Monitoring performance using synthetic data for induced microseismicity by hydrofracking at the Wysin site (Poland)

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Abstract

Ideally, the performance of a dedicated seismic monitoring installation should be assessed prior to the observation of target seismicity. This work is focused on a hydrofracking experiment monitored at Wysin, NE Poland. A microseismic synthetic catalogue is generated to assess the monitoring performance during the pre-operational phase, where seismic information only concerns the noise conditions and the potential background seismicity. Full waveform, accounting for the expected spatial, magnitude and focal mechanism distributions and a realistic local crustal model, are combined with real noise recording to produce either event based or continuous synthetic waveforms. The network detection performance is assessed in terms of the Magnitude of Completeness (Mc) through two different techniques. First, we use an amplitude threshold, taking into the ratio among the maximal amplitude of synthetic waveforms and station dependent noise levels, for different values of signal-to-noise ratio (SNR). The detection probability at each station is estimated for the whole dataset and extrapolated to a broader range of magnitude and distances. We estimate a Mc of about 0.55, when considering the distributed network, and can further decrease Mc to 0.45 using arrays techniques. The second approach, taking advantage on an automatic, coherence-based detection algorithm, can lower Mc to ~ 0.1, at the cost of an increase of false detections. Mc experiences significant changes during day hours, in consequence of strongly varying noise conditions. Moreover, due to the radiation patterns and network geometry, double-couple like sources are better detected than tensile cracks, which may be induced during fracking.
1. Introduction

Induced seismicity related to industrial processes including shale gas and oil exploitation, mining and other energy technologies are current issues that imply enough reasons to be concerned [Nicholson and Wesson, 1990, 1992; McGarr et al., 2002; Davies et al., 2013; Ellsworth, 2013]. The assessment of the potential hazard for these triggered or induced earthquakes has become a relevant and pressing problem, especially because seismicity rates have increased in some locations. In the Western Canada Sedimentary Basin, seismic activity has been conjectured as being induced by hydraulic fracturing [Farahbod et al., 2015, Schultz et al., 2015a], gas extraction [Baranova et al., 1999] or waste water disposal [Horner et al., 1994; Schultz et al., 2014]. Fracking operations in the United Kingdom were stopped for several years after the detection of two earthquakes with magnitudes of M_L 2.3 and 1.5 in the Blackpool area [Clarke et al., 2014]. An interesting case correlated to gas injection operations occurred offshore Spain, in the Gulf of Valencia, recording a maximum moment magnitude M_w 4.3 on 2013 October 1 [Cesca et al., 2014, Gaite et al. 2016]. The major cause of injection-induced earthquakes is associated with the disposal of wastewater into deep strata [Healy et al., 1968] and the largest events in that respect were registered in Oklahoma in November 2011, reaching a peak magnitude of M_w 5.7 [Keranen et al., 2013]. Other instances of induced seismicity, sometimes including events of M > 4, have been observed in recent years [Ellsworth, 2013; Holland, 2013]. This work focuses on recent hydraulic fracturing operations associated to shale gas exploration and exploitation in Poland, due to the increased interest in these techniques in some European countries (SHEER project, www.sheerproject.eu).

Hydraulic fracturing usually induces weak events since the volumes of injected fluids are small [Davies et al., 2013]. However, scenarios with larger earthquakes are possible, e.g. if the injected fluids alter friction conditions and trigger the failure of neighboring faults under pre-existing, tectonic stress. For example, at the Horn River Basin, British Columbia, a sequence of earthquakes reaching M_w 3 was caused by fluid injection in proximity of pre-existing faults (BC Oil and Gas Commission, 2012). Hydrofracking occurs when the pore pressure exceeds the minimal principal stress and the local strength is overcome. As a result of fracturing, microearthquakes and aseismic slip creates the pathways for the gas/oil, enhancing the rock permeability. In general, the crack growth stops when the rupture runs out of energy. However, the progressing crack could find new energy sources, e.g. in presence of tectonically loaded faults. Seismic monitoring of fracturing operations is essential, so that branching out of seismicity is early detected and correlated with geomechanical operations. The ability of a local network to detect weak microearthquakes as well as larger triggered events depends on the seismic instrumentation, station number, network geometry, seismic noise and installation conditions. Consequently, assessing the performance of the monitoring setup, e.g. estimating the expected magnitude of completeness or the smallest detectable magnitude, is a fundamental step for a later reliable analysis of the forthcoming seismicity. In this work, we discuss how to address the problem of detection performance before the target hydraulic fracturing operation takes place. With this goal, we make use of the concept of completeness magnitude (M_c), defined as the lowest magnitude at which 100% of the earthquakes in a space-time volume are reliably detected [e.g., Rydelek and Sacks, 1989; Wiemer and Wyss, 2000; Woessner and Wiemer, 2005].
Multiple techniques have been proposed for the estimation of $M_c$. Mignan and Woessner [2012] classify them as catalog-based and network-based methods. The first group of methodologies is mostly based on the assumption of self-similarity of the earthquake process, implying that $M_c$ is the minimum magnitude at which the observed cumulative frequency magnitude distribution (FMD) departs from the Gutenberg-Richter law [Wiemer and Wyss, 2000; Cao and Gao, 2002; Marsan, 2003; Woessner and Wiemer, 2005; Amorese, 2007; Mignan et al., 2011]. The second category uses the network distribution to estimate $M_c$: this is either done through the analysis of diurnal variations [Rydelek and Sacks, 1989], the comparison of amplitude-distance curves and the signal-to-noise ratio [Sereno and Bratt, 1989], seismic threshold monitoring [Gomberg, 1991; Kværna and Ringdahl, 1999; Kværna et al., 2002], numerical simulation [D’Alessandro et al., 2011a,b; D’Alessandro and Stickney, 2012], Bayesian statistics [Mignan et al., 2011; Kraft et al., 2013; Mignan and Chouliaras, 2014], and detection probability estimates for each seismic station [Schorlemmer and Woessner, 2008; Nanjo et al., 2010; Plenkers et al. 2011; Maghsoudi et al. 2013, 2015]. Furthermore, understanding the microseismic source mechanisms and stress state has gained more interest recently and should be considered in an appropriate estimation of the detection performance [Nolen-Hoeksema and Ruff 2001, Baig and Urbancic 2010].

All the catalogue based methods described above can only be used in a retroprospective manner, typically after several years of monitoring under the assumption of a steady earthquake generation process. This is not useful for planning the monitoring of fracking operations, which last only few months and are highly transient processes. Therefore, we propose a prospective evaluation method where we apply a combination of the aforementioned methods and synthetic data in order to assess the monitoring performance before the fracking operations start. To achieve this goal, we discuss how to generate a realistic synthetic microseismic catalogue and synthetic waveform datasets, accounting for the main characteristics of the expected source mechanisms for hydraulic fracturing as well as realistic noise conditions. The detection performance is assessed for the synthetic data using two different techniques. In the first case, we use an amplitude threshold, taking into account a station dependent noise level and different values of signal-to-noise ratio (SNR). In this case, the detection probability of each station is estimated for each synthetic event, and extrapolated to a broader range of magnitudes and distances from Bayesian statistics. The final map of the magnitude of completeness is then estimated by combining the detection performance of different stations, considering the network geometry. The second approach follows the application of an automatic detection algorithm to the continuous synthetic dataset, comprised of synthetic event waveforms and continuous real noise data. In the present study, we apply a recently developed automated full waveform detection algorithm based on the stacking of smooth characteristic function and the identification of high coherence in the signals recorded at different stations [Lassie, https://gitext.gfz-potsdam.de/heimann/lassie, Matos et al., 2016, Heimann et al., 2017].
2. Monitoring network at the Wysin site (Poland)

In order to assess the sensitivity of microseismicity to hydraulic fracturing operations, we perform a seismic monitoring at a shale gas exploration/exploitation site in Pomerania (Poland). In this area, close to the village of Wysin, Polish Oil and Gas Company (PGNiG) drilled two horizontal boreholes, named Wysin 2H and Wysin 3H, designed for fracturing under Stara Kiszewa Concession No. 1/2011//p for prospecting and exploration of oil and natural gas. The horizontal boreholes are located at 3955 and 3865 m below the surface and they are oriented WNW-ESE with an approximate horizontal length of 1.7 km each.

The seismic monitoring installation is part of a broader survey concept, also monitoring groundwater conditions and air pollution, planned and deployed thanks to the EU project SHEER (www.sheerproject.eu). The network is composed of a surface installation and a shallow borehole installation, covering a region of 60 km$^2$ (Figure 1). The surface network includes 6 broadband stations surrounding the drilling site at distances of 2.1 to 4.3 km, with a good azimuthal coverage (maximal gap 90$^\circ$). In addition, short period stations are arranged in three small-scale arrays, with apertures between 450 and 950 m. Broadband stations are equipped with GÜRALP CMG-3ESP sensors, and record continuously with a sampling rate of 200 Hz. Short period stations are either equipped with a combination of MARK L-4C-3D sensors or GeoSIG VE-53-BB sensors. The sampling rate of all short period stations is 500 Hz. The shallow underground installation is composed of 3 seismometers (Geotech Instruments KS-2000) installed at 50 m depth. The installation was started on summer 2015 and the network is fully operational since November 2015. However, two borehole stations (GW3S and GW4S) had suffered from technical problems and were replaced by two other stations with sensors Nanometrics Trillium Compact Posthole 120s at the end of April 2016. For this reason, we exclusively use seismic data of May 2016 to characterize the noise level at each station. This period precedes the beginning of the hydrofracking operations, which started in June 2016 at a depth of about 4000 m.
Figure 1. Map of seismic monitoring composed of 6 broadband stations (green triangles), 3 small-scale arrays (inset boxes), each one composed of 8 to 9 short period stations (black triangles) and 3 shallow borehole stations (red circles). Blue squares in inset boxes correspond to central locations of each array. Fracking area (red star, vertical borehole) and horizontal boreholes (blue lines) are shown. The inset map shows the fracking area (red square) in Poland.
3. Synthetic microseismic catalogue

We adopt a recently developed tool to generate a synthetic catalogue and waveform datasets, which realistically accounts for the expected microseismicity patterns (Kriegerowski et al., 2015). The procedure consists of two steps: 1) the generation of a synthetic seismic catalogue which reflects the characteristics of the expected seismic activity and, 2) based on that the generation of realistic synthetic full waveforms combined with real noise. We consider two types of seismicity in the study region: i) a background seismicity, taking place independent from the fracking operations, with focal mechanisms controlled by the known orientation of tectonic stress and the unknown orientation of local faults, and ii) induced seismicity, which is controlled in its growth and moment tensors by the superposition of tectonic and induced stresses. For this second group of potential microseismic events, the regional tectonic in situ stress state controls the direction of hydraulic fracture growth in the unperturbed rock formation [e.g., Nolen-Hoeksema and Ruff, 2001; Zang and Stephansson, 2010]. The knowledge about the orientation of the maximum horizontal compressive stress ($S_{H\text{max}}$) is thus vital to establish possible candidate geometries for the expected focal mechanisms. The horizontal fracking drillings are expected to be perpendicular to $S_{H\text{max}}$, as such stress conditions favor the propagation of fractures opening in the direction of the least compressive stress ($S_h$). It has been shown that the processes involving rapid fluid injection can produce tensile failures with significant non-double-couple components, opening in the direction of the minimal compressive stress, and closing after the injection (e.g., Economides and Nolte, [2003] and others). The orientation of microfractures produced by the hydrofracking depends on the superposition of the stress perturbation induced by the hydraulic fracturing process and the background regional stress field.

Our synthetic catalogue should be consistent with the aforementioned conditions. For this purpose, we consider four families of microseismicity, assigning 1000 events to each one (Figure 2); the subjective choice of the number of events has no major implications, since they are only used to assess the detection performance for different magnitudes and rupture types. We use a Hudson source-type plot [Hudson et al., 1989] to discuss the non-double-couple components and a graphical representation of tension (T), pressure (P) and null (B) axis to discuss the focal mechanism orientations. The first group of seismic sources (family 1) resembles the background seismicity: these sources are modeled by double couple (DC) focal mechanisms (this group of synthetic events is hereafter referred as “double-couple” family). Since the orientation of small local faults is unknown, we adopt a random distribution of orientations (i.e. random strikes and dips). The rake value, instead, is controlled by the strike and dip of the rupture plane and $S_{H\text{max}}$ of the background stress. In our study area, located within the East European Craton geodynamic domains, the maximum horizontal stress is oriented $S_{H\text{max}} \sim 15^\circ$ [World Stress Map database release 2008, Heidbach et al., 2008], almost perpendicular to the horizontal fracking drillings. The compressive regime implies the occurrence of thrust or strike-slip events, with no normal faulting (see triangular diagram in Figure 2). To simulate possible minor deviations from a pure DC source due to the fluid injection, we include a random 10% perturbation in the moment tensor entries. According to Baig and Urbancic [2010], induced fractures tend to open in the direction of the minimal compressive stress, closing in the same direction after the injection. We thus model two families of moment tensors, dominated by positive (family 2) and negative (family 3) tensile cracks with dipoles oriented parallel to $S_h$ with a randomized deviations of $\pm 25^\circ$ (according the quality data for this orientation from the World Stress Map); also in this case,
moment tensor configurations are finally perturbed, as for the double-couple family. The last family (family 4), defined as “random full moment tensor”, represents random moment tensor sources and thus account unexpected processes. This family shows a clear dispersion both in the Hudson and focal mechanism orientation plots.

**Figure 2.** a) Examples of focal mechanisms for different families of expected microseismicity in hydraulic fracturing. b) Hudson source-type plot showing the Gaussian Kernel density for the complete synthetic microseismic catalogue where red denotes higher and blue regions lower event densities, respectively. The boxes with dashed grey frames identify the concentrations of seismic sources and the T, P, B axes plots belonging to the double couple, positive and negative tensile crack families. The triangle diagram indicates the distributions of double couple focal mechanism. The blue points dispersion corresponds to the random full moment tensor family. Acronyms in Hudson plot mean isotropic (ISO) and compensated linear vector dipole (CLVD).

A proper representation of microseismicity should further consider a suitable distribution of magnitudes and hypocenters (Figure 3). The instrumental sampling of our fracking experiment (500 Hz) and the distance to the horizontal fracking drillings (~ 4 km depth) do not favor detections with moment magnitude below -1; on the other hand, the few previous hydraulic fracturing experiments in Europe never reported seismicity of magnitude greater than 3 [Clarke
We then adopt a Gutenberg-Richter distribution with $b = 1$ and $a = 1.84$, to distribute magnitudes in between these limits. Moreover, we assume a circular fault model of Madariaga [1976] and an average stress drop of 2.7 MPa for earthquakes within the chosen magnitude range [Kwiatek et al., 2011]. Based on this, we can estimate a maximum rupture length of ~350 m for the largest events. This value can be used to define the spatial distribution of induced seismicity, in coherence with previous results in the United States, where most of the maximum fracture lengths have been less than 100 m, reaching peak values of 600 m [e.g., Davis et al., 2012; Fisher and Warpinski 2012]. We consider that the hypocenters of small fractures are constrained within a volume defined by the maximal possible rupture, which extends 350 m around the segments of the horizontal wells where the fracking takes place. This corresponds to a worst case scenario, where the largest fracture nucleates close to the well and propagates unilaterally for the length of 350 m. While the induced seismicity events (family 2 and 3) are constrained within this volume (Figure 3a), background DC sources (family 1) and random sources (family 4) are randomly distributed in a slightly broader region (Figure 3b). Origin times are distributed randomly within a time period of one month (which is in the order of the duration of the whole fracking process). As a result of this procedure we obtain a catalogue of 4000 synthetic events, divided in 4 families. The catalogue includes the following information: origin time, location, moment magnitude, moment tensor and its decomposition into isotropic, double couple and compensated linear vector dipole (CLVD), radius, duration, stress drop and event family.

**Figure 3.** Distribution of hypocenters and magnitudes for the synthetic microseismic catalogue in the Wysin fracturing area. a) Distribution for the random full moment tensor and double couple families. b) Distribution for the positive and negative tensile crack families. The size and color of each point is scaled to the moment magnitude. Gray star indicates the vertical drilling. Black lines show the fracking boreholes and the thicker line identifies the zone allocated for fluid injection. Panels a) and b) show the map views, c) and d) the side views.
After generating the synthetic seismic catalogue we compute the respective seismograms at all the stations of the monitoring network, both at the surface and at the shallow borehole installations. A realistic local crustal model is necessary to properly compute the synthetic waveforms. A 1D velocity profile could be modeled from ground samples of the vertical fracking drilling. Since we do not dispose of such information, we relied on previous studies on the broader region of interest. We use a P-wave velocity profile extracted from a high-resolution 3D seismic model for Poland, at the location of the fracking site [Grad et al., 2015], which is shown in Figure 4. The S-wave velocity profile was built assuming a typical scaling to the P wave velocity (\(v_p = 1.73 v_s\)), while densities of each layer were obtained from Grabowska et al. [1998]. A constant attenuation factor is used for all layers (\(Q_p=120\) and \(Q_s=60\), Król et al., 2013). The low Q value for S- and P-waves is representative for the sedimentary basin in Poland and leads to a high attenuation in the frequency range of study. The reflectivity method [Wang, 1999] was used to precalculate Green functions up to 500 Hz for the chosen velocity model and a proper range of source depths and epicentral distances. Finally, 3-component synthetic full waveforms (Figure 5a) were generated using the Pyrocko package [http://emolch.github.io/pyrocko/, Heimann et al., 2014], combining the Green's functions and moment tensors of the synthetic catalogue. We convolve synthetic seismograms with the transfer functions of each receiver. Finally, to reproduce true monitoring conditions at the different station locations, we add real noise to synthetic traces (Figure 5b), using recordings at those stations from May 2016. Thereby, we can use different synthetic data sets: noise free synthetic seismograms and noise contaminated continuous seismograms.

![Figure 4](image.png)

**Figure 4.** Local crustal model for the Wysin site. The P-wave velocity profile is obtained for the coordinates 54.09°N and 18.30°E from Grad et al. [2015]. Each layer is identified with the name and the density value in g/cm³. The thick black dashed lines indicate the depth of the west and east horizontal wells.
**Figure 5.** a) Raw synthetic waveforms (displacement) and b) real noise contaminated continuous seismograms (velocity) for one positive tensile crack event with \( M_w = 0.97 \). a) and b) show the same event for the vertical component in each seismic station. The signal in b) is bandpass filtered between 2 Hz - 80 Hz and notch filtered at 50 Hz. Zero time correspond with the origin time.

### 4. Detection performance using amplitude threshold

Any detection algorithm needs to define a threshold or trigger level according to boundary conditions. Records of ambient noise during a time period prior to a seismic experiment are always useful in order to estimate suitable values for such detection level. As a prior approximation to assess the monitoring detection performance, we propose to compare the maximum amplitudes of our synthetic waveforms with an amplitude threshold previously defined according to the real noise records at each station. First, the maximum amplitudes of noise free synthetic full waveforms are analyzed in function of the hypocentral distance \( r \) and the moment magnitude (Figure 6). The amplitude increases exponentially with the magnitude, while due to the geometrical spreading amplitudes decay with inverse dependence to the hypocentral distance \( 1/r \). The variability of focal mechanisms and moment tensors in our catalogue is responsible for the amplitude variations with respect to this general patterns (see amplitude profiles in Figure 6). In fact, we observe in general larger amplitudes associated with double couple sources than tensile cracks. Second, a seismic noise analysis is carried out using one-month data (May 2016) before fracking operations to define the amplitude threshold.
Figure 6. Maximum amplitudes according to the hypocentral distance for each station and the moment magnitude for each source are plotted for the complete synthetic microseismic catalogue. Amplitude profiles are plotted for a fixed hypocentral distance (4.5 km) and a fixed moment magnitude ($M_w = -0.75$) using gray dots. Additionally, we also show these same amplitude profiles considering those events belonging to the double couple (black dots) and tensile crack (gray dots) families.

The detection performance of each station will additionally depend on the specific noise conditions. Therefore, we consider random noise samplings at each station and used them to estimate an average noise conditions in terms of ground displacement (Figure 7). Although the detection procedure would be actually performed on raw traces, our approach was chosen to quantify the detection amplitude in terms of maximal displacements. Choosing a physical magnitude such as displacement for the detection threshold is convenient for comparison with future studies, in order to be independent on the sensor instrumentation. Mean and standard deviation values are obtained from the noise sampling at different hours in order to observe daily
variations. Larger noise levels during day hours (6.00 - 18:00 hours) are found as a general pattern. However, different patterns of smoother variations are also found for some stations (e.g., a noise level increase between 15:00 and 24:00 hours at CHR3 and GW4S, see Figure 7a). We choose the amplitude threshold for each station according to the averaged values during the day and night hours (Figure 7). In this way, we can clearly identify the most noisy stations between 2-80 Hz (e.g. PLA4, PLA7, PLA8) and most quiet ones (e.g. GLO5, GLO7). The borehole stations, which are located at shallow depth (around 50 meters below surface) show similar noise levels between 2-80 Hz as some surface stations. The detector level is then defined according these amplitude thresholds and a fixed signal-to-noise ratio (SNR).

**Figure 7.** Noise analysis in each seismic station using one-month data between 2-80 Hz (vertical component) before fracking operations. a) Mean (gray line) and standard deviation (yellow area) values in displacement are obtained from the random noise sampling taking into account the different hours of the day. Average amplitude threshold for day and night (blue line) and the standard deviation (light blue area) are estimated according the diurnal variation between 6:00 - 18:00 hours. b) Bars diagram with the amplitude thresholds and its uncertainties during day (red bar) and night (yellow bar) for each station.
We can now compare the maximal amplitude of noise free synthetic waveforms at each station and the corresponding station noise level (either for day or night hour, depending on the event origin time). Imposing different SNR requirements, we can estimate detected and undetected events at each station. Thereby, the magnitude of completeness can be calculated straight by the lowest magnitude above which all synthetic events are robustly detected (i.e. detected by at least 4 stations), taking into account both day and night amplitude thresholds (Figure 8). The increase of $M_c$ with required SNR reflects the fact that imposing a larger SNR for detection will decrease the number of detected events and increase the magnitude of completeness. A potential empirical law can adjust this relation with fit parameters $d_1$ and $d_2$:

$$M_c = d_1 \cdot SNR^{d_2} + d_0$$  \hspace{1cm} (Eq. 1)

In this equation, since the noise level is fixed, a low SNR means that events which have low amplitude waveforms (i.e. small magnitude) can be detected; in the extreme case of SNR equal to 0, we should detect all synthetic events, so that $d_0$ can be defined by the minimum magnitude of our synthetic catalogue, in our case, $d_0 = -1$. The variation of $M_c$ quantifies the monitoring performance of our network for different values of the SNR detection threshold. We estimate $M_c \sim 0.60$ during day hours and $M_c \sim 0.55$ during night hours, when considering a realistic $SNR = 2$. Another interesting issue concerns the evaluation of the contribution to $M_c$ for each family of source mechanisms. The tensile crack families constrain the $M_c$ for the complete synthetic catalogue, as these events are more difficult to be detected. Conversely, for the DC family alone, the $M_c$ is reduced to $\sim 0.1$, e.g. considering SNR larger than 1 (Figure 8). The different detection performance arises from the fact that DC sources produce larger amplitudes than tensile cracks with the same magnitude, as previously discussed in Figure 6. It should be noted, however, that this also implies some challenges in the correct estimation of the magnitude for both DC and tensile sources. An amplitude based magnitude definition, ignoring the radiation pattern of different type of sources, may lead to underestimate the magnitude of tensile sources (or overestimate the magnitude of DC sources). Fit parameters in Eq.1 vary slightly for day, night and the selected family: $d_1 \in [1.35 - 1.22]$; $d_2 \in [0.23-0.21]$. Another important aim concerns the application of array techniques to improve the detection performance of our network. In general, the signal-to-noise relation improves with the square root of the number of stations belonging to an array [e.g. Rost and Thomas 2002; 2009]. Applying such approximation to the three arrays, we can add fictitious stations located in the center of each array (Figure 1), with smaller amplitude thresholds. In this case, the fit parameter $d_1$ takes values between 1.29 - 1.17, and $M_c$ is slightly decreased by about 0.05, with respect to the distributed network setup (Figure 8).
Figure 8. Mc versus SNR relation according to the noise levels during day (first column) and night hours (second column). Potential empirical laws can adjust the stepwise increase observed for our synthetic catalogue (first row). The monitoring performance is assessed for the Wysin network in terms of Mc for the SNR values of 1, 2 and 3 (second row). Note that we show the same empirical laws in first and second rows. The monitoring performance is improved using array techniques (third row). Cyan lines identify the curve using the complete synthetic
catalogue, red lines those for the events included in the double couple family and black lines those for the tensile crack family only.

Our next purpose aims to extend spatially the previous values of $M_c$ around the fracking area for a realistic case of $SNR = 2$. We can obtain a map to assess our spatial performance combining the probability of detection ($P_d$) and empirical relations from Bayesian statistics. Taking into account each station and its corresponding amplitude threshold, we can divide the catalogue into detected ($N^+$) or not detected ($N^-$) events (Figure 9a). The $P_d$ at a single station for different magnitudes ($M$) and source-receiver distances ($r$) from the complete synthetic catalogue is estimated according to [Scholermmer and Woessner 2008]:

$$P_d(M,r) = \frac{N^+}{N^+ + N^-} \quad (Eq. 2)$$

As a result, we obtain estimates of each single station detection probability as a function of magnitude and hypocentral distance (Figure 9a). However, this information is not complete for a broader domain of magnitudes and hypocenters, because of the limited spatial and magnitude distribution of the synthetic catalogue. In general, detection probabilities should not decrease with increasing magnitude or with decreasing source-receiver distance. The single station detection performance can be extrapolate through empirical relationship such as in Mignan et al. [2011]:

$$M_c(r,k) = C_1 r^{C_2} + C_3 \quad (Eq. 3)$$

where $M_c$ is dependent on the distance $r$ to the $k^{th}$ nearest station with fit parameters $C_1$, $C_2$ and $C_3$. We scan the configurations of these coefficients, which are allowed to span within reasonable intervals ($C_1$ in $[4,12]$, $C_2$ in $[0.04, 0.10]$, $C_3$ in $[-3, -10]$) [Mignan et al. 2011, Mignan and Chouliais 2014, and Schultz et al. 2015]. These curves divide the magnitude-distance space in a region of large magnitude and small distances, where the detection is more likely, and a region of small magnitude and large distances, where the event detection is more difficult. The best configuration of $C_1$, $C_2$ and $C_3$ to define the completeness magnitude is here chosen only looking at the first region (below the curve) by (1) imposing that the number of detected events in this region by at least 95% and (2) by maximizing the number of events in this region (Figure 9). A shift is observed in this empirical relation towards larger magnitudes for the noisiest stations and, conversely, for quiet stations. The same analysis is performed for each array, which has the best detection performance (Figure 9). A regular grid at an averaged depth for the horizontal fracking drillings of 3.91 km is fixed to map spatially the $M_c$, based on the previous empirical relations and imposing again the simultaneous detection by at least 4 stations (Figure 10). Ignoring the noise heterogeneity on the surface, then the minimum values of the $M_c$ would be found at the array locations, because of the larger station density. Considering real station-dependent noise conditions alter significant the spatial distribution of the detection performance, with a decrease in the $M_c$ around the fracking area to match similar values such as those in Figure 8.
A synthetic event is considered detected if the maximum amplitude is larger than the average noise value. Plots are divided in a grid for different magnitudes and source-receiver distances, and we calculate the probability of detection for each station according to Schorlemmer and Woessner (2008).

Probability of detections for each broadband station:

\[
P(D|M, L) = N_+ + N_- = \text{Detected events}
\]

\[
N_-= \text{Non detected events}
\]

Note: These results depend on our spatial distribution of synthetic sources. However, we can obtain linear empirical laws a posteriori according to these results in order to extrapolate the information for the complete domain (magnitude & hypocentral distance).

**Figure 9.** a) Plot of all detected (brown crosses) and not detected events (blue circles) for the synthetic catalogue using an amplitude threshold previously calculated with real noise and SNR = 2 in the seismic station GLOD and the fictional stations for the array GLOX (first row). Probability of detections in the previous two stations (second row). Black dashed lines show the empirical relationship obtained by equation 3. b) Empirical relationship for all stations (solid lines) and fictional stations for the array (dashed lines). Stations in array GLOD are shown in green, array PLAC in red, array CHRW in blue, and borehole stations in yellow. The inbox for
the broadband stations show in black color the stations SZCZ, STEF and SKRZ; GLOD in green; PLAC in red; CHRW in blue.

**Figure 10.** Spatial monitoring performance at Wysin site in terms of magnitude of completeness using an amplitude threshold estimated from real noise during day hours (first column) and during night hours (second columns) with SNR=2 (first row). Improved spatial monitoring performance using array techniques (second row). Gray color scale identifies the number of synthetic events detected for each station.
5. Detection performance using coherency

Automatic event detection and location procedures for monitoring local and regional seismicity are widely used by the seismological community. Coherence techniques have improved the traditional automatic detectors [e.g. short-term average (STA)/long-term average (LTA) techniques] and have been employed in microseismicity case for hydrofracking (López-Comino et al., 2017). Our next approach proposes to apply a recently developed automated full waveform detection and location algorithms (Lassie, https://gitext.gfzpotsdam.de/heimann/lassie, Matos et al., 2016, Heimann et al., 2017), using real noise contaminated continuous seismograms. We simulate a continuous synthetic dataset by convolving synthetic seismograms from the complete catalogue with the instrumental response and adding real noise, which is chosen randomly from the May 2016 dataset but constrained around the average timing of the signal, so to preserve the daily variation of seismic noise. This python-tool earthquake detector is based on the stacking of characteristic functions of P- and S-waves according to the energy variations calculated from the square amplitudes of each trace. It follows a delay-and-stack approach, where the likelihood of the hypocentral location in a chosen seismogenic volume is mapped by assessing the coherence of arrival times at different stations (see Cesca and Grigoli, [2015] for an overview). However, in the Lassie implementation, the adoption of smooth characteristic function calculated from normalized amplitude envelopes allows to reduce the spatial and temporal sampling [Heimann et al., 2017]. Data are first band-pass filtered between 2 Hz – 80, Hz including an additional notch filter at 50 Hz (see Figure 5b). The characteristic P- and S-wave functions for each station are then calculated, shifted and stacked according to P and S average velocities in our study region. These operations results in a spatiotemporal matrix of coherences values. The detection is performed searching the maximal spatial coherence at each time step, defining a detection every time this value trespasses a chosen threshold (Figure 11).

The performance of this tool strongly depends on the selection of the coherence threshold. Consequently, we need to define an optimal detector level, able to detect weak events while not increasing excessively the number of false detections (Figure 12). First tests indicate that events with $M_w$ lower than -0.6 are entirely hidden in the real noise requiring too low detector levels, which would produce a great number of false detections. We show here the results using thresholds larger than 700 to remove these inconsistencies. A conservative choice would correspond to values able to minimize the number of false detections generated for random coherences in our dataset. A better alternative is to require a threshold, for which the number of real detections is larger than the number of false detections. Our synthetic catalogue suggests appropriate thresholds could be chosen between 800 and 1000, with better performance during night hours, where the false detections disappear at threshold of ~ 950. The detection performance depends on the chosen detector threshold in a similar way as in the previous case, using amplitude threshold with different SNR values (Figure 8 and 12). $M_c$ shows again a stepwise increase with the detection threshold, but the monitoring performance is significantly improved thanks to the application of this waveform based technique. If we consider a reasonable threshold (e.g. 950) where only 1% of false detections are accepted, the $M_c$ reaches values around 0.4 and 0.1 during day and night hours, respectively.
**Figure 11:** Example of synthetic event with $M_w = 0.8$. a) Waveforms sorted by hypocentral distance for some example stations. b) Characteristic function (normalized amplitude envelopes) for each trace. These are used for travel-time stacking corrected with P-wave speed (red lines) and S-wave speed (green lines). The markers indicate the (best-fit) synthetic arrival time of the respective phases at each sensor. c) Coherence (stack) map for the search region. Dark colors denote high coherence values. A white star marks the location of the detected event. Sensor locations are shown with black triangles. d) Global detector level function in a processing time window from -8 to +4 seconds around the origin time of the detected event. The cut-out time window used for the coherence map is shown in gray color. White stars indicate this detection within the same processing time window, exceeding a detector level threshold of 1000.

**Figure 12:** Detection performance using coherence techniques [Heiman et al., 2017] for the synthetic catalogue with different detector thresholds. Continuous synthetic dataset is generated adding real noise randomly distributed during day (left) and night (right) hours. The number of real detections corresponding with the synthetic catalogue (black line) and the number of false
detections (gray dashed line) are shown. Black dots represent the values of magnitude of completeness for different detector threshold.

6. Discussion and Conclusions

The monitoring performance of a microseismic monitoring network is addressed through a robust parameter, such as $M_c$. However, this measure is usually estimated retroprospectively, once we know the detected and located seismicity from a defined catalogue in a given region. In addition, the effects of changes in the number and type of instruments, as well as the available locations for installation, cannot be tested retroprospectively. Our approach aims to evaluate a prospective testing process that could generate induced seismicity taking as a starting point a seismic network previously designed and installed. The particular case of hydrofracking at the Wysin site is a good real example involving a combination of shallow and shallow depth monitoring. A realistic microseismic synthetic catalogue allows quantifying in terms of $M_c$ our particular monitoring performance using noise recording before the fracking operations. Synthetic waveforms analysis could reveal important aspects about the seismicity we may record during and after fracking. Moreover, an adequate noise analysis is essential to know the current situation of our monitoring before the fracking operations starts.

An average amplitude threshold is estimated for each station from real noise recording reflecting diurnal variations that affects the detection performance. Although the lowest noise level are expected a priori in the shallow borehole stations, some surface stations are able to reach between 2-80 Hz similar or event better noise conditions. We used the raw synthetic seismogram to compare the maximum amplitudes of synthetic waveforms and average noise levels. The resolved detection performance can be adjusted by empirical relationships for different SNR values. This helps to extrapolate our estimations of completeness magnitude to a broader study region. We found that the detection performance is strongly varying for different day hours, with a better performance during quiet night hours. At the same time, $M_c$ also differs for different source processes, so that tensile-cracks are more difficult to detect than DC sources with the same magnitude. This may have important consequences when coming to the interpretation of detected seismicity, since the DC background seismicity may be better detected than induced seismicity. Assuming a SNR = 2, we estimate a $M_c \sim 0.55$ around the fracking area, with an increase of 0.05 during day hours. Combining the distributed network with the application of 3 small-scale arrays in about 3 km distance to the boreholes, $M_c$ can be lowered to $\sim 0.45$ at the fracking region.

The application of a novel automated detection algorithm, based on the detection of coherence signals at multiple stations, even in presence of noisy records, is able to improve substantially the detection performance. An essential requirement is to choose a reasonable detector level to avoid greater number of false detections and maximize the real detections at the same time. Again, these procedures are usually applied during and after the fracking operations. However, combining synthetic events and real noise, we have been able to create realistic noise contaminated continuous seismograms, which allow to define a suitable threshold for the detector and to quantify the expected $M_c$. We estimate for the Lassie detector [Heimann et al., 2017] an efficient threshold around 950 for which 1% of false detections are accepted. The $M_c$ is
improved using this methodology, so that we could detect all synthetic events with $M_w$ larger than 0.1 during night hours.

This study proposes a valuable approach to combine synthetic catalogue, synthetic waveform generation and noise recordings during a pre-operational phase, to properly prepare detection tools and to estimate their performance, prior to the beginning of geomechanical operations which may trigger or induced seismicity. The generation of realistic synthetic data requires an accurate investigation of source parameters and local structural models. If these conditions are met, the synthetic data can be a useful tool to assess the detection performance, but can also be used to assess the performance of further seismological analysis, e.g. to judge the uncertainty on location procedures, or to evaluate the potential of modeling/inversion techniques for source parameter determination. The approach can be easily adapted to other environments implying the detection and characterization of induced microseismicity.

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