Classification of Multibeam Sonar Image Using the Weyl Transform

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Abstract. In this paper we develop a novel classification method for multibeam sonar images based on the Weyl transform. The texture descriptor based on Weyl coefficients describes effectively the multiscale correlation features appearing in the sonar images. Our classification approach combines the Weyl coefficients with statistical features that are commonly used in the analysis of seabed sonar images and captures the morphological variation and geoacoustic characteristics of the seafloor. We employ a neural network as a classifier. The proposed combined feature extraction method demonstrates better performance than the commonly used statistical methods in this application.

Keywords: Multibeam data processing · Multibeam sonar image · Feature extraction · Weyl transform · Acoustic sediment classification

1 Introduction

Backscattering from the seafloor is the result of an intricate interaction of the sound pulse with the water-sediment interface and relates to three basic quantities: the acoustic impedance contrasts between the propagation and sediment media, the volume inhomogeneity and the roughness. Due of this, backscatter directly relates to the seafloor nature and such hydroacoustic measurements can

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be used to characterise it in the interest of geology, sedimentology and biology [1,2]. A conventional multibeam echosounder system is capable of collecting backscatter data and bathymetry data, from which we are able to obtain a variety of features of the seabed to distinguish the sediment type [3,4]. Texture-based techniques rely on the extraction and characterization of the textural information of each seabed type. All state-of-the-art methods, in order to have a reliable texture analysis, remove the angular dependency on each analysis zone which shares the same backscatter profile [5]. A well-established approach currently is to use the first-order [6] and the second-order statistical features [7]. The objective of this study is to develop more effective feature extraction methods to improve the reliability of acoustic sediment classification.

Recent studies have demonstrated that the Weyl transform [8,9] offers an excellent framework for data representation and texture analysis in general. The main contribution of this paper is to explore the potential of seabed sediment classification based on the Weyl transform. Furthermore, we develop an effective classification method for sonar images that combines the Weyl features and complementary statistical features, which are capturing the morphological variation and geoacoustic property. The experimental results show clearly that the proposed combined textural descriptor can effectively discriminate between the different classes of sediment. The paper is organized as follows: Sect. 2 reviews briefly the Weyl transform theory. Next, in Sect. 3 we present our proposed method for texture characterization of multibeam sonar images. The experiment results are presented in Sects. 4 and 5 concludes the paper.

2 Weyl Transform

The Weyl transform has recently shown remarkable results in the context of texture classification with standard texture images [8], outperforming some common textural descriptors including HOG [10] and LBP [11]. The transform has a desirable property of being invariant to a large class of multiscale signed permutations. In particular, different ways of orienting and translating the same texture will produce the same Weyl descriptor and patches sampled from the same texture should share similar Weyl transforms [8,12].

2.1 The Binary Heisenberg-Weyl Group

The binary Heisenberg-Weyl group HW_{2^m} is a group of permutation matrices and matrices that resemble permutation matrices with sign changes in some of the rows. Those square matrices of size 2^m exist for each power of 2 and are defined as tensor products

$$D(a,b) = D(a,0)\,D(0,b) = x^{a_{m-1}} z^{b_{m-1}} \otimes \cdots \otimes x^{a_0} z^{b_0}. \tag{1}$$

where

$$x = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

and $a = (a_0, \ldots, a_{m-1}),\ b = (b_0, \ldots, b_{m-1}) \in \mathbb{Z}_2^m$ are two binary m-tuples.

Formally, the binary Heisenberg-Weyl group HW_{2^m} of order 2^{2m+2} is defined as $HW_{2^m} = \{i^\lambda D(a,b) \mid \lambda \in \{0,1,2,3\}$ and $a, b \in \mathbb{Z}_2^m\}$.

2.2 The Weyl Representation

As shown in [8], the signed permutation matrices $D(a,b)$ with $a^T b = 0$ form an orthonormal basis of the vector space of real square symmetric matrices with respect to the inner product given by $\langle R, S\rangle := \mathrm{tr}(R^T S)$. In particular, each real symmetric matrix R can be represented as a linear combination of the basis elements as

$$R = \sum_{\substack{a,b\in\mathbb{Z}_2^m\\ ab^T=0}} \left\{\frac{1}{2^{m/2}}\mathrm{tr}\left[R\cdot D(a,b)\right]\right\}\frac{1}{2^{m/2}}\,D(a,b). \tag{2}$$

Given a vectorized signal $y \in \mathbb{R}^{2^m}$, it's covariance matrix $yy^T \in \mathbb{R}^{2^m\times 2^m}$ is real, symmetric matrix and as such can be represented as

$$\begin{aligned} yy^T &= \sum_{\substack{a,b\in\mathbb{Z}_2^m\\ ab^T=0}} \left\{\frac{1}{2^{m/2}}\,\mathrm{tr}\left[yy^T\cdot D(a,b)\right]\right\}\frac{1}{2^{m/2}}D(a,b) \\ &= \sum_{\substack{a,b\in\mathbb{Z}_2^m\\ ab^T=0}} \omega_{a,b}(y)\frac{1}{2^{m/2}}D(a,b). \end{aligned} \tag{3}$$

Coefficients $\omega_{a,b}(y)$ are the *Weyl coefficients* of the signal y and the corresponding isometric mapping $yy^T \mapsto \omega_{a,b}(y)$ is the *Weyl transform* [8].

3 Methodology

3.1 Texture Descriptor Based on Weyl Transform

The Weyl transform distinguishes the different textural structures by quantifying multiscale symmetry features [9]. Moreover, invariance to multiscale transformations ensures that the Weyl representation of image patches with the same textural structures exhibit similarity.

We divide the whole multibeam sonar image into a number of small patches using a moving window of size $S_w \times S_w$ ($S_w = 2^r, r \in \mathbb{Z}^+$). Each patch can be vectorized in a raster-scanning fashion which results in $S = 2^{2r}$ dimensional vector. Let $m = 2r$, $a = (a_{m-1}\ldots a_0)^T$ and $b = (b_{m-1}\ldots b_0)^T$. Then the Weyl coefficients of patch Y are computed by using (3). Figure 1 shows how we obtain the Weyl representation of a selected patch from a multibeam backscatter image.

An ideal texture descriptor should represent the samples of the same class with a compact and isolated cluster. We randomly select 800 patches of size 8×8 from 4 classes of multibeam backscatter images and compute the Weyl coefficients of

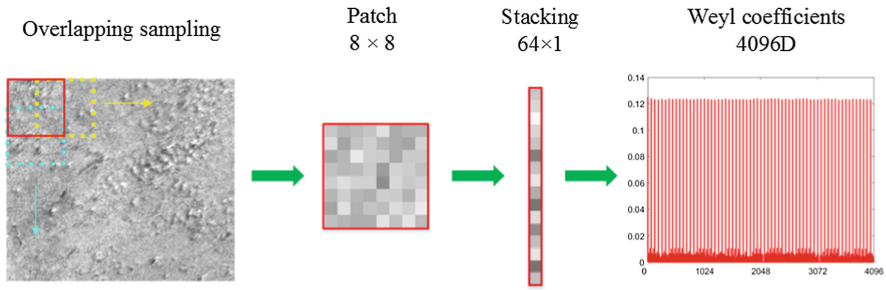

Fig. 1. Computation of the Weyl coefficients for a sonar image.

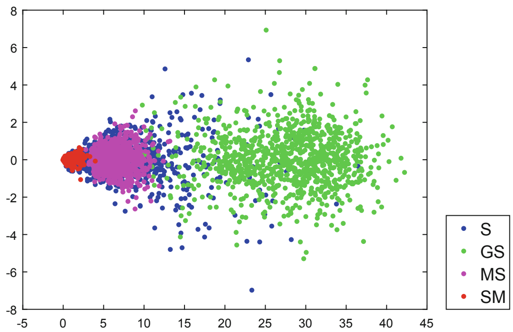

Fig. 2. Weyl coefficients with the dimension reduced to 2 using PCA.

all samples. For visualization purpose, we use PCA to reduce the dimensionality of the 4096-dimensional feature vector to two-dimensional one. Figure 2 shows the backscatter patches represented in Weyl coefficients after the dimensionality reduction. Different colors correspond to different seabed sedimentary classes: *Sand* (S, blue), *Gravelly Sand* (GS, green), *Muddy Sand* (MS, magenta), *Sandy Mud* (SM, red). This example shows that the proposed texture descriptor based on the Weyl transform discriminates well between GS/MS/SM and GS/S/SM classes, but not between S and MS classes. Due to the fact that sand and muddy sand show similar textures and similar distributions of pixel values (Fig. 3), the Weyl descriptor is not able to discriminate well between those two classes.

3.2 Combined Features for Multibeam Sonar Image

The Weyl transform captures textural characteristics more related to the local correlation. A complementary approach is to extract features, which mainly reveal the global zonal characteristics. Hence, we adopt statistical methods to extract characteristic features of the sonar image, that we refer to as Classical Statistical Features. In particular, we include: first-order statistics (backscatter-based), second-order statistics (backscatter-based) and terrain characterization (bathymetry-based).

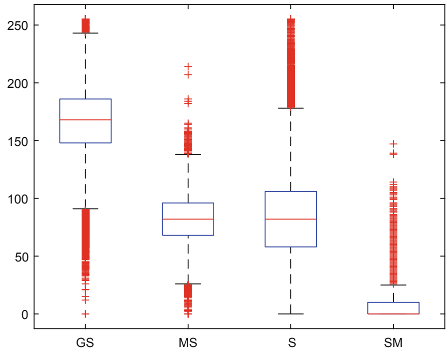

Fig. 3. Boxplot of the distribution of greyscale values for different sediments.

We calculate the first-order statistics from local patches using zonal statistics, including mean, maximum, minimum, quartile, standard deviation, kurtosis and skewness [6]. The second-order statistics are calculated from the Grey Level Co-occurrence Matrices (GLCM) [7]. We derive the entropy and homogeneity from the GLCM. Terrain modeling based on multibeam bathymetry data can make a significant contribution to the prediction of benthic habitat. The adopted terrain features include slope, rugosity and benthic position index [13,14]. We apply the feature selection algorithm of Boruta [15] to reduce the feature set to the more discriminative ones. Then the resulting most relevant statistical features are combined with the Weyl coefficients to generate a feature vector by stacking all the components. We normalize the features such that they are in the same range and thus contribute appropriately to the classification result.

4 Experimental Results

4.1 Dataset

We use the data set from a hydroacoustic survey conducted by Royal Belgian Institute of Natural Sciences in Oostende Harbour, Belgium, in November 2017. The multibeam data originates from the Kongsberg Maritime EM2040 dual system installed on RV Simon Stevin and were acquired at 300 KHz in normal mode, CW pulse form and 101 µs pulse length [16]. Backscatter and bathymetry data are both with a 1 m horizontal resolution (Fig. 4). The ground-truth data are collected from a number of grab samples, including Sand, Sandy Mud, Muddy Sand and Gravelly Sand. We demarcate 12 subblocks on the surveyed area, where the sediment type is already known by grab sampling analysis. Then we take 8×8 patches by overlapping sampling with a sliding step of 4 pixels from each of subblock and 17622 samples are available in total. In the experiments, we randomly take 1000 samples for every class of the sediment, including backscatter data, bathymetry data and their labels. The training set contains 200×4 samples and testing set contains another 800×4 samples, which are both randomly taken from the whole dataset.

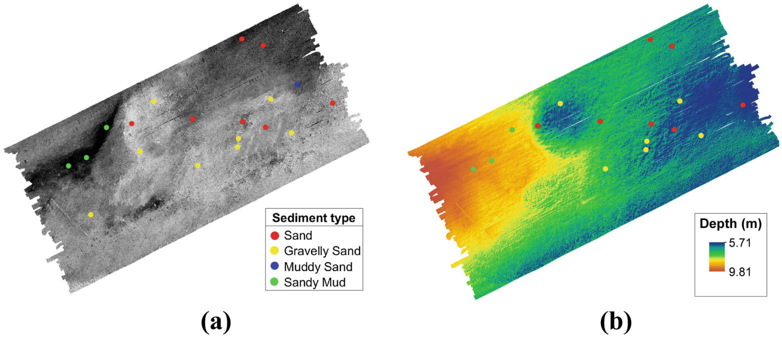

Fig. 4. (a) backscatter data and grab samples; (b) bathymetry data.

4.2 Results

To validate the performance of the proposed texture descriptor, we perform sediment classification on multibeam sonar images by feeding the combined Weyl-Statistical features to a 2-layer neural network. Each test patch is assigned to a sediment type. We compare the performance of Classical Statistical Features alone, Weyl coefficients alone and the Combined Features. From Sect. 3 we know that Classical Statistical Features are extracted both from backscatter data and bathymetry data, while the Weyl coefficients are computed only using backscatter data. Even though the bathymetry data is not used, Tables 1 and 2 indicate that the Weyl coefficients can isolate distinct sediment types with comparable accuracy as the Classical Statistical Features. Table 3 shows the classification accuracies using the combined Classical Statistical Features and Weyl Transform Features. The results in Fig. 5 show that the combined features significantly improve the classification accuracy for the sand class, compared to the first two methods. The overall accuracy of the combined method is also better than any single method.

Table 1. Classification results using Classical Statistical Features.

Ground truth	Prediction					
	S	GS	MS	SM	Total	Accuracy
S	384	71	324	21	800	48%
GS	13	774	13	0	800	97%
MS	73	3	724	0	800	91%
SM	62	0	12	726	800	91%
Total	532	848	1073	747	3200	82%

Table 2. Classification results using Weyl Transform Features.

Ground truth	Prediction					
	S	GS	MS	SM	Total	Accuracy
S	416	45	300	39	800	52%
GS	62	732	6	0	800	92%
MS	112	0	688	0	800	86%
SM	48	0	0	752	800	94%
Total	638	777	994	791	3200	81%

Table 3. Classification results using Combined Features.

Ground truth	Prediction					
	S	GS	MS	SM	Total	Accuracy
S	579	25	179	17	800	72%
GS	85	713	2	0	800	89%
MS	131	0	669	0	800	84%
SM	13	0	10	777	800	97%
Total	808	738	860	794	3200	86%

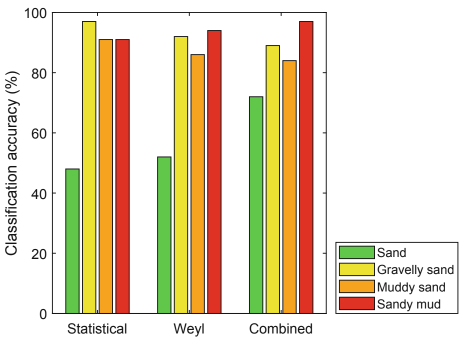

Fig. 5. Classification accuracy of the three feature extraction methods.

5 Conclusion

We designed a novel feature extraction method for seabed sediment classification based on the Weyl transform. We showed that the Weyl coefficients of multibeam sonar images can discriminate between different classes of sediment. We also proposed a combined feature extraction method based on the Weyl transform and Classical Statistical Features to capture better the characteristics of the seafloor both locally and globally. The combined feature vector proves to be more powerful in the classification of sediments than the Weyl transform alone or statistical features alone. Examples on Oostende Harbour dataset demonstrate the efficiency of the proposed feature extraction method for seabed sediment classification using multibeam sonar images.

References

1. Gaida, T., Tengku, A.T., Snellen, M., Amiri-Simkooei, A., Van Dijk, T., Simons, D.: Geosciences **8**, 455 (2018)
2. Montereale-Gavazzi, G., Roche, M., Lurton, X., Degrendele, K., Terseleer, N., Van Lancker, V.: Mar. Geophys. Res. **39**, 229–247 (2018)
3. Diesing, M., Mitchell, P., Stephens, D.: ICES J. Mar. Sci. **73**, 2425–2441 (2016)
4. Brown, C.J., Smith, S.J., Lawton, P., Anderson, J.T.: Estuarine, coastal and shelf. Science **92**, 502–520 (2011)
5. Nguyen, T.K.: Seafloor classification with a multi-swath multi-beam echo sounder. Ph.D. thesis, Ecole nationale supérieure Mines-Télécom Atlantique, Nantes (2017)
6. Janowski, Ł., Tęgowski, J., Nowak, J.: Ocean. Hydrobiol. Stud. **47**, 248–259 (2018)
7. Haralick, R.M., Shanmugam, K., Dinstein, I.H.: IEEE Trans. Syst. Man Cybern. **6**, 610–621 (1973)
8. Qiu, Q., Thompson, A., Calderbank, R., Sapiro, G.: IEEE Trans. Signal Process. **64**, 1844–1853 (2016)
9. Ahn, H.K., Qiu, Q., Bosch, E., Thompson, A., Robles, F.E., Sapiro, G., Warren, W.S., Calderbank, R.: Classifying pump-probe images of melanocytic lesions using the Weyl transform. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, Alberta, Canada. IEEE (2018)
10. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. In: International Conference on Computer Vision and Pattern Recognition (CVPR 2005). IEEE Computer Society, San Diego (2005)
11. Marko, H., Matti, P.: IEEE Trans. Pattern Anal. Mach. Intell. **28**, 657–662 (2006)
12. Howard, S.D., Calderbank, A.R., Moran, W.: J. Appl. Signal Process. **2006**, 111 (2006)
13. Wilson, M.F., O'Connell, B., Brown, C., Guinan, J.C., Grehan, A.J.: Mar. Geodesy **30**, 3–35 (2007)
14. Walbridge, S., Slocum, N., Pobuda, M., Wright, D.: Geosciences **8**, 94 (2018)
15. Kursa, M.B., Rudnicki, W.R.: J. Stat. Softw. **36**, 1–13 (2010)
16. Kongsberg Maritime. EM 2040 data sheet (2012)