at sea have demonstrated that the latest generation of commercial off-the-shelf sidescan sonars was able to image mine types, even stealthy mines with low acoustic signatures. Concurrently, a method of advanced image analysis has been developed, based on the quantification and recognition of acoustic textures. This method has been extensively calibrated and ground-truthed in complex terrains, and the results presented here show that it can be applied successfully to the detection of mines.

1. Introduction

Sea mines have played a significant role in the majority of naval conflicts since the American Civil War and can create major problems even in peacetime (i.e. mines from past conflicts or terrorist actions). The sheer importance of research and development work carried out in the field of mine counter-measures (MCM) is a testimony to the significance of the problem. Mines constitute an inexpensive and readily available weapon, easy to deploy and effective against ships and submarines alike. They can be used in either defensive or offensive roles. A country can lay mines in its own harbours and coastal waters in order to deny access to invasion forces, or lay mines in other countries’ waters to damage and/or delay shipping by disturbing the sea lines of communications.

Mines can be cleared by minehunting, using a minehunting sonar and disposal vehicles or divers, or minesweeping, using towed or remotely controlled vehicles which activate the mines by imitating target signatures. However, before a mine field can be cleared or neutralized, the mines need to be located. Peacetime trials and wartime actions showed that active high-resolution sonar is the only tool which can

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detect mine-like objects (MLOs) on the sea floor with acceptable success rates and on large areas (e.g. Horwitz et al. 1993, Brissette 1997, Buck 1997). The same studies also conclude that, without sophisticated classification techniques, it is very difficult to distinguish between real mines and objects that physically resemble mines.

This study aimed at combining two different advances in sidescan sonar applications. First, recent trials at the Naval Underwater Weapons Center (NUWC, Newport, Rhode Island, USA) have demonstrated that the latest generation of sidescan sonars was able to image many mine types with reasonable accuracy (Kozak 1997). But the size of the mines and their low acoustic signatures mean they are difficult to detect visually on large areas of more or less homogeneous sea floor. Concurrently, a method of advanced image analysis has been developed at the Southampton Oceanography Centre (SOC, Southampton, UK), based on the quantification and recognition of acoustic textures (Blondel 1996, Blondel et al. 1998). This method has been extensively calibrated and ground-truthed in complex terrains. It has so far been used mainly for geological studies, and the present study assessed its potential for the detection of mines.

2. Mine detection

The physical compositions and modes of emplacement can be very varied (e.g. Janes Information Group 1995, Brissette 1997). Moored mines are anchored to the sea floor at a desired depth below the surface. They are more effective in deep waters (greater than 60 m) and are activated by contact (for the older models) or by magnetic or acoustic influence. The typical size of a moored mine is of 1–2 m$^3$ (Janes Information Group 1995). Tethered mines are left on or near the sea floor and detect targets passively before using homing devices to reach them. These mines are predominantly used off the continental shelf in very deep waters and play an important role in antisubmarine warfare. Ground mines are laid directly on the sea floor and are predominantly used in shallow waters, e.g. around harbours, rivers or coastal shipping routes. They are composed of materials like glass-reinforced plastic or steel, and their sizes range from cylindrical to multi-faceted. These factors influence the acoustic signature of the mines and make them more or less difficult to detect.

Mines are best detected with sidescan sonar imagery (Horwitz et al. 1993, Brissette 1997, Buck 1997; Kozak 1997) or, in specific conditions, with some of the most modern high-resolution multibeam systems (Brissette 1997). Sidescan sonar produces images of the sea floor, made of points whose values are proportional to the amount of energy backscattered, and are expressed as grey levels. The backscattering is affected, in decreasing importance, by the geometry of the sensor–target system (relative angle of ensonification), the morphological characteristics of the surface (e.g. micro-scale roughness) and by its intrinsic nature (composition, density, relative importance of volume and surface reverberation) (e.g. Blondel and Murton 1997). Therefore, the acoustic appearance of mines will be of bright elongated scatterers accompanied by shadows. When analysed visually by experts, the structure of the acoustic echo/shadow pattern may reveal the existence of mines and, sometimes, even the type of mine encountered (Brussieux and Martin-Lauzer 1998).

The amount of acoustic energy backscattered by each mine, and the actual extent of the backscattering area, will depend on the type of mine and how stealthy it is. The accompanying shadow will depend on the height of the mine above the sea floor and its orientation respective to the imaging sonar. Finally, there are many other MLOs on the sea floor that may produce the same types of acoustic patterns.
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3117 (cf. Blondel and Murton 1997): small rock outcrops, pockmarks, lobster traps, deep scours (from icebergs or trawls) and man-made debris (especially around harbours and along busy shipping lines). The recognition of the differences between the acoustic images of MLOs and mines usually relies on the recognition of the differences between small-scale acoustic textures: differences in organization (e.g. elongated, circular, random), the spatial extent of the acoustic targets, and their small-scale roughness. Therefore, the optimal classification technique should account for, and quantify, these characteristics.

3. Sea-floor characterization with TexAn

Remotely sensed images in general, and sidescan sonar images in particular, are mainly described by their tonal and textural properties. However, most physical processes, and their surface manifestations, cannot be described only with their tonal properties. The same is true of most MLOs. Textural properties correspond to the spatial organization of the grey levels within a neighbourhood. Differing textures are intuitively described as smooth or rough, small-scale or large-scale, random or organized. Theoretical and experimental studies show that they are best quantified with stochastic methods, such as grey-level co-occurrence matrices (GLCMs) (e.g. Haralick et al. 1973, Blondel et al. 1993).

GLCMs address the average spatial relationships between pixels of a small region, by quantifying the relative frequency of occurrence of two grey levels at a specified distance and angle from each other. The distance $D(d, \theta)$ between pixels is very sensitive to the orientation $\theta$. This is particularly true for sidescan sonar images, in which the insonification angle varies across-track, but also along-track because of the movements from the sonar platform (roll, pitch, yaw). Two identical structures may be imaged with distinct look-angles, and their textural signatures appear different. To ensure that the textural indices of any non-isotropical texture are not significantly influenced by the angle at which it is ensonified, the co-occurrence matrices are averaged for angles $\theta = 0^\circ, 45^\circ, 90^\circ$ and $135^\circ$ (Blondel 1996). The distance $D(d, \theta)$ is now reduced to the inter-pixel displacement $d$, which needs to be suitably chosen. If the image is quantized on NG grey levels, each point of the image will be described with an NG x NG matrix. For a traditional image quantized with 256 grey levels, this means that each point will be associated with a matrix of $256 \times 256$ floating-point values. The reduction in the number of grey levels yields a reduction in the size of the matrices, but it does not ease their storage or interpretation. Because they are difficult to manipulate and interpret, GLCMs are described by statistical measures, called indices. More than 25 textural indices are available from the current literature (e.g. Haralick et al. 1973, Blondel 1996). Their usefulness for sonar images has been assessed in detail (e.g. Blondel et al. 1993, Blondel 1996; Blondel and Parson 1998), and only two indices have been retained: entropy and homogeneity. They are combined in the software package called TexAn (Textural Analysis) and developed at the SOC (Blondel et al. 1998).

Entropy measures the lack of spatial organization inside the region where the GLCM is computed. Entropy is high when all co-occurrence frequencies are equal, i.e. very low. This corresponds to areas of rougher textures. Conversely, entropy is low when the texture is smoother and more homogeneous. Sedimentary facies will be represented by low entropies, which increase with the number of heterogeneities (gravel patches, ripples, rocky outcrops). More complex structures such as slumps or turbidity channels will present higher entropies again. In regions affected by
volcanic activity, lava flows will exhibit entropies commensurate with their morphological roughness (low for sheet flows, higher for pillow or lobate flows). All geological features visible on sonar images are characterized by specific entropy signatures, independent of their geographical location. Local-scale variations will also be enhanced by changes in entropy. This is important in the detection of MLOs, which will show acoustic textures contrasting with their backgrounds and will, in some cases, be associated with shadows.

Homogeneity is directly proportional to the amount of local similarities inside the computation window. This parameter was specially modified to ensure its invariance through linear transformations of the grey levels (Blondel 1996). If the angle-varying gain or time-varying gain are changed, or the image contrast is changed but the sea floor remains the same, then the modified homogeneity parameter will remain the same. Homogeneity will be higher in regions of homogeneous backscatter or in regions with a few grey levels organized along at the scale of the computation window. Homogeneity is able to quantify the differences between smooth sediments and faulted or deformed areas (including ripples or slumps) or between lava flow morphologies. It should also be useful to differentiate between unorganized structures and organized structures like the MLOs (usually elongated).

Studies on various terrains (e.g. Blondel et al. 1993, Blondel 1996, Blondel and Parson 1998, Blondel et al. 1998) showed that entropy and homogeneity were sufficient to distinguish the different types of geological environments (figure 1). Entropy and homogeneity are computed for each point in the original image and quantized between 0 and 255. Because of its mathematical definition, homogeneity is always negative. The quantized homogeneity has been inverted on a logarithmic scale: low quantized homogeneity values (near 0) will correspond to large amplitudes of the original homogeneity; conversely, high quantized homogeneities (near 255) will correspond to very low values of the original homogeneity. Figure 1 shows how entropy and quantized homogeneity vary for test geological regions. They were computed for square regions 100-pixel wide, and 80+ texture measurements were made for each region. The sediments are smooth and homogeneous and will be associated with lower entropies and higher homogeneities (near 0, in this case), concentrated in the same interval. The fault scarps are more organized, with a diagonal elongation, but more heterogeneous, and the sonar-facing scarp shows a mottled texture. Accordingly, the entropies are higher and the homogeneity lower (varying from 120 to 180), covering a wider interval. Finally, the volcanic mounds present rougher textures (with entropies concentrated around 180) and homogeneities varying widely. The exact location in the entropy/homogeneity space of texture measurements will vary with the sonars used and the types of structures imaged.

The distribution of entropy and homogeneity creates two-dimensional look-up tables, where each pair of entropy/homogeneity measurement corresponds to one particular type of sea floor. Regions on the sea floor with a similar geology will be associated with points close to each other in the look-up table. The shape of clouds of points, or the presence of clusters of points away from the main regions, may reveal subtle differences in the acoustic textures: types of sediments, density of faulting, or ‘concealed’ details which had not been noticed previously. Julesz (1973) demonstrated during experiments on human vision that the eye could not distinguish between textures with different second-order statistics, proving the advantage of this particular technique. Blondel and Parson (1998) and Blondel et al. (1998) show some applications of this property in sedimentary environments. This method has
Previous studies have demonstrated that two texture measurements are enough to recognize the different types of acoustic units (Blondel et al. 1993, Blondel 1996, Blondel and Parson 1998, Blondel et al. 1998). Entropy is a measure of textural roughness, and homogeneity (negative and quantized on a logarithmic scale) measures the amount of local similarities. This figure shows the separation between geological end-members imaged with the sidescan sonar TOBI (Blondel and Parson 1998). The exact location of the entropy/homogeneity measurements will vary with the sonars used and the environments surveyed.

not been used previously in areas with man-made structures, but it is theoretically capable of detecting MLOs as well. It will be interesting, therefore, to assess its potential, in particular for the distinction of mines from MLOs.

4. Application of TexAn to mine images

The images presented here were all acquired during recent trials at the NUWC (Kozak 1997). The trials were conducted with mine types that are representative of both traditional steel mines and the newer high-technology plastic/stealth types. The sidescan sonar used was the Klein System 2000, one of the latest generation of commercial off-the-shelf (COTS) sidescan sonars employing full digital designs. The Klein System 2000 simply consists of a small lightweight instrumented towfish, a single coaxial cable and the surface processing unit. It is easy, therefore, to deploy and use with many types of platforms. The present images were obtained at a frequency of 500 kHz and did not undergo any processing after acquisition.
4.1. Conventional mines

The first type of mine (‘A’, figure 2(a)) is usually launched from submarines. It presents a low acoustic signature and is essentially a torpedo modified with mine components. The body is metal-cased, and the dimensions are about 4.1 m in length and 0.5 m in diameter. Figure 2 shows it in a sedimeted environment, ensonified from the right of the image. The size of the image is approximately 35 m horizontally (across-track) by 25 m (along-track). The grey levels are proportional to the backscatter; acoustically reflective regions are bright, shadows and less-reflective regions are dark. The very dark region covering the extreme right of the image corresponds to the water column. The mottled sediments on the sea floor are interrupted by a near-diagonal scour mark, most probably left by a fishing trawler. Several small MLOs are found in the image. They are dark structures associated with lighter returns at further range and, therefore, may be pockmarks of some sort, the dark areas being the parts of the sea-floor depression in the shadow and the bright areas to the slopes facing back toward the sonar. Others are bright structures associated with darker regions immediately adjacent and are interpreted as small rocks or boulders with acoustic shadows. The mine is the very narrow object (a few pixels wide at most), lying in the middle of the image at a 45° relative angle.

The second type of mine (‘B’) is much smaller (figure 2(b)). Cylindrical in shape, its dimensions are about 1.4 m in length and about 0.5 m in diameter. The image covers approximately 10 × 10 m on the ground and was ensonified from the right. The very dark region at the extreme right of the image corresponds to the water column. It varies in width, which may be explained by slight variations in the altitude of the sonar above the sea floor or by slight changes in the topography of the sea floor itself. This image shows mainly sediments with a mottled texture and varying grey levels. The sea floor is crossed by several quasi-linear tracks, again associated with trawlmarks. There are less boulders and small depressions on the sea floor, and the average backscatter levels are significantly higher than on the previous image, particularly at far range. The mine itself is in the centre of the image and is lying on the sea floor at a 45° angle. The target was imaged at a range of approximately 20 m from the towfish. Its shape is elongated and very thin (one or two very bright pixels at most).

Entropy and homogeneity were computed for the two images and quantized between 0 and 255. As a first approximation, the look-up tables were partitioned into cells with colours arbitrarily distributed in the red–green–blue space, ranging from purple, through blue, green and yellow, to red (figure 3(b) and (c)). The arbitrary assignation of colours to the different cells induces a separation more or less by entropy levels. Purple colours correspond to the lower entropies, red to the highest. Figure 3(a) shows the classification of the image with mine ‘A’, and figure 3(b) shows the look-up table for the image. Similarly, the look-up table for the image with mine ‘B’ is presented in figure 3(c) and the classification of the image in figure 3(d).

The water column is masked in both images (hashed pattern), as it does not contain any useful information. Most of the two classifications show predominantly yellow-orange tones, which correspond to the sedimentary sea floor. Some of the pockmarks and boulders are visible as circular orange regions on a yellow background. The outline of the large diagonal scour mark is visible, marked by an alignment of orange areas elongated in the same direction. The regions coloured in green correspond to intermediate textures, with medium entropies. They are found at very far range, where the amplitude of the acoustic echoes decreases noticeably,
Figure 2. (a) 500-kHz image of a conventional-type mine ('A'). The image covers approximately $35 \times 25$ m on the ground and was ensonified from the right. The grey levels are proportional to the amount of backscatter. The mine is the very narrow object (a few pixels wide at most) lying in the middle of the image at a $45^\circ$ relative angle. The other individual objects are boulders or small depressions of the sea floor (pockmarks). The long, diagonal structure spanning the middle of the image is a trawlmark. (b) 500-kHz image of another conventional-type mine ('B'). The image covers approximately $10 \times 10$ m on the ground, and was ensonified from the right. The sea floor is criss-crossed by quasi-linear trawlmarks and shows less boulders and pockmarks. The mine is near the centre of the image and shows a very thin section.
and at very close range, near the first returns from the sea floor. Despite the arbitrary choice of colours, the mines can be readily detected (figure 3(a) and (d)). They appear as elongated bright-red targets associated with highly contrasted purple patches. The bodies of the mines are associated with entropies between 141 and 152 and homogeneities between 211 and 230. These high values of entropy are explained by the rougher acoustic texture of the sea floor close to the mines: the texture of sediments is perturbed by the bright backscattering body of the mine and the associated shadow. The homogeneity values correspond to low amounts of local similarities, again attributable to the presence of the mine and its shadow in the midst of the sedimentary textures.

4.2. ‘Stealth’ mines

The next two types of mine (figure 4) were selected for their very low acoustic signatures (Kozak 1997). Mine ‘C’ is one of the newest high-technology anti-invasion ground mines. It is made of a plastic case and has a conical and low-profile shape. Its dimensions are about 1 m in diameter at the base and 0.5 m high. Figure 4(a) shows the mine on the sea floor, at a range of approximately 25 m from the towfish. It is associated with a long shadow, clearly indicative of a conical shape. The darker, diagonal linear feature nearby is most probably a trawlmark. The overall texture of the sediments in the image is very mottled, with a large quantity of small, bright reflectors, interpreted as pockmarks and small rocks.

Mine ‘D’ is a recently manufactured mine with a plastic case. Combined with its sloping angled faces and low profile, it produces a ‘stealth’ acoustic signature. The mine is nearly 1 m long, 0.8 m wide and 0.4 m high. Figure 4(b) shows the mine lying on the sea floor, at about 25 m from the towfish. The acoustic image of the mine covers a few bright pixels and is associated with a small shadow a few metres long. Because of the complex acoustic signature of this mine, it is difficult to determine the aspect angle. Left of the mine, a vertical dark line corresponds to another trawlmark. The two other rectangular objects seen above and below the mine are New England lobster traps (Kozak 1997). The texture of the sea floor around the

Figure 3. (a) Automatic classification of the sonar image of mine ‘A’. The textures associated with each small region of the sea floor were computed, and the intervals of entropy/homogeneity were attributed arbitrary colours. The reflections from the water column (extreme right) are masked with a hashed pattern. Mine ‘A’ and its associated shadow are clearly visible on the sedimentary background. The other mine-like objects on the sea floor do not have the same textures and are correctly assigned to the sedimentary background (yellow and orange tones). Although their detection was not aimed for, some individual boulders and sea-floor depressions are visible as small areas of homogeneous orange or yellow tones. (b) Look-up table showing the distribution of entropy and homogeneity for the region around mine ‘A’. The two textural measurements have been quantized between 0 and 255. Purple corresponds to the lower entropies and homogeneities, red to the highest entropies and homogeneities. (c) Look-up table showing the distribution of entropy and homogeneity for the region around mine ‘B’. The different intervals of entropy/homogeneity have been attributed arbitrary colours, similar to the ones used in (a). (d) automatic classification of the sonar image of mine ‘B’. The reflections from the water column (extreme right) are masked with a hashed pattern. Mine ‘B’ and its associated shadow are clearly visible on the sedimentary background. Likewise, some individual structures are visible as small areas of homogeneous orange or yellow tones (e.g. the small pockmark above the mine).
mine is similar to the texture around mine ‘C’—very mottled, with a large proportion of small, bright reflectors.

Entropy and homogeneity were computed and quantized between 0 and 255. The classification of the image containing mine ‘C’ is shown in figure 5(a) and the accompanying look-up table in figure 5(b). The look-up table for the image containing mine ‘D’ is presented in figure 5(c) and the resulting classification in figure 5(d). The first observation is that the look-up tables have similar shapes to the look-up tables for the two other mines (figure 3). The homogeneity values have similar ranges, but entropy values are restricted to smaller variations. This may be explained by differences in the textures of the underlying sea floor (more mottled and, therefore, with higher entropies) or by the lower acoustic signatures and sizes of the mines (smaller backscatter, smaller shadows). The previous studies showed that mines ‘A’ and ‘B’ are associated with entropies between 141 and 152 and homogeneities between 211 and 230. The same intervals have been highlighted in red in the current look-up tables and the rest of the intervals left in grey (figure 5(b) and (c)). Only the pixels of the two images whose entropy and homogeneity fall into these intervals are represented in red (figure 5(a) and (d)).

Mine ‘C’ has a low acoustic signature, and the NUWC trials showed that it was one of the most difficult to detect with a sonar system (Kozak 1997). It can be detected visually on the sonar imagery by its shadow, because the conditions of acquisition (altitude of the imaging platform above the sea floor and distance from the mine) were favourable. But the textures computed with TexAn unambiguously detected the mine from its entropy/homogeneity signature (figure 5(a)). This means that the mine could have been detected in other survey conditions, even without a concomitant shadow. Six other regions were detected by the algorithm and are shown in red on the image, but their sizes are too small to be actual MLOs. Four of these regions cover only 1 pixel, and the other two are elongated across-track with respective lengths of 2 and 4 pixels only. These correspond to lengths of a few tens of centimetres at most, clearly too small for mines. The selected intervals of entropy and homogeneity are sufficient, therefore, to detect mine ‘C’ without ambiguity.

The visual detection of mine ‘D’ is more difficult, as the body of the mine itself only covers a few pixels, of a backscatter level comparable to some of the bright reflectors around which are interpreted as small pockmarks, boulders and lobster traps. The shadow associated with the mine is much smaller too, very close and very similar to the dark, large trawlmark on the left. The mine, therefore, is not discernible on the basis of its proper acoustic reflectivity or the differences between the mine and its immediate background (first-order statistics). Figure 5(d), however, shows that mine ‘D’ is readily identified from its texture (second-order statistics). The points highlighted in red follow exactly the contours of the mine’s body. No other MLOs were detected in the image. Even the lobster traps, of similar dimensions and at similar ranges, were not detected by the algorithm.

5. Conclusion

The images presented in this article are the result of the most recent advances in COTS sidescan sonar technology (Kozak 1997). Even the most recent mines with low acoustic signatures are visible on these types of sonar imagery. But their small size makes them difficult to detect on large portions of sea floor, particularly in homogeneous sedimentary environments, and they need to be clearly differentiated
Figure 4. (a) 500-kHz image of a new type of mine ('C') with a low acoustic signature. The mine lies in the middle of the image and is associated with an elongated shadow. It was ensnared from the right. The diagonal structure nearby is a trawlmark. The texture of the image is generally mottled, with many small, bright reflectors. (b) 500-kHz image of another 'stealth' mine ('D') with a low acoustic signature. The mine lies near the middle of the image, nearly along the vertical. The vertical dark segment left of the image is another trawlmark. The two rectangular objects above and below the mine are lobster traps. The texture of the image is very mottled, with many small reflectors of backscatters comparable to the mine itself.
from other MLOs that could lay on the sea floor but do not require the same level of attention.

In a different environment and with different aims, a method of advanced image analysis was developed, based on the quantification and recognition of acoustic textures (Blondel 1996, Blondel et al. 1998). This method has been extensively calibrated and ground-truthed in complex terrains around the world. It had so far been used mainly for the geological studies of mid-ocean ridges and had shown a clear potential in discriminating very subtle acoustic textures (Blondel et al. 1993, Blondel et al. 1998) or in detecting specific features in very large regions (Blondel 1996, Blondel and Parson 1998, Blondel et al. 1998). The present study aimed at assessing the potential of this technique for the detection of mines.

It was demonstrated here that it was possible to detect the mines and isolate them, unambiguously, from their background, by using their textural properties, computed with the TexAn software package (Blondel et al. 1998). The unsupervised association of colours with the textures associated with the mine and its shadows enable the fast differentiation of the mine from its background. The automatic detection of the mines is also possible by only highlighting the points whose textures match specific intervals of entropy and homogeneity. This application of textural-analysis techniques developed by Blondel (1996) and Blondel et al. (1998) to COTS sidescan sonar imagery acquired by Kozak (1997) proved highly successful. All mines were detected without ambiguity, despite the presence of other MLOs in the vicinity (e.g. boulders, lobster traps). These results were obtained for both conventional-type mines and ‘stealth’ mines with very low acoustic signatures.

These results now need to be extended to other images of mines, in a combination of different settings, imaging frequencies and with varied types of MLOs in the vicinity. When studying particular mid-ocean ridge terrains, the extension of TexAn to other frequencies showed, for example, that the textures of geological units could vary in the entropy/homogeneity space, creating new look-up tables for each new frequency (Blondel et al. 1998, Blondel submitted) but still allowing accurate recognition. The extension of mine detection to other frequencies should establish new look-up tables for the automatic recognition of the mines at each new frequency or for each new type of sonar. Once validated, this method of automatic mine detection could be used on all sorts of minehunting platforms, from surface vessels to ROVs (remotely operated vehicles) or even AUVs (autonomous unmanned vehicles) with artificial-intelligence capabilities. Once the range of the technique and its limits are better defined, the combination of the acquisition technology and the analysis with TexAn will pave the way for effective, low-cost mine-detection surveys.

Figure 5. (a) Automatic classification of the sonar image of mine ‘C’, superimposed on the original sonar image. The red points correspond to the intervals of entropy/homogeneity associated with the mine. The advantage of this type of representation is that it enables the operator to see the possible targets and the surroundings at the same time. The mine is correctly detected and appears as a single group of red points. Other red points are visible, but they are single pixels and a simple size threshold would remove them. (b) Look-up table showing the distribution of entropy and homogeneity for mine ‘C’ and the neighbouring sea floor. The intervals of entropy/homogeneity previously corresponding to the mines are highlighted in red, the others were left in grey. (c) Idem for mine ‘D’. (d) Automatic classification of the sonar image of mine ‘D’, superimposed on the original sonar image. The mine is correctly detected (cluster of red points in the centre of the image) and there are no false detections.
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