ENVIRONMENTALLY ADAPTIVE AUTOMATIC DETECTION OF LINEAR SEAFLOOR FEATURES IN SIDESCAN SONAR IMAGERY: THE CASE OF TRAWL MARKS DETECTION

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Abstract: *This paper makes a detailed introduction to the design of a new automatic linear seafloor feature detection algorithm and its implementation on sidescan sonar (SSS) records, with its focus on trawl marks (TMs) detection. TMs are long linear scars on the seafloor, which are products of bottom trawl fishing. In image processing, detection of lines is a classical problem that seems to be more challenging on underwater acoustic imaging as the line segments are intermixed with wide-ranging environment backgrounds, and acoustic radiometric and geometric artifacts. Therefore, classic edge detection techniques based on the intensity gradient of the image do not yield reliable detection on SSS images. This proposed method integrates the characteristics of the linear features of interest in an environmentally adaptive procedure and is divided into three major steps. At the first step, preprocessing image techniques are applied to the original images. In the main stage, a spatial-domain filter is implemented through multi-scale rotated Haar-like features and integral images that measures the level of multiple oriented contrasts between adjacent areas. Seafloor characterization based on Anisotropy and Complexity calculations over the Haar-like filter's responses identifies three types of seafloor texture: complex (e.g. biogenic mounds, clutter), anisotropic (e.g. TMs, ripples), and plain (e.g. undisturbed sand). At the same step, another function over filter's responses produces a map that highlights the accurate locations where the candidate linear features prevail. The produced map is automatically binarized, morphologically processed and every linear image object is undergone properties measurement. The final linear features are selected according to a set of geometric and background textural feature criteria. In this study, is presented a set of assignment criteria that is tailored to the specific needs of TMs detection and is followed by TMs quantification that provides valuable measures for the estimation of bottom trawling impacts.*

Keywords: *automatic detection, sidescan sonar, trawl marks, Haar-like features, seafloor features, line detection*

1. INTRODUCTION

Seafloor features and objects detection are major interrelated areas of interest within the field of underwater acoustics. Along with the advancement of development in automatic seafloor feature detection, however, there is increasing concern over the type of underwater system and image processing method to be used. Sidescan sonar (SSS) system has established proven capabilities to identify seafloor types and detect seafloor features, despite the fact that its efficacy depends on operational limitations (e.g. position of the towfish). Linear and curvilinear seafloor features, whether natural or man-made, such as ripples, pipelines and trawl-marks (TMs) constitute an essential part of the description of the seafloor. The appearance of seafloor linear features on SSS imagery vary in their characteristics, e.g., geometric, gray-level values (intensity), density and surrounding area characteristics. In image processing, most common line detection techniques are based on edge detection. However, the high performance of edges on SSS imagery (e.g. stripe image noise, acoustic radiometric and geometric artifacts, boundaries of boulders or coral reefs) is having a serious effect on the accuracy of linear feature detection. This paper will focus on detecting TMs which are the result of the interaction of towed bottom fishing gears with the seafloor. Although the impacts of bottom trawl fishing have been the subject of intense debate within the environmental science community, a very small number of studies have been paid attention to automatic TMs detection. A major problem with this kind of concept is that the linear seafloor features are well visualized only if they are parallel to the axles of the insonified bottom strips (Fig. 1).

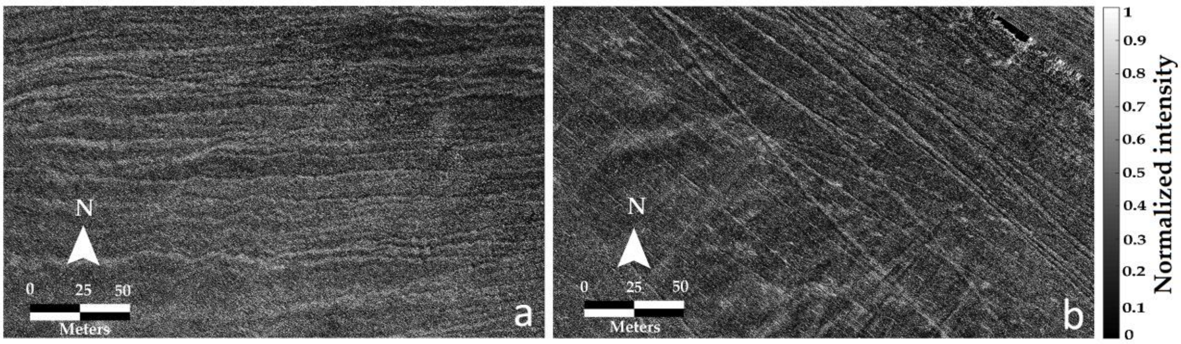

Fig.1: SSS images with high presence of trawl marks when the survey line is (a) almost perpendicular to the TMs direction, and (b) almost parallel to the TMs direction.

The methodological approach that is presented in this paper aims at detecting automatically linear seafloor features and is a mixed methodology based on linear edge detection, while suppressing texture elements of complex and featureless background. The study of Fakiris et al. [1] identifies several advantages of using seafloor texture information in underwater detection methods and achieves real time environmentally adaptive seafloor characterization through rotated Haar-like features and integral images. In the proposed method, we extend the aforementioned study in a useful way to produce linear edge maps utilizing a multi-scale version of rotated Haar-like features and appropriate calculations over their set of responses. The remainder of this paper is organized as follows. Section 2 will provide the scheme of the image processing techniques used in this work and establish criteria for identifying TMs. The experimental results of the approach on a real SSS mosaic are shown in Section 3 and are validated using corresponding analysis results of the SSS mosaic generated through a manual procedure that was proposed in the study of Patsourakis et al. [2]. Concluding remarks and a few thoughts for future work are made in Section 4.

2. IMAGE PROCESSING TECHNIQUES

In this section is presented a baseline overview of the image processing techniques used in this method (Fig. 2). Most of these techniques are widely used by the image processing and computer vision research communities. These were suitably applied in combination for the purpose of detecting candidate line segments in SSS images that possibly are parts of linear seafloor features of interest. The last subsection proposes a set of criteria that can be used to determine whether a line segment may most certainly be a TM.

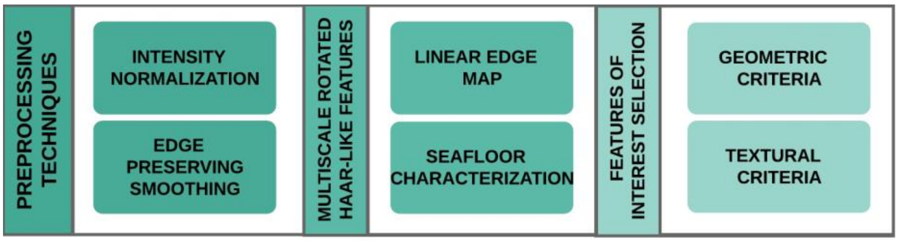

Fig. 2: The major stages of algorithm analysis and design.

2.1. Preprocessing techniques

A preprocessing stage occurs prior to the process of detecting seafloor features and identifying seafloor textures, in order to achieve efficient image restoration. Non uniform intensities and artificial shadow areas are noted in SSS images due to fluctuations of the backscattered energy. The first step of the algorithm utilizes the Homomorphic filtering, a popular technique in satellite and medical image processing for correcting non-uniform intensities and highlighting the desired image areas [3]. In the Homomorphic filtering process, the Fourier transform is used which provides access to the frequency domain. Following this, the Gaussian high-pass filter is applied to attenuate low frequency components which represent the gradual changes in the image intensities. Finally, non-uniform image intensity is normalized while the edges (high-frequency components) are maintained.

Once the Homomorphic filtering is applied, the output image is smoothed for the purpose of image noise reduction. We utilize Bilateral filtering with Gaussian kernels a non-linear filter which is synthesized by domain and range filtering [4]. To achieve edge preserving smoothing, the Bilateral filtering runs through the image pixel by pixel, replacing every pixel with a weighted average of the pixels that are close spatially and photometrically with it. Supposing that points are similar and nearby, Bilateral filtering allows the replacement of the centered point x with an average of the pixels in its vicinity. Inversely, if the pixels are not close, the Bilateral filtering bring neuter affects to the centered point x. To conclude, bilateral filtering smooths out the slight difference of neighboring pixels caused by noise, while sharp edges are preserved through the range component.

2.2. Multi-scale rotated Haar-like features

In the main stage of the algorithm, we use Haar-like features which consist of a white and a black rectangle enclosed in a template. Haar-like structure is represented as 0s and 1s in a geometrical order and the filter’s response is calculated as the subtraction of the summation of the pixel values inside the two adjacent rectangles. Haar-like features have the advantage that they can be calculated directly from an integral image, speeding significantly up data processing. Normal Haar-like features were developed by the authors of [5] and are broadly used but those are not rotation invariant. A number of researchers have presented rotated Haar-like features methods, including Fakiris et al. [1] that presented an extended set that covers twelve rotations (Fig. 3.b) and is capable of depicting features of almost any orientation. The rotated integral image, for a given integer rotation, is calculated by summing the pixels in the relevant aligned quadrant above the given pixel. For a more information-rich result, in this study we implement a multi-scale version of rotated Haar-like features. We utilize a sequence of rotated two-rectangle Haar-like features with common aspect ratio but whose widths respectively correspond on terms of an arithmetic progression. This subsections' filters are performed for each designed scale of the set of Haar-like features rotated at twelve directions that are capable of measuring the contrast between two adjacent oblong areas of the seafloor.

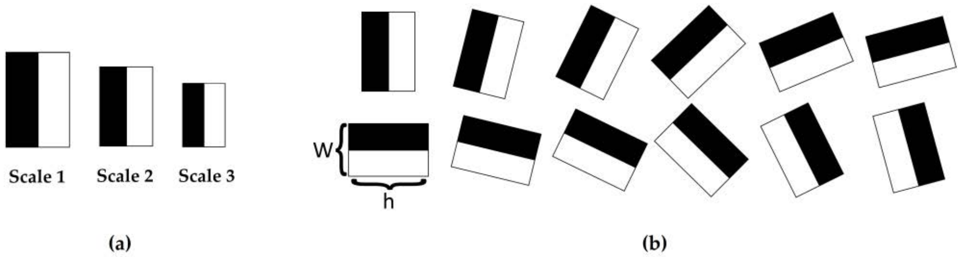

Fig 3: (a)The sequence of the two-rectangle Haar-like features with different scales and common aspect ratio (b)The Haar-like feature, rotated at twelve angles (revised from [1]*).*

2.3. Seafloor characterization

Texture can be described according to its two main characteristics: its contrast and orderliness, forming two groups of qualitative terms. Haar-like filtering can be used to quantify both contrast and orderliness, as a single feature that can assess the local variation of intensities but also highlight certain pre-specified structural geometries. Based upon the local averages of filter responses, two seafloor characterization measures have been estimated: Anisotropy and Complexity, that are described thoroughly in [1]. Anisotropy refers to the level of heterogeneity of filters' responses given for each direction [6] and therefore high values of Anisotropy indicates that at least one direction responses overrides the others. Complexity filter highlights the high-contrast areas where seafloor features are anarchical distributed with respect to their direction. The Anisotropy and Complexity threshold values discriminate the three types of texture: anisotropic (TMs, ripples), complex (biogenic mounds, clutter) and featureless (plain sand), were set manually by the human interpreter and pre-trained using a small part of the dataset.

2.4. Linear seafloor features detection

The second utility of multi-scale rotated Haar-like features concerns linear seafloor features detection (segmentation). Effort has been put to designing a new Haar-like filters with the use of the raw Haar-like filter's responses in order to scale down the analysis and achieve feature–level segmentation of sub-meter analysis. A function over the filter responses aims at enhancing the figure of the linear seafloor features. Linear edge enhancement filtering (LEE) works for each pixel of the image and is defined as:

$$(LEE)= (MRF)^2 \quad (1)$$

where MRF (Maximum Response Filter) is the maximum contrast over all directions. For the binarization of the produced linear edge map, the Gaussian adaptive thresholding method is used, in which the threshold value is a weighted average of the pixel values in a manageable sized neighborhood (x,y) around pixel x.

For each scale of the rotated Haar-like features a binary image is produced with the extracted potential linear seafloor features. The binary images are combined with the logical operation "union" that synthesize a final binary image which contains each scale's extracted linear edges. All white connected pixels in the binary image are labelled as unique linear foreground objects and their properties are measured, such as their length and their orientation. Some lines intersect and their false orientation could lead to mistaken and incomplete analysis. Therefore, the intersected lines are split before the orientation of the identified image objects is computed. The splitting of the lines is achieved through logical and morphological operations by removing a small surrounding area around the junction points of the lines' skeletons.

Via the feature space we seek to substantiate which line structures correspond to linear seafloor features of interest. Final linear seafloor features selection is designed based on objects' geometric signature and the background environment features in the affected area. Following, this is a set of criteria that narrows the detected linear image objects down to those corresponding to TMs have been designed. The first geometric discrimination of the lines of interest is built upon their physical size. Lines with length more than 10m are kept for further analysis. Additionally, we excluded line segments that have orientation perpendicular plus-minus 5 degrees from the survey line. As for the textural criteria, objects in the image whose Anisotropy background values lie under the manually chosen threshold are excluded from analysis. Moreover, areas that are characterized by high complexity are deleted from the regions of interest.

3. EXPERIMENTAL RESULTS

3.1. Data acquisition and validation data set

The SSS data were collected in September 2006, on the western end of the Gulf of Patras (western Greece, Mediterranean Sea). The seafloor of the survey area is constituted by TMs, biogenic mounds and plain sand. The survey was conducted in a parallel-pass survey design to produce a SSS mosaic with 100% coverage of the seafloor with pixel size of 0.2 m. Six tracks were required (with a total length of 13.962 km) to cover an area of 2.98 km^2. Acoustic backscatter data of the seafloor were acquired with an EG&G 272TD sidescan towfish, connected to a top-side processor unit (EdgeTech 4200-P) and with the data acquisition software Discover (EdgeTech). The sonar towfish was towed at an average height of 45 m above the seafloor and was operated at a sound pulse frequency of 100 kHz. The swath range was set to 200 m and the ship speeds ranged between 3 and 4 knots.

The results of the application of the automatic TMs detection method in the SSS mosaic were evaluated using a dataset of manually extracted TMs. The results obtained by Patsourakis et al. [2] has preceded this, in which the same SSS mosaic were processed, and each individual TM was extracted manually, delineated and mapped on ArcGis software. The data results of the manually and automatically extracted TMs were undergone spatial analysis to derive their mean density, length and direction of TMs per 50x50m square area. For the purpose of statistical analysis and comparison between the manually and automatically quantified detected TMs, the blocks were classified into four classes according to the TMs' total length.

3.2. Results and discussion

Figs 4 through 6, below, show correspondingly the application of algorithm's main steps: preprocessing techniques, seafloor characterization through Anisotropy and Complexity definitions, and linear seafloor features detection.

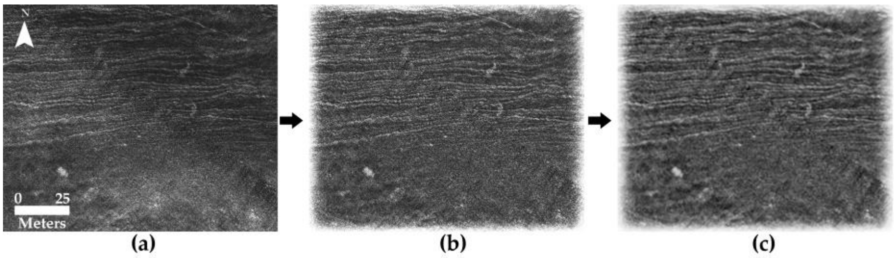

Fig 4: (a) The original SSS image, (b) the SSS image after application of Homomorphic filter and (c) after edge preserving filtering.

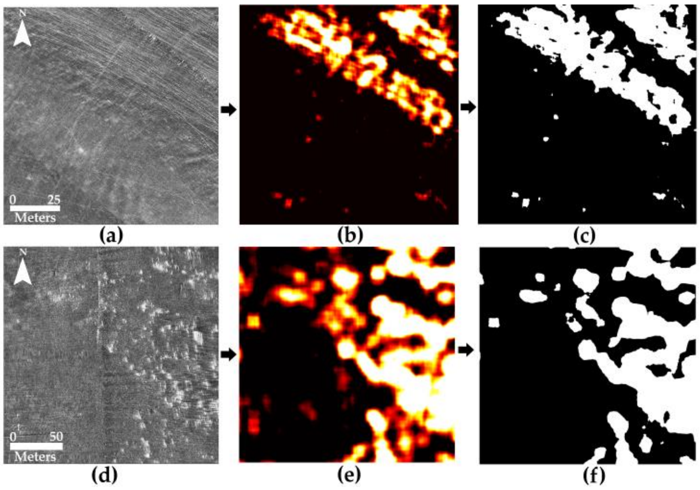

Fig 5: (a) SSS mosaic area with plain sand and TMs, (b) the Anisotropy map of up-left image, (c) fishing grounds segmentation, (d) SSS mosaic area with plain sand and biogenic mounds, (e) the Complexity map of low-left image, (f) biogenic mounds segmentation map.

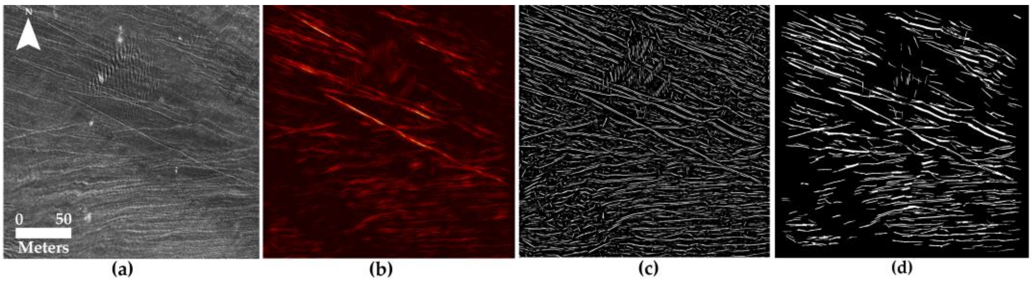

Fig 6: (a) The original SSS image depicting TMs of various orientations and contrasts, (b) the LEE filter over the preprocessed image, (c) linear edge segmentation map, (d) the final selected linear seafloor features.

The automatically detected TMs in SSS mosaic are shown in Fig.7.b. The Fig.8 visualize the fishing stress and the preferred axles of towing both for the automatic and manual TMs digitization cases, giving the means for visual comparison. Cross tabulation matrix (Fig 9.a) is used to evaluate the one-to-one correspondence of the classes and the high concentration of scores in the diagonal indicates consistency and stable correlation between the corresponding classes of the two datasets. The Cohen's Kappa coefficient that evaluates the agreement between the corresponding class limits is equal to 0.65, indicating a substantial agreement of all class ranges that are used to classify the blocks of the manually and automatically derived TMs. Accuracy of automatic TMs detection method is also evaluated by comparing the two data sets that are defined by thresholds of the total TMs length used as binary classifiers. High accuracy values are in the diagonal of the accuracy vs threshold diagram (Fig 9.b), indicating highly accurate results as the total-length threshold increases (excluding more and more low TM density areas from the analysis). It is clear that TMs and other proud linear features (such as sand-ripples) are more difficult to be detected when they get perpendicular to the swath direction, where their contrast and shadow length decrease. Fig 9.c confirms the above hypothesis, showing an increased error per unit area as the deviation of the TM orientation from the survey-lines' equivalent gets higher. This finding is opposite to what one should expect, i.e. decreased ability of the system to detect TMs as the direction deviation gets higher, leading to increasing their underestimation. This paradox can be interpreted just in one way: what is expected to bias computer aided detections is also biasing human-interpretation.

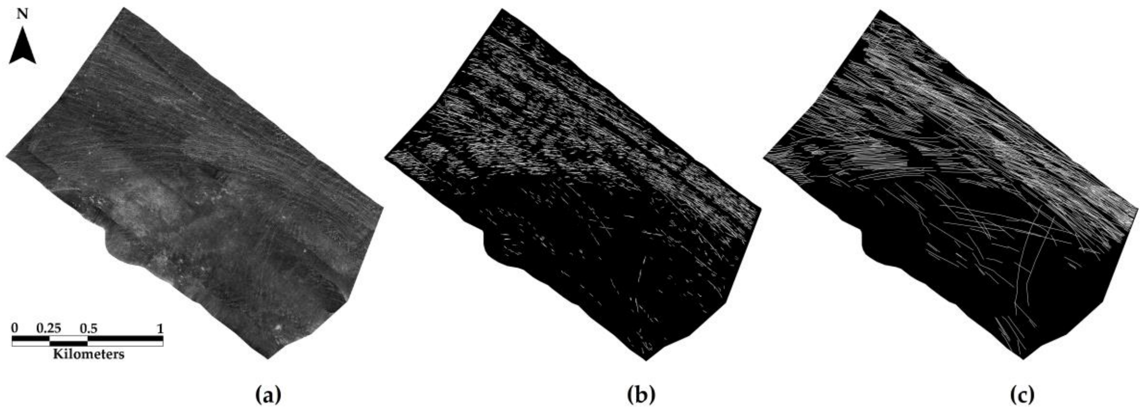

Fig 7: (a) The SSS mosaic of the study area, (b) a binary image showing the automatically extracted TMs and (b) an image depicting the manually digitized TMs (dataset from [2]*).*

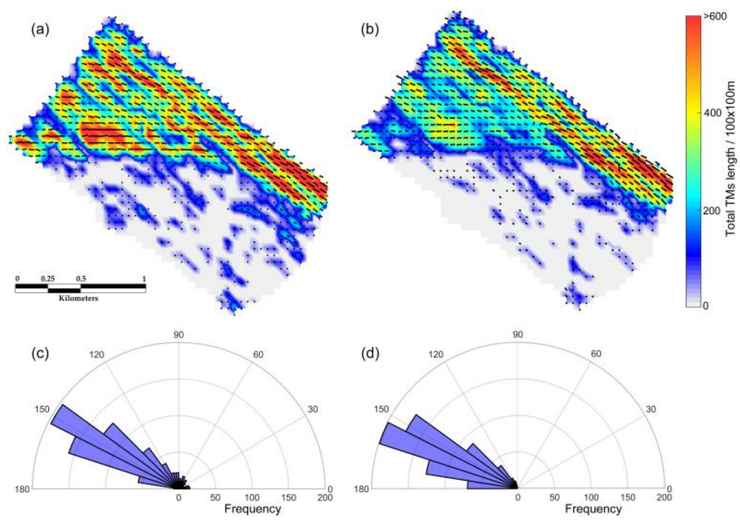

Fig 8: (a), (b) Quiver (vector) plots visualizing the mean length and orientation of the TMs within each analyzed block for the automatic and the manual TM detection cases respectively, overplayed to maps of the total length of TMs per 10.000 m² (100x100m block) unit area. (c), (d) Rose diagrams of the corresponding quiver plots.

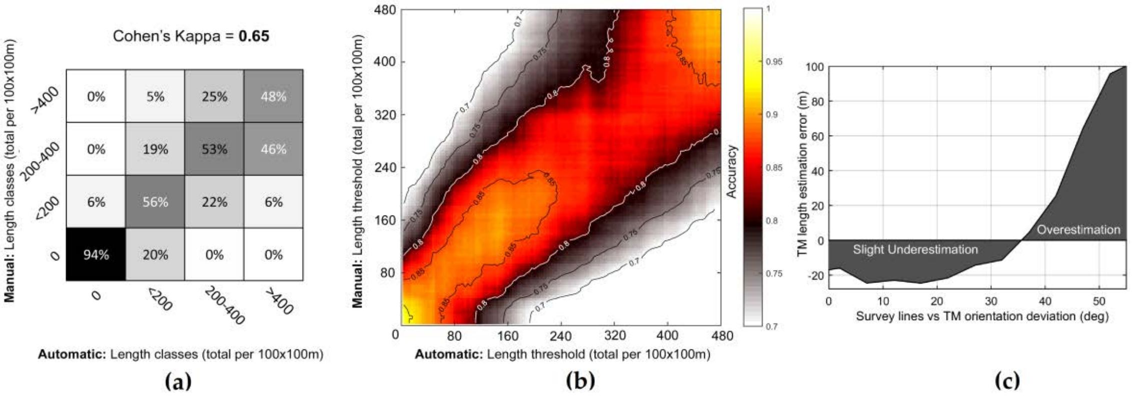

Fig 9: (a) The cross-tabulation matrix for the four-classes scenario and (b) accuracy versus TM length per unit area threshold and (c) the *total TM length error per 100x100m versus the deviation of TM orientation from the survey-line's equivalent.*

4. CONCLUSION

In this paper a new method was presented that achieves automatic detection and spatial quantification of linear seafloor features under challenging conditions of acoustic imaging when general-purpose SSS data are used. The algorithm was demonstrated on sidescan sonar images of board-scale and structural complex habitats, and detected successfully trawl-marks of great variability in orientations, intensities and contrasts. The preprocessing stage was a necessary step that gives at TMs a more discrete appearance in SSS image data while the information about the texture of the seafloor has a valuable impact on eliminating false alarms at the zones where TMs are absent. The exported data of this linear seafloor features detection when focusing on TMs could be used for rapid assessment of fishing impacts on the seafloor. A natural progression of this study is to implement some of its features in conjunction with machine learning principles through the use of extended sonar datasets of linear features.

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