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Method selection of microseismic studies depending on the problem being solved

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The article compares two methods of microseismic studies of the maximum likelihood method and the Capon method for detecting the position of microseismic event when observed from the surface in the conditions of the developed deposit or by monitoring the hydraulic fracturing. The results of computational experiments for determining the accuracy of localization of model microseism in space, as well as for various noise levels, for various types of microseismic events and for the allocation of recurring events are presented. Based on the results of the experiments, the conclusion is drawn that the problems of identifying non-recurring events are more confidently solved by maximum likelihood methods, while for the detection of zones of increased fracturing, the method of Capon is best suited.

Keywords: hydraulic fracturing monitoring, natural fracturing monitoring, microseismic events, maximum likelihood method, superresolution method, Capon method, seismic moment tensor

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Introduction

Microseismic events location is increasingly used in oil and gas geophysics for solving various geological and technological challenges. The main areas of microseismic technologies application are natural fractures monitoring and hydraulic fracture monitoring aimed to optimize the subsequent oilfield development. Natural fractures monitoring allows identify zones of increased fracturing, where the obtained information is used to optimize wells spacing grids. Determination of both hydraulic fractures and natural fractures direction is of great interest for solving problems of geomechanics.

Obviously, such a variety of challenges cannot be solved by only one method and even one approach of microseismic sources location. There are a rather large number of known location techniques (Anikiev et al., 2014; Gajewski et al., 2007; Gajewski, Tessmer, 2005; Gharti et al., 2011), several studies were devoted to compare them (Kushnir et al., 2014; Maxwell, 2014). Unfortunately, the comparison is often done without taking into account the problem being solved, the noise situation and the accuracy of information on the environment velocity characteristics. Below we present a comparison of the two most popular approaches of microseismic sources location for solving various problems, as well as making some conclusions on the optimal area of their application.

Known theoretical approaches to microseismic sources location

Currently, there are two approaches to microseismic events location. The first approach includes diffraction stacking methods (Anikiev et al., 2014; Gajewski et al., 2007), time reverse modeling (Gajewski, Tessmer, 2005; Gharti et al., 2011) and maximum likelihood methods (Birialtsev et al., 2017) allowing to restore the intensity of microseismic events in space and time up to the accuracy of signal sampling rate at a receiver. This approach is used for identification of microseismic sources location directly by readings of the field signals.

The second approach (Kushnir et al., 2014), which is known as super-resolution methods or spectral methods, is based on microseismic sources location on a finite duration signal accumulated over its time interval, where the location can be performed only after signal accumulation. In this case, time of microseismic event occurrence is determined with an accuracy of the accumulation interval, however, the accuracy of microseismic event spatial coordinates determination is significantly higher in comparison with the methods of the first approach.

Differences in these two approaches can be clarified by considering the mathematical assumptions underlying these approaches. For generality, we will consider a

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microseismic event using the seismic moment tensor introduced by Aki and Richards (Aki, Richards, 1980), which allows combining fracture opening and closing with shear displacements in one microseismic event.

Let's denote the magnitudes of the seismic moment tensor components as M_i, where i is a particular seismic moment tensor component. Imagine an array of $k = 1..K$ sensors and denote the recorded signal as $z_k(t)$. The recorded signal can be considered as the sum of the noise $n_k(t)$ and the useful signal s_k^i from a microseismic event with a magnitude M:

$$z_k(t) = n_k(t) + \sum_i M^i s_k^i(t) \tag{1}$$

Covariance matrix of the signals vector Z recorded at each sensor has the following general form:

$$\mathrm{cov}(Z) = \mathrm{cov}\left(N + \sum_i M^i S^i\right) = \mathrm{cov}(N) +$$

$$+ \mathrm{cov}\left(N, \sum_i M^i S^i\right) + \mathrm{cov}\left(\sum_i M^i S^i\right) \tag{2}$$

Complete covariance matrix in (2) consists of a noise covariance matrix, a signal covariance matrix and a mutual noise and signal covariance matrix.

The mutual covariance matrix is a scattering matrix and we assume it zero in case of active microseismic sources location. In the first approach, we assume that the signal covariance matrix is negligible and the field signal covariances are due only to the noise covariance. In the second approach, we assume that the signal covariance is greater than the noise covariances and the covariance matrix of the field signal with sufficient accumulation time corresponds to the covariance of the useful signal from a microseismic event.

For the first approach, the maximum likelihood method is the most common technique including, as special cases, the methods of diffraction stacking and time reverse modeling. In (Birialtsev et al., 2017) it was shown that it is possible to determine the seismic moment tensor by solving the following system of equations:

$$\sum_k a_{1k} M^k = b_1 \tag{3}$$

where

$$a_{1m} = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij}^{-1}\left(s_i^m s_j^l + s_j^m s_i^l\right) \tag{4}$$

$$b_1 = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij}^{-1}\left(z_i s_j^l + z_j s_i^l\right) \tag{5}$$

Thus, if we neglect the covariance matrix of the useful signal, then the equations for the seismic moment tensor components are linear and can be solved relatively easily.

It is also obvious that such a solution is not applicable to the second approach, since in this case the covariance matrix of the field signal depends nonlinearly on seismic moment tensor components. For the second approach, we are forced to assume for the time being that the microseismic event source is isotropic, all tensor components of which are equal.

Super-resolution methods are based on the following approach: from the field data, we have the cov(Z) covariance function, which consists of the useful signal covariances. The vector of the simulated signal S(r) is constructed depending on the position of the source in the space r, and the value of the test function is constructed for a set of positions r:

$$F(r) = \frac{1}{S(r)\,\mathrm{cov}(Z)^{-n}\,S(r)'}, \tag{6}$$

The maximum of F(r) corresponds to the position of a microseismic event source. The –n exponent of the covariance function corresponds to different methods in the framework of the super-resolution approach, n = 1 corresponds to the historically first and most noise-resistant super-resolution method, the Capon method.

Computational Experiments

For a practical comparison of the first and second approaches applicability in solving various geological and technological challenges, a number of computational experiments were carried out with both maximum likelihood method and the Capon method as the most typical representatives of both approaches. Both methods were implemented in accordance with the stated formulation. A model experiment was carried out for the case of a homogeneous medium with a velocity V_p under the following conditions (Fig. 1).

An array of 225 model sensors were located evenly over an area of 1 square kilometer. Signal source was placed under the center of the area at a depth of 500 meters. The signal position was identified along the same grid in the source plane in 4 planes above and below the source with a vertical step of 50 meters. The model source function is Puzyrev wavelet with a central frequency of 25 Hz.

In the first experiment (Fig. 2) was tested the statement about a higher resolution of the super-resolution methods compared to the maximum likelihood method. Indeed,

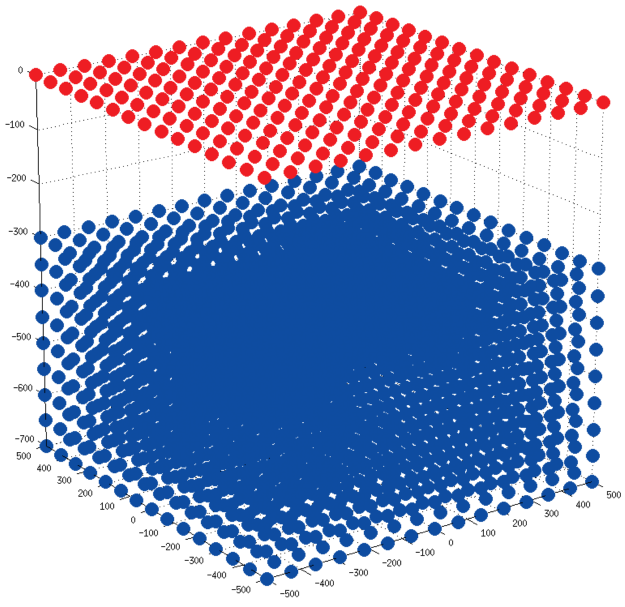


Fig. 1. Computational experiment scheme

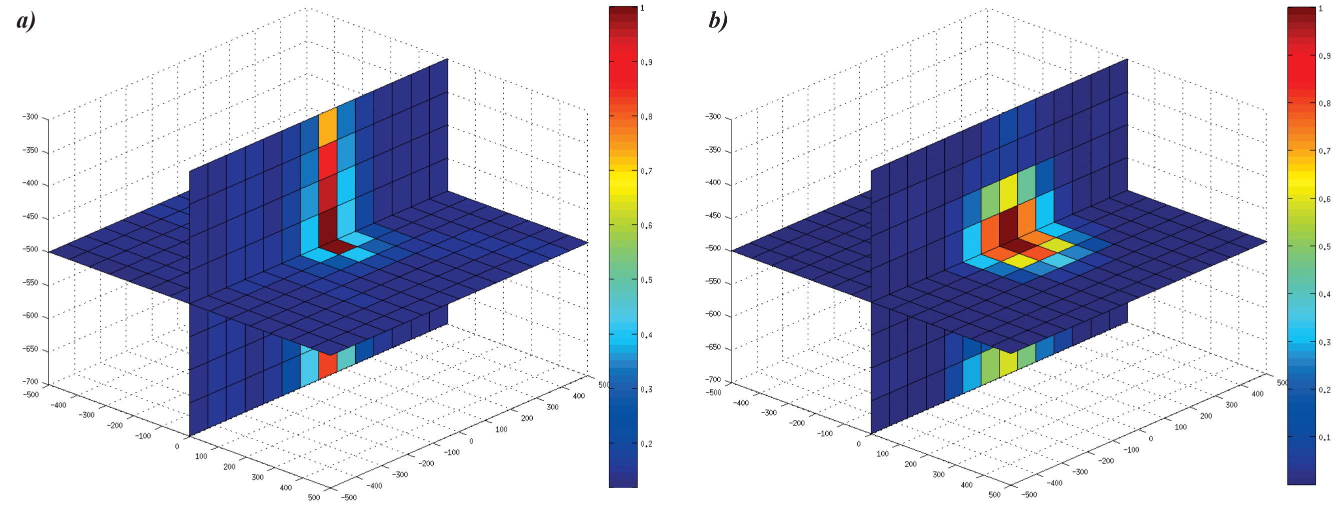


Fig. 2. Accuracy of localization of the model microseism by the methods of Capon (a) and maximum likelihood (b) in space for a low noise level

the area of microseismic event localization in the plane of the source looks more delineated, however, vertical smearing of this area is significantly higher than that of the maximum likelihood method.

The second experiment was conducted in order to compare the noise immunity of the Capon methods with Maximum Likelihood method in the horizontal plane of a microseismic event. The top group of images in Fig. 3 corresponds to the Maximum Likelihood method, the bottom images corresponds to the results obtained by Capon method. The signal-to-noise ratio corresponds to 1/7, 1/12, 1/17 from left to right, respectively.

It can be seen that at low noise level, the intensity of microseismic event location zone by the Capon method is much higher than that of the maximum likelihood method; however, as the noise level increases, the Capon method sharply loses its accuracy; in case of further increase in noise, the real source is not located. On the contrary, the maximum likelihood method demonstrates a gradual decrease in intensity of microseismic source location area with a moderate level of artifacts for all the noise levels studied.

The following computational experiment was carried out to determine the possibility of microseismic event location for various types of microseismic events. As can be seen in Fig. 4, isotropic and tension crack events

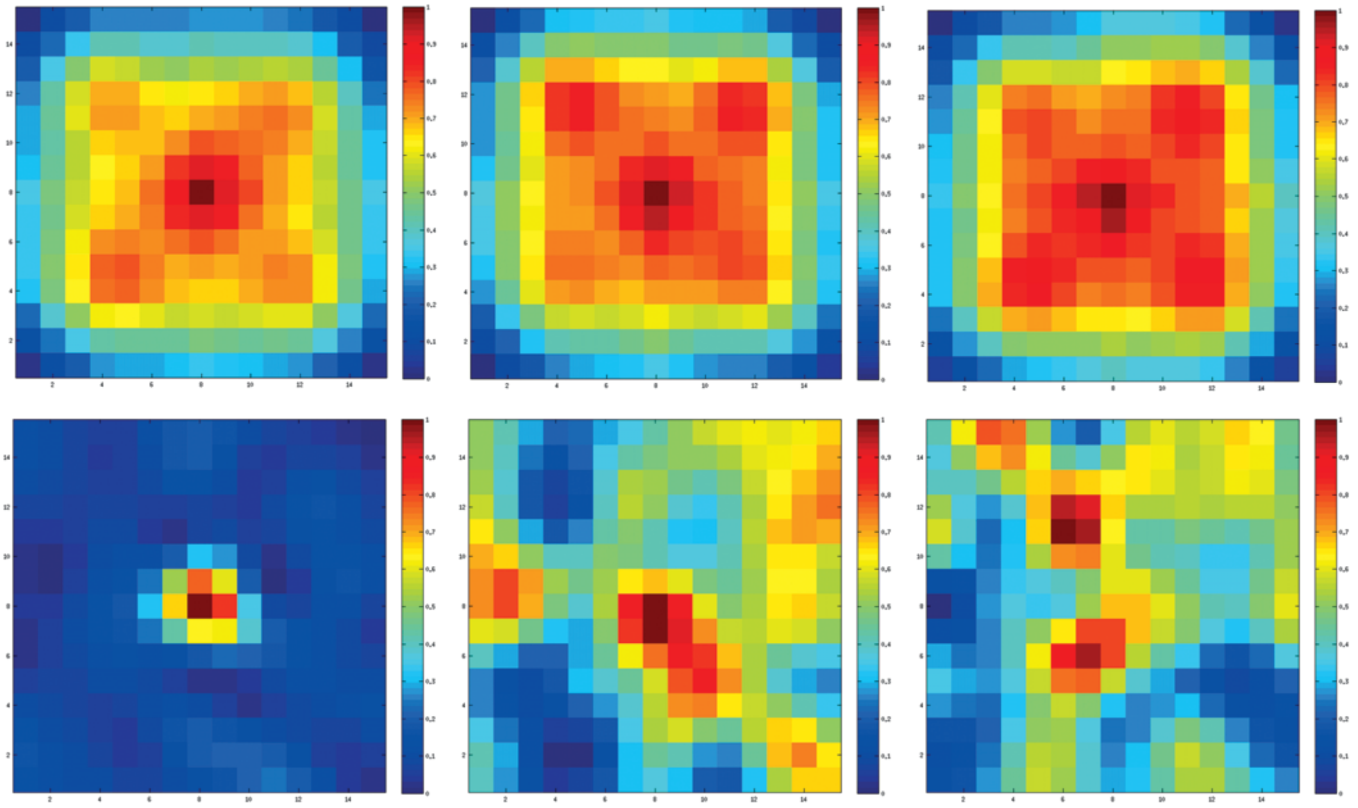


Fig. 3. Comparison of localization accuracy of microseisms by the Capon method and the maximum likelihood method for different noise levels

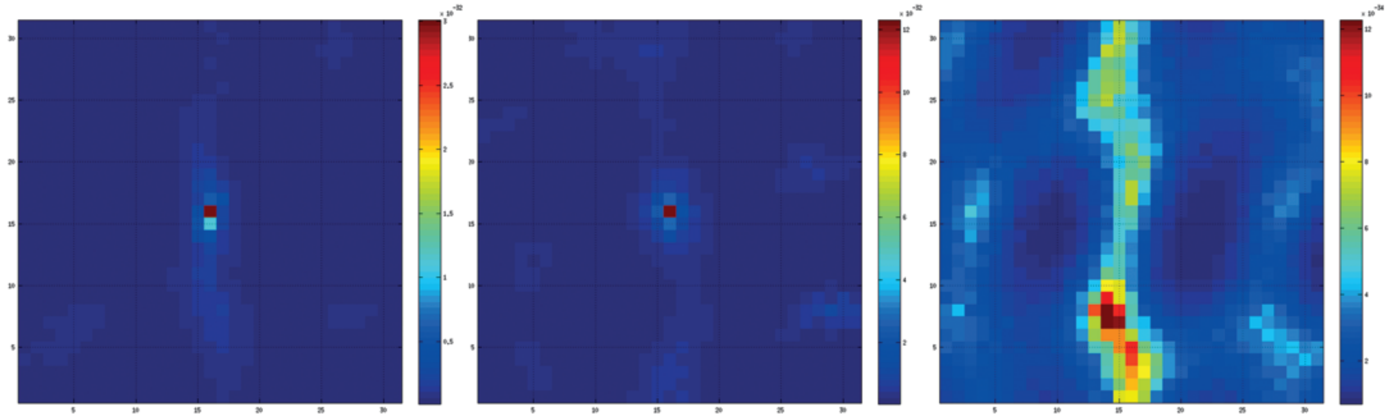
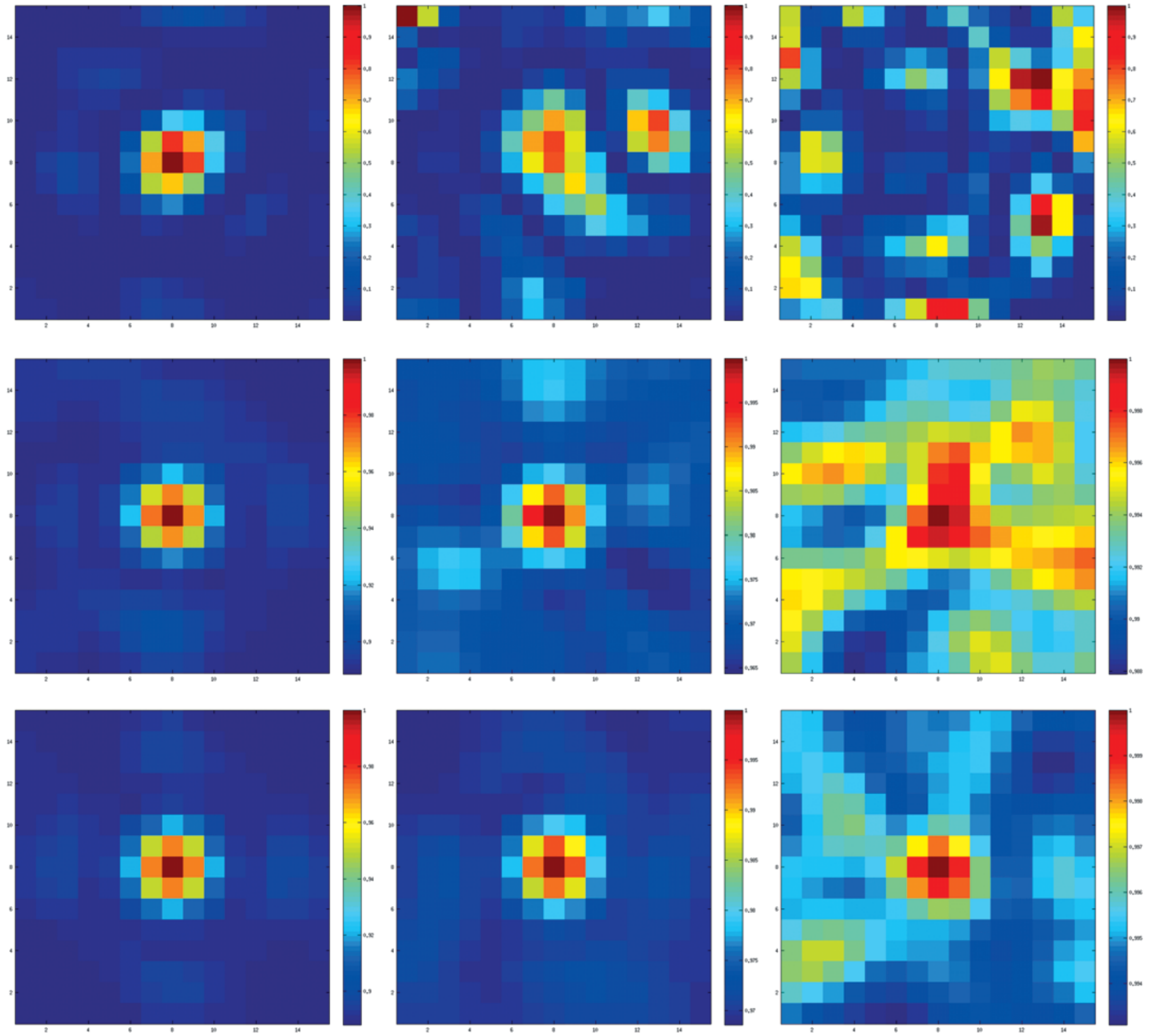


Fig. 4. The localization of various types of events by the Capon method: isotropic (a), tension crack (b) and shear-type (c)



Signal-to-noise ratio of 1/10 **Signal-to-noise ratio of 1/20** **Signal-to-noise ratio of 1/50**

Fig. 5. Comparison of the maximum likelihood method (top row) and the Capon method with an accumulation time of 15 minutes (middle row) and 2.5 hours (bottom row) for different signal/noise levels

are accurately located, however a shear-type event caused the appearance of an elongated artifact with a maximum at a considerable distance from the real place of the event.

The above experiments were performed with single events. In some cases, microseismic events have a recurring pattern, for example, during an event of natural fracturing or long-term impact on a reservoir by water flooding or thermal methods.

In the last experiment, the noise immunity of maximum likelihood and Capon methods were compared on example of recurring events location. A pseudo-field signal consisting of white noise and aperiodically appearing model signals was simulated for this experiment. Experiments were conducted with signal-to-noise ratios of 1/10, 1/20 and 1/50. The maximum likelihood method was used to identify individual signals aimed to get the best location accuracy option, and the Capon method was used with two accumulation times of 15 minutes and 2.5 hours of model time. The result is shown in Fig. 5. It is clearly seen that with a decrease in signal-to-noise ratio, the maximum likelihood method is characterized by the presence of artifacts and the useful signal is not detected with increasing noise level. The only way to improve the noise immunity of the maximum likelihood method in this case is to increase the number of sensors. The Capon method allows improving noise immunity by increasing the accumulation time.

Conclusion

The experiments have shown that both studied approaches are not universal. The problems of non-recurring events identification, especially in case of high surface noise conditions, e.g. hydraulic fracture monitoring, are more confidently solved by the maximum likelihood method, allowing to calculate the seismic moment tensor, which makes it possible to identify the source mechanism of microseismic event as well as direction of the corresponding fracture caused the event.

Identification of fractured zones, especially when the target horizon is known, and the challenges of flood zones monitoring and thermal effects on the formation are more confidently solved by super-resolution methods such as the Capon method.

The most complex and challenging tasks, such as natural fracturing direction identification should be solved by the combined application of both methods.

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