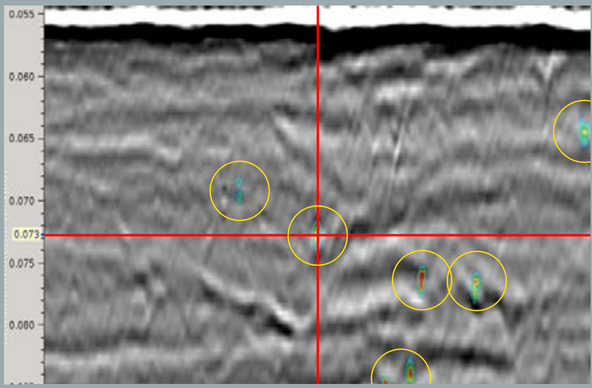
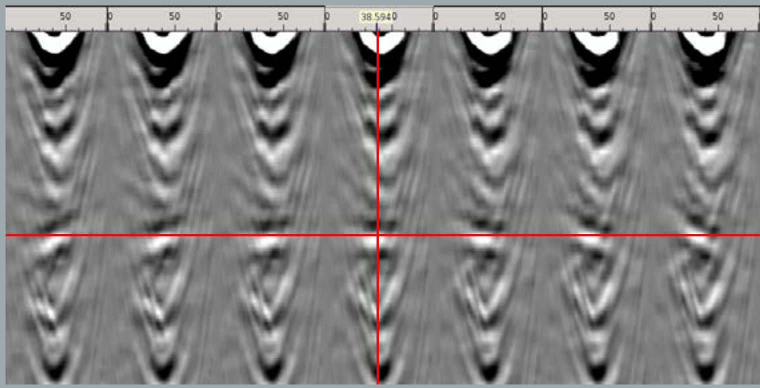


1



2

BOULDER-DETECTION MIT MACHINE LEARNING

1 *Subsurface image computed from seismic data; colour spots show locations of high probablity for the presence of boulders*

2 *Illumination representation of part of the subsurface at which a boulder was identified; the cross-hair points into the symmetry center of the identified pattern and indicates the lateral position of the boulder at 73 m depth*

Piles of windmills of offshore windparks must be firmly coupled into the subsurface layers deep below the sea-floor. Large boulders, that would be obstacles for the planting process of such piles, must be identified in the phase of defining the exact locations of windmills. Seismic data sets acquired for site-planning of windparks for the purpose of assessing subsurface stability conditions have limited frequency content. We developed a new methodology for object identification below seismic wavelength (here: 1 m) from such data by means of machine learning methods.

Key to this methodology is the preprocessing of the data by a prestack migration method that highlights the weak-amplitude diffractions contained in the seismic data.

Pattern recognition in seismic sections

Together with colleagues from Fraunhofer IWES and sponsored by BMWI we developed a process that maps the seismic data into a domain in which diffraction responses show a typical pattern. The task of finding such patterns, thus to localize the associated diffracting objects, is similar to the task of assigning pixels of photos to object classes, which constitutes a problem that can successfully be solved with the help of deep neural networks (DNNs).

Here, however, we are dealing with a high-dimensional problem, as even for 2D seismic, i. e. 2D subsurface images, illumination-direction and velocity-variation contribute two additional dimensions. Further, the Earth's subsurface is not accessible so that the networks cannot be trained with the ground truth for real data; rather, we have to rely on training solely based on synthetic data generated and perturbed towards the appearance of real data.

Benefit for the user: reduced amount of data

Our results demonstrate that transfer learning from synthetic to real data works and that our DNNs that consist of a large number of convolutional layers offer the necessary complexity for computing the probability for the existence of diffracting objects of 1m scale length even in noisy data. After application of this automated process, the user is left with the task to further interpret the seismic data only in those areas that are marked by high probablility values.