# MULTIBEAM AND SINGLEBEAM MULTIFREQUENCY CLASSIFICATION OF BOTTOM HABITATS - THE COMPLEMENTATION OF TWO APPROACHES

Jaroslaw Tegowski[a], Lukasz Janowski[a], Karolina Trzcinska[a], Maria Rucinska-Zjadacz[a], Pawel Pocwiardowski[b], Klaudia Kusek[a]

[a]Institute of Oceanography, University of Gdansk, al. Marszalka Pilsudskiego 46, 81-378 Gdynia, Poland
[b]NORBIT-Poland Sp. z o.o., al. Niepodleglosci 813-815/24, Sopot, Poland

Jaroslaw Tegowski, Institute of Oceanography, University of Gdansk, al. Marszalka Pilsudskiego 46, 81-378 Gdynia, Poland, fax: +48585236678, email: j.tegowski@ug.edu.pl

***Abstract:*** *The development of multi-frequency multi-beam (MBES) and single-beam (SBE) echosounders has enabled progress in acoustical classification methods for bottom sediments and habitats. In this study we present the results of habitat classification based on the image analysis of bathymetry and backscattering strength maps recorded by MBES NORBIT iWBMS (model STX) at frequencies of 150kHz and 400kHz and analyses of echo envelopes recorded by SBE Simrad EK 80 at frequencies of 38kHz, 120kHz and 333kHz. The survey was carried out in the South Baltic Sea on an area of approximately 1.2 km2, where the southern boundary of the study polygon was 1 km distant from the Rowy harbour. The Rowy area is characterized by diverse habitat conditions and presence of marine vegetation unique in this part of the Baltic Sea. The MBES data approach benefit from object-based image analysis and development of K Nearest Neighbour supervised classifier. Another data set was calculated for single-beam echosounder signals, including echo energy parameters and wavelet transform parameters for all the three frequencies. Automatic classification methods utilized fuzzy logic and k-means algorithms. Based on the ground-truth samples and ROV seafloor images we have identified six habitat classes and selected the most relevant features of the bathymetric and backscatter data. The results of the valid classification reached almost 80%, demonstrating that the combination of measurements with multi and single beam echosounders as well as multifrequency registrations can advance progress in habitat mapping, which is one of the goals of the ECOMAP EU BONUS project.*

***Keywords:*** *Multibeam echosounder, singlebeam echosounder, bottom habitats, multifrequency classification*

## INTRODUCTION

Recently, leading manufacturers of echosounders and sonars have been equipping their devices with the ability to measure on different frequencies of the transmitted acoustic signals. As in the case of multispectral satellite measurements of the Earth's surface, multispectral acoustic methods should significantly increase the amount of information about the bottom and help in the remote sensing classification of sediments and habitats.

In the scope of the ECOMAP EU project (Baltic Sea environmental assessments by opto-acoustic remote sensing, mapping, and monitoring), bottom research was carried out in the Rowy test area using the NORBIT iWBMS STX multibeam and the Simrad EK80 singlebeam echosounders. Both echosounders can operate in multifrequency mode, giving new possibilities for non-invasive recognition and classification of benthic habitats. Analysis of the data recorded with a singlebeam echosounder provided additional information for the classification of bottom habitats using a multibeam echosounder.

## STUDY SITE

The study site is located in the shallow marine area of the Polish part of the Southern Baltic Sea in the close neighbourhood of the Rowy harbour at the coast (Fig. 1). The area is characterized by low depths, from 4 to 20 m below sea level. Considering its relatively small spatial extent, the morphology of the seabed consists of crests and valleys of complex shapes. The bathymetry deepens from south-east to north-west direction concealing the main shoal at the center of the area. This moraine structure is made of boulders and gravels on outcrops of glacial tills partly covered by red algae communities. Large boulders are commonly colonized by dense cover of *Mytilus trossulus* bivalves. Previous research confirms existence of other substratum outside the glacial tills outcrops, that are: sands, very fine sands, fine sands, sandy gravels and gravelly sands [1].

## MATERIALS AND METHODS

Underwater acoustic data were collected using multibeam echosounder (MBES) equipment (Norbit iWBMS) mounted on the Zelint research motor boat. Scientific surveys took place in 27 and 28 of May 2018 using two working frequencies: 150 kHz and 400 kHz. The MBES device was supplemented by integrated Applanix Wave Master GNSS/INS navigation system. All measurements were carried out with sweep time of 500 µs and maximum ping rate of 30 Hz. Design of surveys included maintenance of a constant speed of 5.5-6 knots and complete spatial coverage of the area.

Single-beam Simrad EK 80 echosounder measurements took place in 20 and 21 October 2018 and were carried out during the cruise rv Oceanograf to the Rowy area. The measurements were carried out simultaneously for three frequencies of the transmitted signal at frequencies of 38kHz, 120kHz and 333kHz. The SBE data were processed using the Sonar5 software and own programs written in Matlab.

Multibeam echosounder (MBES) bathymetry and backscatter datasets were processed using QPS Qimera and Fledermaus Geocoder Toolbox (FMGT) software. The first software was used for bathymetry processing, including data cleaning and generation of bathymetry grids. Bathymetry grid raster for 400 kHz dataset had 0.5 m cell size, while for 150 kHz it had 0.75

m pixel size. The same resolutions per frequency were used to generate backscatter mosaic grids. They were created using FMGT software and following settings: 'flat' type of Angle Varying Gain AVG correction with window size of 300 and 'blend' style of overlapping lines management. Methods of backscatter data processing were described in details in Schimel et al. [2]. Bathymetry of the area based on 400 kHz frequency was shown at the Fig. 1. Maps of backscatter intensity for both working frequencies are visible at Fig. 2. Mentioned MBES

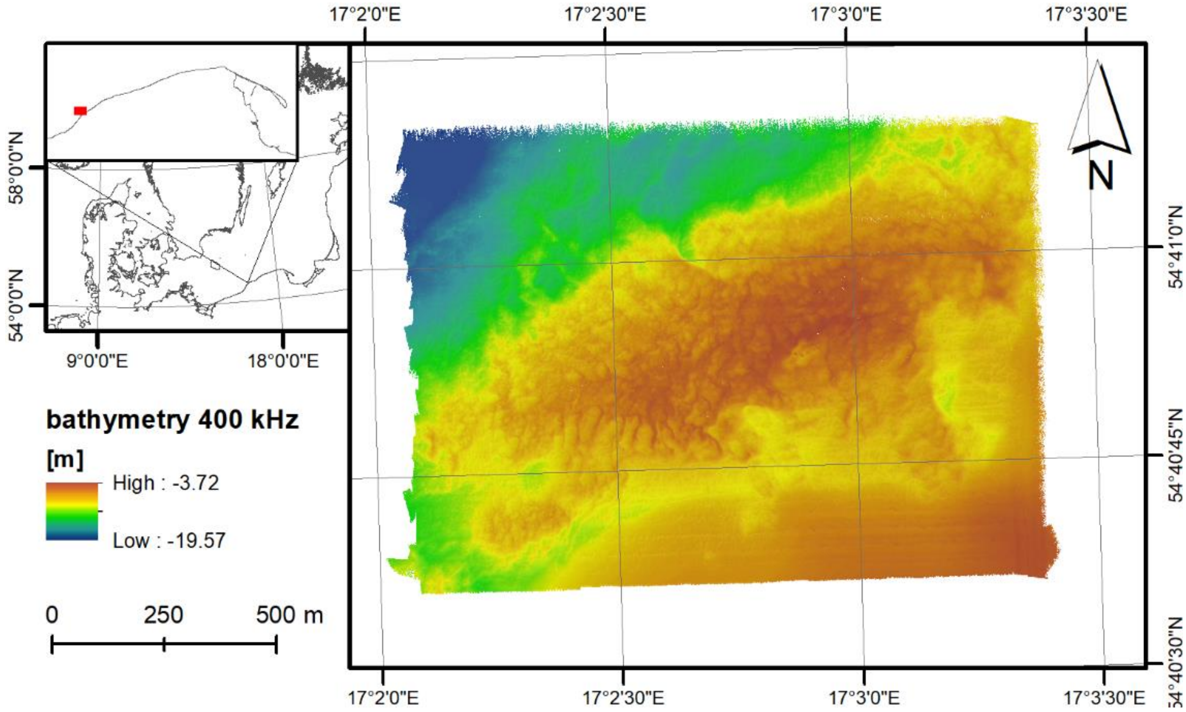


*Fig. 1: Site location within the Polish coast of the Baltic Sea (left), bathymetry of the area generated from 400 kHz MBES measurements (right).*

datasets in conjunction with ground-truth samples were used for further habitat mapping.

Ground-truth *in situ* information was gathered from sediment samples and ROV video inspections. We adopted habitat identification scheme from the work of Janowski et al. [1].

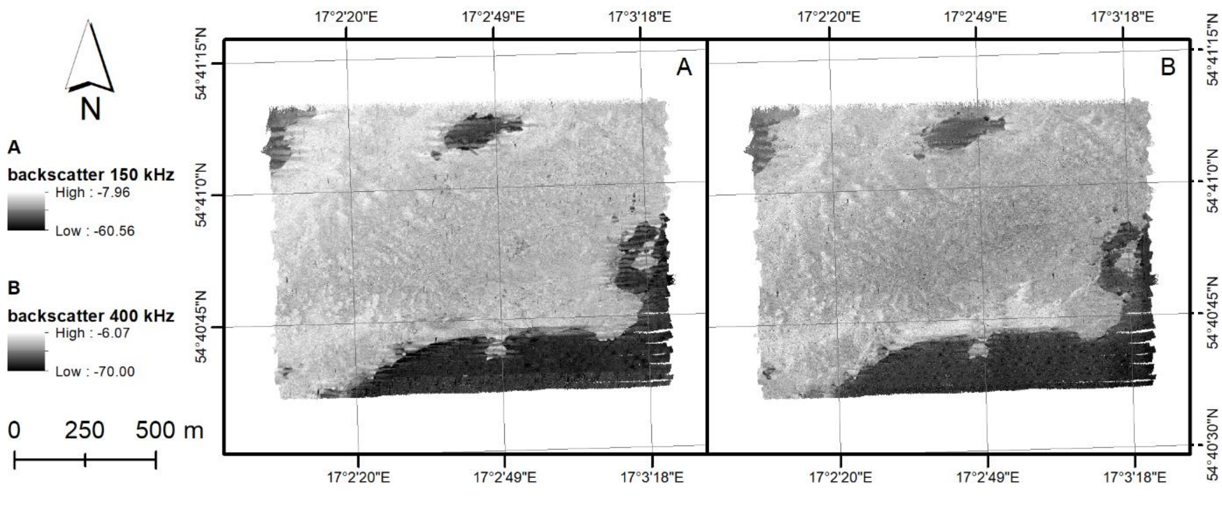


*Fig. 2: Backscatter intensity grids generated using FMGT from MBES measurements for two frequencies: 150 kHz (A) and 400 kHz (B).*

Abovementioned template separated properties of multibeam echosounder backscatter for five acoustic facies, including class of boulders (B), red algae (R), sandy gravels and gravelly sands (SG_GS), sands (S), very fine and fine sands (VFS), and additional class of artificial structures (A). Separation for five numbers of ground-truth classes was justified from an acoustic point of view considering distribution of MBES backscatter intensity.

Methodology of image analysis presented herein was performed on a basis of Object-Based Image Analysis (OBIA) and supervised classification of created segments using K Nearest Neighbour (KNN) classification method. We generated image objects of backscatter mosaic images using bottom-up region merging technique, named multiresolution segmentation. Segments creation started when single pixels of similar backscatter values were merged into larger areas. They grow until reaching the homogeneity criterion, described in details in Benz et al. [3]. The main parameter influencing the homogeneity criterion is scale, defining relative size of generated image objects. In this study we adopted scale 3 and highly common values of other homogeneity parameters used for creation of segments in benthic habitat mapping [4-6].

Ground-truth samples allowed us to perform supervised classification of segmented image. We used training samples form the division into training and validation samples from Janowski et al. [1] to train K Nearest Neighbour (KNN) supervised classifier [7]. Mentioned algorithm allows to assign class for a certain segment based on K number of nearest neighbours. In our case we defined K=1, so each image object was classified depending on the location of its nearest training sample. The classifier analysed dependencies between labelled training data in feature space consisting of four MBES datasets: bathymetry 150 kHz, bathymetry 400 kHz, backscatter 150 kHz and backscatter 400 kHz.

Generated results were compared with spatial locations of validation subset of ground-truth samples supporting creation of confusion matrix. Performance of classification was evaluated using accuracy assessment statistics based on estimated errors [8]. Measures calculated in this study included: user's and producer's accuracy, overall accuracy and Kappa Index of Agreement [9].

We have selected a polygon from a map of benthic habitats created with a known precision, in which we compared and tested the results with the classification of the singlebeam echosounder (SBES).

The map of benthic habitats created with known precision was the basis for the selection of a testing area in which we studied the results of SBE habitat classification. The polygon area was selected along SBE transects and its spatial location is visible as black frame over the result in Fig. 5, where an example of echograms recorded on three frequencies is shown in Fig. 4.

SBE data were subjected to an analysis consisting in the extraction of consecutive envelopes of echo pulses and computation of a set of their wavelet transform parameters [10]. These

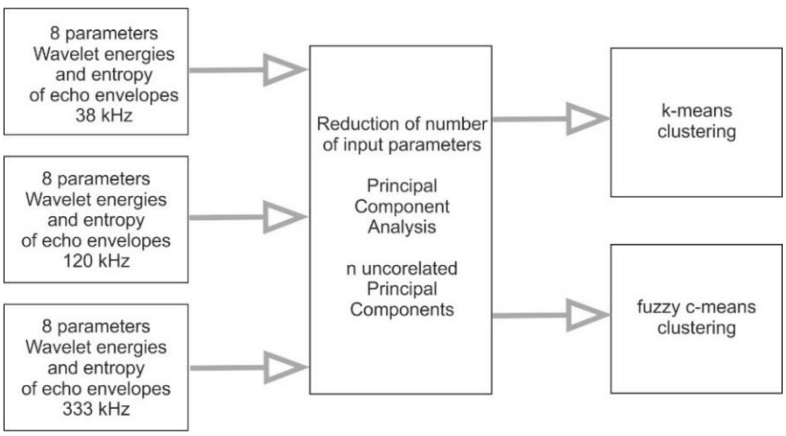


*Fig. 3: Classification scheme for bottom habitats - SBE dataset.*

parameters were then an input to Principal Component Analysis and further to classification procedures of k-means and fuzzy c-means. Fig. 3 shows habitats classification diagram used for data collected by SBE.

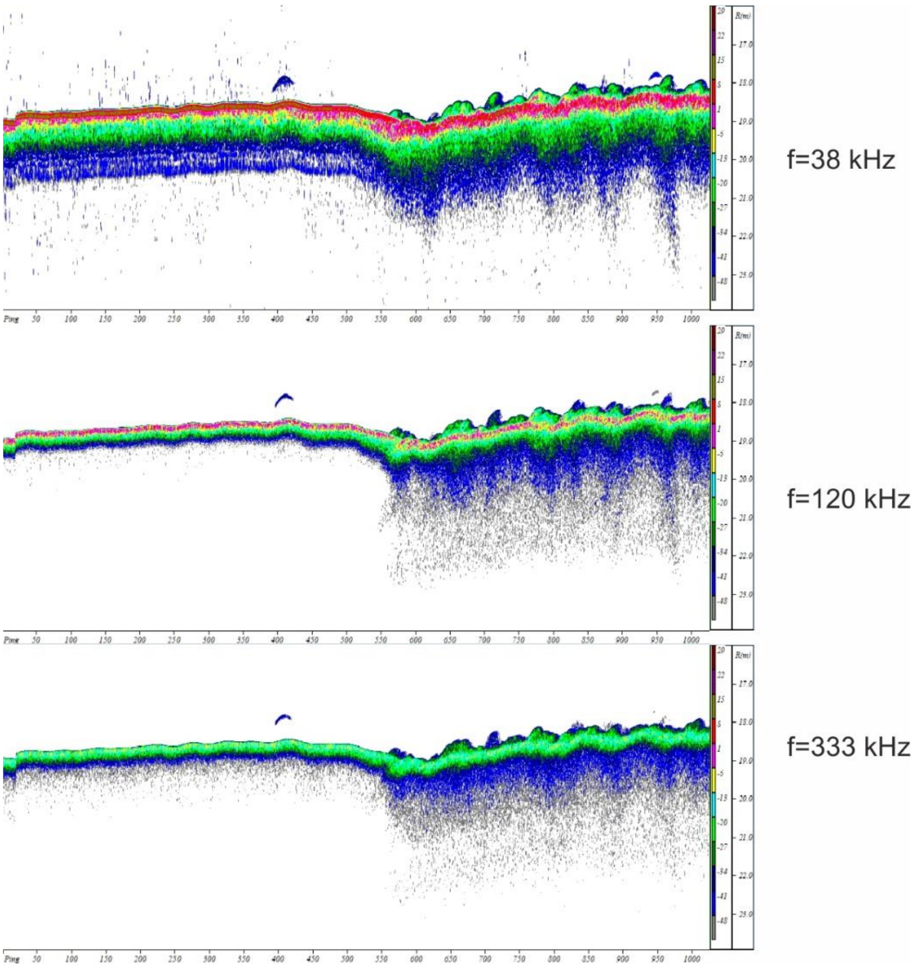


*Fig.4: Example of echograms recorded in the Rowy area with the use of SBE operating simultaneously on three frequencies - 38kHz, 120 kHz and 333 kHz.*

Developed benthic habitat map of the Rowy area is visible in Fig. 5. It clearly distinguishes properties of MBES datasets, like the central convex spot of red algae occurrence or stronger backscatter absorption in sand and very fine sand classes. Spatial delineation between B and SG_GS classes suggests depth related dependence, which is evident after comparison with MBES bathymetry of the area (Fig. 1).

For the data recorded by the singlebeam echosounder, it was checked how many evident habitats can be separated on the area marked with the frame depicted in Fig. 5. As shown in Fig. 6, in the space of parameters formed by three vectors containing wavelet energies and entropy of echo envelopes recorded on three frequencies, four clusters corresponding to the habitats visible in the area marked with a frame in Figure 5 are clearly marked. Sands (S),

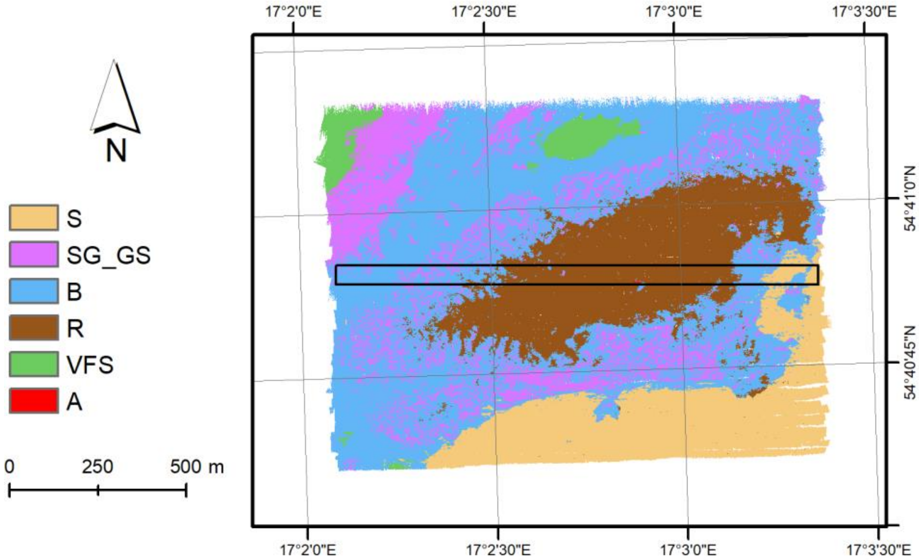


*Fig.5: Result of Object-Based Image Analysis for the Rowy area using KNN classifier and multiresolution segmentation scale 3. Black frame represents spatial extent for comparison between MBES and SBES*

boulders (B), red algae (R) and gravelly sands (SG-GS) were found in the framed area. We have additionally tested a number of spectral, energy and wavelet parameters of echo envelopes. It was found that wavelet energies and wavelet entropy were sufficient for correct classification of habitats using SBE data.

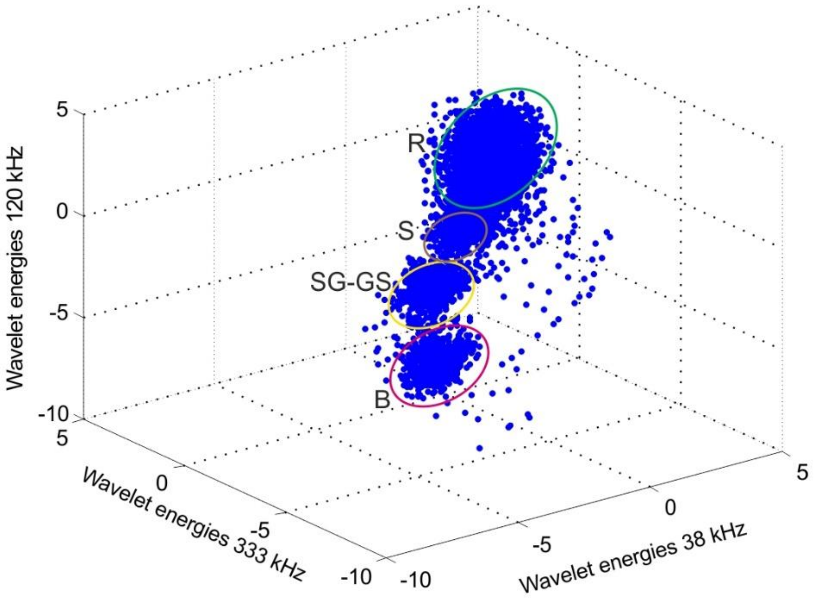


*Fig.6: Wavelet energies plot containing four clusters indicating separate features of seafloor sound reflectivity on the area marked with the frame depicted in Fig. 5.*

Confusion matrix and accuracy assessment statistics confirm high prediction performance of the KNN classifier based on multifrequency MBES dataset (Table 1). Overall accuracy measure shows 79%, whereas Kappa statistic indicates that classification conformity was significantly greater than random.

| Confusion matrix | | | | | | |
|---|---|---|---|---|---|---|
| User \ Producer Class | S | SG_GS | B | R | VFS | Sum |
| S | 14.3 | 0.0 | 0.0 | 0.0 | 0.0 | 14.3 |
| SG_GS | 0.0 | 7.1 | 7.1 | 0.0 | 0.0 | 14.3 |
| B | 7.1 | 7.1 | 28.6 | 0.0 | 0.0 | 42.9 |
| R | 0.0 | 0.0 | 0.0 | 21.4 | 0.0 | 21.4 |
| VFS | 0.0 | 0.0 | 0.0 | 0.0 | 7.1 | 7.1 |
| Sum | 21.4 | 14.3 | 35.7 | 21.4 | 7.1 | 100.0 |
| Accuracy assessment | | | | | | |
| Producer's | 0.67 | 0.50 | 0.80 | 1.00 | 1.00 | |
| User's | 1.00 | 0.50 | 0.67 | 1.00 | 1.00 | |
| Overall Accuracy | 0.79 | | | | | |
| KIA | 0.71 | | | | | |

*Table 1: Confusion matrix and accuracy assessment results. Confusion matrix values were presented as percentages.*

## DISCUSSION

This study presents methodological aspect of MBES classification for benthic habitat mapping. Based on previous experiences in the study area [1], we developed a simple mapping procedure that benefits from multifrequency MBES datasets and is still precise. Our approach assumes simplification of previous developed benthic habitat mapping workflow by omission of the feature extraction and selection procedures and arbitrary selection of only primary attributes of MBES backscatter. Majority of benthic habitat mapping research confirms that MBES bathymetry and backscatter are the most important of all features and therefore we assume that in some cases they may be enough to perform successful supervised classification of benthic habitats [11], especially for multifrequency MBES datasets. Therefore, we confirm usefulness of more than one frequency to benthic habitat mapping, but on the other hand, omission of feature extraction and selection steps for traditional single frequency MBES datasets may require a further study.

The additional use of multifrequency SBE data for classification confirmed its usefulness for classification of bottom habitats. Parallel use of two hydroacoustic systems is particularly useful in case of difficulties in classification with high spatial resolution.

## CONCLUSIONS

Both MBES and SBE bottom imagery segmentation schemes have many promising features which allow them to be applied for extracting bottom habitats. The first method, based on image analysis, allows quick habitat recognition, while the second method, based on envelope analysis, can be used for accurate classification with high resolution, especially in places with uncertain habitat identification results. The multi-frequency data has enabled progress in acoustical classification methods for bottom sediments and habitats.

## ACKNOWLEDGEMENTS

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