Application of the Multichannel Wiener Filter to Regional Event Detection Using NORSAR Seismic-Array Data

by J. Wang, J. Schweitzer, F. Tilmann,* R. S. White, and H. Soosalu

Abstract Seismic arrays for detection of small earthquakes benefit from array processing aimed at reducing noise levels. We present a frequency-dependent multichannel Wiener filtering (MCWF) technique, which employs an adaptive least-squares method to remove coherent noise in seismic array data. The noise records on a number of reference channels are used to predict the noise on a primary channel, which can then be subtracted from the observed data. A sequence of aftershocks caused by the $M_w$ 6.1 21 February 2008 mainshock in Spitsbergen was recorded by the ARCES array in northern Norway. This aftershock sequence was filtered using the multichannel Wiener filters in both triggered and continuous modes. The Spitsbergen (SPITS) array, at a much closer distance to the source region, provides reliable reference information on the true number of detectable aftershocks. The conventional delay-and-sum beamforming combined with a band-pass filter could detect only 513 aftershocks with 181 false alarms, using a series of constraints comprised of signal-to-noise ratio, back azimuth, and slowness; the multichannel Wiener filtered results found 577 aftershocks with 165 false alarms using the same constraints. A complete automatic multichannel Wiener procedure is developed for event detection on continuous data. An appropriate signal-to-noise ratio threshold for aftershock detection of 2.7 is suggested. Compared to the beamforming method, the MCWF also reduces false alarms when detecting the same number of aftershocks.

Introduction

NORSAR, as the operator of the Norwegian National Data Center (NDC) for the Comprehensive Test-Ban-Treaty, automatically monitors regional seismicity in northern Europe and reviews regional events covering Fennoscandia and surrounding areas, as well as teleseismic earthquakes and other seismic events (Mykkeltveit et al., 1983). The NORSAR arrays were designed with the aim of optimizing the output of the delay-and-sum beamforming by decorrelating the noise but not severely degrading the signal similarity over the array aperture (Ingate et al., 1985). However, the low-frequency ambient noise is still coherent across arrays that have apertures of the order of a few kilometers, such as the ARCES array. Therefore, the regional events recorded by the ARCES array are used to test the application of the multichannel Wiener filter (MCWF), using an adaptive filter designed in this paper.

One of the earliest applications of the Wiener filter to seismic data was proposed by Claerbout (1964). He discussed a prediction-error filter as the optimum filter to predict noise at a future time and then to subtract the prediction from the actual noise present at that time. The filter does not predict the signal, so a large output indicates a signal if the noise is highly predictable. This is the principle of the Wiener filter. The theory can be used for both single and multiple traces, such as those recorded by a seismic array. Another representative adaptive optimal filter was discussed by Shen (1979). He presented the constrained minimum power adaptive algorithm, which minimizes the output power of the filtered data subject to constraints.

The adaptive filter has been widely used for a variety of purposes. For example, in exploration seismology, Rosenberger et al. (1999) applied an adaptive filter to marine data sets to suppress multiples. Özbek (2000a, 2000b) used it to suppress ground roll in land seismic shot gathers. In earthquake seismology, Douglas (1998) used a minimum power filter to improve the signal-to-noise ratio (SNR) for short-period $P$ waves, and McLaughlin et al. (2007) used a Wiener filter for the improvement of regional earthquake phase detection.

Özbek (2000a, 2000b) summarized both methods: (1) the prediction-error filter, which he refers to as multichannel adaptive interference canceling; and (2) the minimum power filter, which he refers to as adaptive beamforming with
generalized algebraic linear constraints. He does not only give the detailed algebra for the normal equations, but also demonstrates the effectiveness of the filter for ground roll suppression on shot gathers. In addition, he discusses some prefilter techniques to separate the signal from noise. The main advantage of these adaptive optimal filters is that no assumption of plane wave propagation across the array is required. On the other hand, one of the widely used seismic-array processing methods is the delay-and-sum method, also known as conventional beamforming. This method maximizes the array response for the assumed direction and slowness of the coherent signal but is not optimal because the coherent part of the seismic noise at each frequency usually will be concentrated at particular wavenumbers (Douglas, 1998).

The MCWF discussed in this paper is an adaptive optimal filter. It optimizes the conventional beamforming by removing coherent noise from each trace before stacking. We first briefly describe the principle of filter design, then apply the filter in two different scenarios: (1) we test the efficiency of the MCWF using already known and analyzed events as test data; and (2) we demonstrate the practical online application of the MCWF for automatic event detection using continuous data. The MCWF shows great potential for improving the detection capability by significantly suppressing ambient noise.

Methodology

The principle of the MCWF is to use the noise on a number of reference traces to predict the noise on the primary channel and then to subtract the predicted noise from the actual data. A detailed description is given in Wang et al. (2009), but we summarize the main points here. The difference between the predicted and actual data of the primary channel is minimized in the least-squares sense. The problem is formulated in the frequency domain as a set of linear equations. The filter coefficients are obtained as the least-squares solution of those equations. Consider $n$-channel data, where channel $\mathbf{A}_i$ is taken as the primary channel, and note that the Einstein summation convention is used in the following. We minimize the difference $E$ between the predicted and actual data of the primary channel in the least-squares sense:

$$E = |\mathbf{A}_j(\omega) - \mathbf{T}_{j,i}(\omega)\mathbf{A}_i(\omega)|^2, \quad (j = 1\ldots n, j \neq i).$$

(1)

$\mathbf{A}_i(\omega)$ are the spectra of $\mathbf{A}_i$, where $\omega$ is the frequency. The transfer functions $\mathbf{T}_{j,i}(\omega)$ between the reference channels $\mathbf{A}_j$ and primary channel $\mathbf{A}_i$ are estimated by data-adaptive multichannel filters in the frequency domain. All quantities are understood to be complex-valued functions of frequency $\omega$.

To find the minimum of $E$, we set the derivative of $E$ with respect to the transfer function to be zero:

$$\frac{\partial E}{\partial \mathbf{T}_{j,i}} = 0, \quad (j = 1\ldots n, j \neq i).$$

(2)

For each $j$ ($j = 1\ldots n, j \neq i$), the derivative with respect to $\mathbf{T}_{j,i}$ gives

$$-2(\mathbf{A}_i - \mathbf{T}_{k,i}\mathbf{A}_k)\mathbf{A}_j^* = 0, \quad (k = 1\ldots n, k \neq i).$$

(3)

Rewriting this, we obtain

$$\mathbf{A}_k\mathbf{A}_j^*\mathbf{T}_{k,i} = \mathbf{A}_i\mathbf{A}_j^*, \quad (k = 1\ldots n, k \neq i).$$

(4)

The transfer functions are then defined by the solution of this matrix-vector equation.

To avoid tuning the transfer functions to the signal, the transfer functions are always determined by data segments that precede the section to be filtered. The cross-spectral matrices are averaged over multiple windows to stabilize the inversion for the transfer function. The cross-correlation values are updated in a rolling manner, and the strength of the filter is controlled by the window length and the number of windows.

To further stabilize the inverse problem, we solve equation (4) with a damped singular value decomposition, where the damping factor is usually between 0.0001 and 0.1.

We apply the transfer functions to the data that includes the potential signal. The noise on the primary channel is predicted by convolving the transfer functions $\mathbf{T}_{k,i}$ with the reference channels $\mathbf{A}_k$. The real primary channel $\mathbf{A}_i$ minus the predicted noise yields the filtered primary channel $\mathbf{A}_i'$:

$$\mathbf{A}_i' = \mathbf{A}_i - \sum_{k=1,k \neq i}^{n} \mathbf{T}_{k,i} \cdot \mathbf{A}_k.$$ 

(5)

Finally, each channel in turn is made a primary channel, as in equation (5), and the filtered traces are then stacked after applying an appropriate time shift $\Delta t_i$ as for beamforming

$$\tilde{\mathbf{A}} = \sum_{i=1}^{n} \mathbf{A}_i'. $$

(6)

The potential effectiveness of an array for noise suppression is greatly dependent on the spatial distribution of the interfering noise (Backus et al., 1964). That is to say, the coherency of the noise controls the predictability from the reference channels, which determines how much coherent noise will be suppressed. If seismic noise were completely random, then the output of the primary channel would be completely unpredictable. In that case, the transfer function would approach zero, and the filtering method described here would effectively be equivalent to regular beamforming. The cross-spectral matrices describe the coherence between the primary channel and the reference channels. It is an adaptive process and suitable for use with passive seismic monitoring arrays in which the ambient noise might not be stationary.

Data

An earthquake with magnitude $M_w$ 6.1 occurred on 11 February 2008 (052:02.46.17.41 UTC) in the Storfjorden-Heerland Svalbard region (77.01° N, 19.01° E; depth, 15 km), followed by a large number of aftershocks (Pirli et al., 2010). This area still shows an elevated level of seismicity more than
three years later. Most aftershocks have magnitudes below 3; that is, they are small regional events with regard to the 25-substation ARCES array (3 km across) in Norway (Mykkeltveit et al., 1987) at a distance of about 850 km (Fig. 1). This study aims to determine how much the MCWF techniques can help with event detection by comparison with other methods, such as beamforming combined with band-pass filtering, the standard method employed by NORSAR’s automatic data processing. We apply a frequency-dependent MCWF, as well as the standard processing, to the ARCES array data to detect aftershocks.

The two NORSAR arrays, SPITS (at epicentral distance ~150 km) and ARCES (at epicentral distance ~850 km), and aftershocks from the Storfjorden-Heerland Svalbard region in 2008 (Pirli et al., 2010) are used for this study (Fig. 1). The nine-substation SPITS array (1 km across) (Mykkeltveit et al., 1992) provides reliable reference information on the true number of detectable aftershocks. In the first instance, the filter is applied to windowed data according to the aftershocks detected by SPITS. When one attempts to detect small earthquakes from a large distance, the benefit of an array close to the source region is not normally available. Therefore, a second scheme is developed to apply the MCWF to the continuous data at ARCES during the period from Julian day 053 to 055, a period with a great number of aftershocks without too much overlap between events. The number of detected events from the MCWF filtered data is compared to that from the band-pass filtered data, both operating on the continuous data.

An aftershock with an origin time 2008.055:18.59.02 UTC is used to demonstrate the improvement of the SNR by the application of the MCWF. The $P_g$ phase is detected by SPITS at 18.59.26. Based on the theoretical travel-time difference between the source and the SPITS and ARCES arrays, the approximate onset time of $P_n$ arriving at ARCES is evaluated to be about 19.00.58. Sixty seconds of ARCES-array data (18:59:42–19:00:42) preceding the event are taken as the noise reference data. The next 180 s (19:00:42–19:03:42) are filtered with the MCWF. A window length of 5 s and a damping factor of 0.01 are used for the MCWF for optimal results. Figures 2a and 2b, respectively, display the raw and individually MCWF filtered traces of 25 elements of the ARCES array. They are band-pass-filtered with a Butterworth filter at 3–8 Hz, with order 3. The same band-pass filter is used throughout this paper, unless indicated otherwise. Because of the weakness of the signals, it is difficult to tell the exact onset time of the signals. However, $P_n$ and $S_n$ are still visible, and their arrival times match the expected aftershock signals for the ARCES array. The arrivals of $P_n$ and $S_n$ are marked by arrows. By comparison, both phases appear more distinctly on the individual MCWF-filtered traces than on the band-passed traces. In particular, the $P_n$ onset is almost invisible in the band-passed traces but is unambiguous in the MCWF traces. Figure 3 shows an enlarged view of the 0–25 s waveform of the first five stations of Figure 2.

Beamforming is used for locating the direction from which the signal comes and its apparent velocity. Each slowness magnitude and azimuth pair defines a trajectory through the time-windowed data, along which the array power is computed. When all trajectories have been computed, the power is expressed in dB and plotted as in Figure 4. The highest peak is the most likely slowness of the signal. However, weak signals can easily be obscured by ambient noise in the slowness analysis. In fact, the automatic NORSAR event-detection program does not report the aftershock that was discussed previously in this paper on the ARCES array. The $S_n$
phase of the event at 2008.055:18.59.02 is used to demonstrate the achieved improvement by applying the MCWF on the raw data before the slowness analysis. Figure 4a shows the slowness analysis from the data of 25 array elements. The expected apparent velocity and back azimuth of the after-shocks is marked as a reference by a black square on the slowness plots. The expected maximum only shows up as a local maximum, whereas the global maximum is caused by energy unrelated to the $Sn$ phase. After being filtered with the MCWF, the SNR is improved sufficiently for the slowness analysis to highlight the signal peak uniquely in Figure 4b. In order to quantify the signal strength relative to the noise, we use the well-known STA/LTA ratio: one estimates the power over a long time interval, the so called “long-term average” (LTA), and over a short time interval, the so called short-term average (STA). The maximum of the ratio STA/LTA represents the SNR and is compared with an adjustable threshold. To keep the results comparable between the MCWF procedure and the NORSAR event-detection program, we use the definition of SNR given by Schweitzer et al. (2002). The STA of a seismic trace $A(t)$ is

$$
\text{STA}(t) = \frac{1}{L} \sum_{j=0}^{L-1} |A(t - j)|, \\
L = \text{sampling rate} \times \text{STA length},
$$

where $L$ is the number of samples of the time series $A(t)$ to be summed. The recursive definition of the LTA is

$$
\text{LTA}(t) = 2^{-\zeta} \times \text{STA}(t - \varepsilon) + (1 - 2^{-\zeta}) \times \text{LTA}(t - 1),
$$

where $\varepsilon$ is a time delay, typically a few seconds, and $\zeta$ is a steering parameter for the LTA update rate. The parameter

Figure 2. Event with origin time 2008.055:18.59.02 UTC. (a) Waveforms of the band-passed recordings from the 25 vertical elements at ARCES. (b) The band-passed waveforms of 25 individually MCWF filtered traces of the ARCES array. The approximate arrival times of $Pn$ and $Sn$ are marked. The x axis shows time relative to the reference time marked at its left edge.

Figure 3. Event with origin time 2008.055:18.59.02. (a) First 25 s of the band-pass-filtered records from Figure 2, for five of the elements at ARCES. (b) The corresponding waveforms of the first five individually MCWF-filtered traces of the ARCES array. The picks are marked on the individual traces.
The STA/LTA implies that the linear power estimate of the noise is based on the emergent signals on the LTA. The recursive formula for the SNR is needed to prevent a too-early influence of the often-emergent signals.

\[ \text{SNR}(t) = \frac{\text{STA}(t)}{\text{LTA}(t)} \]  

A value of 6.0 is used for \( \zeta \). A delay time \( \epsilon \) of 5 s is used for updating the LTA as compared to the STA. The STA window length is set to 1 s. The sampling interval is 0.025 s.

Figure 4. Slowness analysis of both (a) band-passed and (b) individually MCWF-filtered \( S_n \) waves for an event with origin time 2008.055:18.59.02. The analysis window length is over 3 s long. The black square shows the theoretical back azimuth and slowness for the source region and the travel-time difference between ARCES and SPITS. 1 and 2 s windows are used for \( P \) and \( S \) waves, respectively.

Test Data Procedure

In order to efficiently test the method against thousands of events from a known location to establish performance statistics, we apply the MCWF on the ARCES array data. Detections by the SPITS array are used to define the search windows for the 2008 data, for aftershocks that are potentially detectable at the more distant ARCES array.

Workflow

Because the SPITS array is much closer to the seismic source region than is the ARCES array, aftershocks with high SNR detected by ARCES will also be detected by SPITS. On the other hand, weaker aftershocks can be detected by the SPITS array but might not necessarily be detected by the ARCES array due to the much smaller signal amplitudes at ARCES. Therefore, the detections by the closer SPITS array provide reliable reference times of aftershocks. The procedure of the MCWF application is summarized in the following four steps, some of which will be explained in detail later:

- Step I: Select SPITS detections.
- Step II: Apply the MCWF to the ARCES array data within the search window defined by the SPITS detections and the travel-time difference between ARCES and SPITS. 1 and 2 s windows are used for \( P \) and \( S \) waves, respectively.
- Step III: Carry out a slowness analysis of filtered traces, and select signals with SNR above 3, for which a back azimuth and apparent velocity fall into the expected range of the detected aftershocks reported by NORSAR (see Data and Resources).
- Step IV: Visual inspection to exclude signals from other sources that happen to match the slowness and azimuth criteria during the automatic detection.

**Step I and Step II.** The apparent velocities and the back azimuths of \( P_g \) or \( P_n \) phases detected by both SPITS and ARCES arrays are reported in the bulletin (see Fig. 5). These detections are associated with events and located by the Generalized BeamForming (GBF) method, the routine automatic NORSAR event location program (Ringdal and Kverna, 1989). Figure 5 gives the range of slowness parameters of the detected aftershocks reported by NORSAR (see Data and Resources).
which contain potential signals. Around the predicted arrival time of the signals, we ran a few windows around the predicted arrival time of the signals. Around the predicted arrival time of the Sn phase, we consider 20 s of individually MCWF-filtered data. The slowness analysis is made in each moving 2-s window, with 50% overlap between neighboring windows. For each slowness analysis, if the apparent velocity and back azimuth fall into the acceptable range.

Step III and Step IV. Two criteria are used in these steps to select potential aftershocks: (1) the SNR of the MCWF-filtered Sn beam is above 3, and (2) the back azimuth and apparent velocity from the slowness analysis fall into an acceptable range.

In this example, the SNR threshold, an empirical value, is based on the MCWF-filtered Sn beam, rather than the MCWF-filtered Pn beam, because the energy of Sn for these events at ARCES is usually higher than Pn. An averaged back azimuth of 355° and apparent velocity of 10 km/s are used for delay-and-sum beamforming Pn, and 3.2° and 5.3 km/s are used for delay-and-sum beamforming Sn signals. The back-azimuth difference between Pn and Sn is due to the well-known heterogeneity effect of variability along the travel path (Schweitzer, 2001).

After the candidates matching the first criterion are selected, the slowness analysis follows to further select the events. The choice of an appropriate window for slowness analysis is difficult when the signal is weak. To overcome the uncertainty resulting from a single slowness analysis window, we ran a few windows around the predicted arrival time of the signals. Around the predicted arrival time of the Sn phase, we consider 20 s of individually MCWF-filtered data. The slowness analysis is made in each moving 2-s window, with 50% overlap between neighboring windows. For each slowness analysis, if the apparent velocity and back azimuth fall into the ranges of 3–7 km/s and 355°–015° (see Fig. 5), the event is marked as “true,” otherwise it is marked as “false.” The same procedure can also be applied to the Pn beam, except that the window length for the slowness analysis is 1 s due to the higher frequency content of the Pn waves. The apparent velocity and back azimuth values for the slowness analysis of Pn are 8–13 km/s and 350°–010°, respectively. If both the Pn and Sn slowness maxima are within the prescribed range, the event is accepted as a detection.

For comparison, we repeat the same procedure of step III on the Sn beam of band-passed data. Table 1 summarizes the number of matched candidates in each step found by comparing two methods: (1) MCWF and (2) conventional beamforming combined with a band-pass filter. Among the 5050 detections at the SPITS array with an SNR above 30 in step I, there are 1085 detections with the MCWF Sn beams at ARCES with an SNR above 3 and 1021 detections with conventional Sn-beam SNR above 3 (see Table 1). We found 742 detections out of 1085 MCWF beams and 694 detections out of 1021 conventional beams (from band-passed raw data). This means that, even when the detections are filtered to those falling into the back-azimuth range of 355°–015° (Fyen, 1989; Schweitzer et al., 2002), the MCWF retains a significantly higher number (742) relative to conventional beams (694). The candidates determined from the MCWF Sn beam and band-passed Sn beam are checked by eye in the last step.

The Sn beam from the band-passed data detects 513 aftershocks with 181 false alarms. By comparison, the Sn beam from the individually MCWF-filtered data found 577 aftershocks with 165 false alarms (see Table 1). The MCWF
Procedure found 10% more events with a 10% lower false alarm rate than the conventional beamforming combined with an appropriate band-pass filter. It is worth pointing out that the conclusion in this study could be different if a different narrow band-pass filter was used in the conventional beamforming method.

The false event alarms occur due to several reasons. One of the main reasons is disturbance by noise spikes. On some noisy days, a lot of spikes can be observed in the data. The MCWF cannot remove them because they are not predictable. Those spikes usually have high amplitudes, so the first criterion (SNR ≥ 3) will be satisfied. If the back azimuth of the slowness analysis happens to fall into the range of 350°–010°, it will be accepted as a detection. This problem can be partly solved by applying a stricter velocity criterion. However, a tight apparent velocity range runs the risk of rejecting some potential events when the signal is so weak that the apparent velocity reported by the slowness analysis has a large uncertainty.

Magnitude of Aftershocks

The MCWF detected more events when using the SPITS detections than the conventional beamforming method. Those events are missed by beamforming because of the low SNR. This section investigates the distribution of the magnitudes of these missing events. A list of events from the aftershock region is obtained from the NORSAR bulletin. The aftershock region is defined by longitude 17.0°–21.3°E and latitude 76.0°–77.6°N. The event locations were made with the GBF method. GBF automatically groups and locates seismic arrivals based on theoretical travel times for a grid of points covering the target area (Ringdal and Kværna, 1989).

The bulletin reports 365 events by the GBF method. The single phase magnitude is defined according to Báth (1965): $M = \log(\text{amp}) + Q$. For these regional events, no magnitude estimate is based on $P$-type onsets because they are not easily measured. The amplitude is determined from the maximum amplitude of the best beam coming out of the automatic slowness analysis using different band-pass filters (Fyen, 1989; Schweitzer et al., 2002). Hence, the amplitudes of these aftershocks come from either $S_n$ or $L_q$ phases. For those 365 events reported by the GBF method, Figure 7 illustrates the relationship between $\log 10$(amplitude) and the reported GBF magnitudes of the aftershocks. The amplitude is the value of the ARCES beam with the best SNR. $\log 10$(amplitude), and the GBF magnitude of ARCES detections follows a linear relationship according to the magnitude definition (Báth, 1965):

$$M = \log(\text{amp}) + Q.$$  

The MCWF method was successful in detecting the aftershocks reported by the NORSAR bulletin. The black dots in Figure 7 plot the amplitudes from the MCWF results against NORSAR-bulletin GBF magnitudes of the aftershocks. A regression line is a fit to those dots (i.e., MCWF amplitudes) with magnitudes larger than 2.5 because smaller events do not match the linear relationship well.

Although more events are identified by the MCWF, the magnitudes of events are not lowered. The curved shape of the scatter plot (Fig. 7) visible for magnitudes smaller than 2.5 could be due to imprecise amplitude measurements resulting from the automatic MCWF procedure. The GBF magnitudes are automatically calculated, like all the GBF results. They are also often only based on a small number of magnitude observations at few stations without any station corrections.

Table 1 presents the number of selected candidates in each step.

<table>
<thead>
<tr>
<th>Method</th>
<th>Criterion</th>
<th>Number of Matching Events</th>
<th>Number of True Alarms</th>
<th>Number of False Alarms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step I: Initial Search Pool</td>
<td>SPITS $Pg$ conventional beam STA/LTA ≥ 30</td>
<td>5050</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step II: Event Selection Start</td>
<td>ARCES MCWF $Sn$ beam STA/LTA ≥ 3</td>
<td>1085</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ARCES conventional $Sn$ beam STA/LTA ≥ 3</td>
<td>1021</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>+ band-pass filter</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STEP III: Event Selection Continue</td>
<td>ARCES MCWF $Sn$ beam Back azimuth [355° 015°]</td>
<td>742</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ARCES conventional $Sn$ beam Apparent velocity 3–7 km</td>
<td>694</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>+ band-pass filter</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STEP IV: Double Check by Eye for Final Results</td>
<td>ARCES MCWF $Sn$ beam</td>
<td>577</td>
<td>165</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ARCES conventional $Sn$ beam + band-pass filter</td>
<td>513</td>
<td>181</td>
<td></td>
</tr>
</tbody>
</table>

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Figure 8 shows the distribution histogram of the number of event detections by both the NORSAR bulletin and the MCWF procedure. The events detected by the MCWF
filter events blindly; that is, by filtering the continuous data with the MCWF without the benefit of prior information. As a test, the 3 × 24-hour continuous data on Julian days 053–055 are filtered continuously using the automatic MCWF detection procedure. Julian day 053 is one day after the mainshock when there are not too many overlaps among aftershocks, but it still remains an active period (see Fig. 6).

workflow

The automatic MCWF procedure is to filter the whole data in a continuous mode and delay-and-sum to form the MCWF Sn beam. The Sn beam, instead of the Pn beam, is used to select the events because the Pn beam does not reliably detect weak aftershocks. The selection of aftershocks is conducted using the same method as described previously in step III (i.e., the SNR and the back azimuth and apparent velocity from the slowness analysis are used to select the potential aftershocks).

- Step 1: We take 120-s data from the continuous data stream as the noise reference; the transfer functions based on these data are used to filter the next 120 s of data. The filtered data are multiplied by a triangular window.
- Step 2: The data filtered in step 1 are taken as the noise reference data for the next 120 s until the end of the continuous data.
- Step 3: Repeat these steps, but use a sliding window starting 60 s later than the window in step 1.
- Step 4: Sum the results for the half-overlapping triangular windows of steps 2 and 3 as individually filtered outputs.
- Step 5: The individually filtered outputs are delay-and-summed into the MCWF Sn beam by a back azimuth of 003.2° and apparent velocity of 5.3 km/s, the average value of aftershocks reported in the NORSAR bulletin.

Figure 9 illustrates the improvement of the SNR in the automatic MCWF procedure. An event with origin time

Continuous-Data Procedure

In daily routine practice, an event origin time is not available. It would thus be required that the algorithm can
decreased a little. Therefore, the SNR threshold to select the detections according to the time indicated by SPITS detections at a much higher rate. The ARCES array data are filtered by the MCWF algorithm, which can test detection efficiency, including the false alarm rate. The shock zone provide a reliable reference data set with which we can test detection efficiency, including the false alarm rate. The number of false alarms from the band-passed data is nearly three times as high as for the MCWF filtered data.

Sn2008.054.08.35.51 is detected by the automatic MCWF-filtered Sn beam but missed by the delay-and-sum band-passed Sn beam. Theoretically, the SNR for continuous data should be improved by a similar factor as in the test procedure described earlier. However, the window is updated by 50% overlap between windows in the automatic filtering process. It is thus possible that the automatic procedure does not use the optimal noise reference data in some cases during filtering. For example, some events might happen to be split into two neighboring windows, potentially including earthquake signals in the noise reference. This can be compensated in the next window with 50% overlap, but part of the signal is lost in the first round filtering step so that the SNR could be decreased a little. Therefore, the SNR threshold to select the candidates should be set lower than 3, which is the value used in the triggered data procedure, where the noise reference preceding the signal is properly chosen with the help of a reliable arrival time indication.

The appropriate threshold is investigated by trying a range between 2.3 and 3.2, with 0.1 increments. The number of detections at each threshold are shown in Figure 10. A trade-off exists between detecting more events and including more false alarms. With an SNR threshold of 2.3, there are 78 events detected by band-passed data and almost the same number of events (79) detected by the MCWF-filtered data, but the number of false alarms from the band-passed data is nearly three times as high as for the MCWF filtered data.

**Results**

Concluding the discussion, the NORSAR arrays (SPITS and ARCES) and aftershocks from the Storfjorden-Heerland Svalbard region are used to test the improvement of the MCWF for detecting weak regional events. Detectors by SPITS close to the aftershock zone provide a reliable reference data set with which we can test detection efficiency, including the false alarm rate. The ARCES array data are filtered by the MCWF according to the time indicated by SPITS detections at a much closer distance than ARCES in 2008. Events are considered reliable when two criteria are satisfied: (1) an SNR threshold value is exceeded and (2) the back azimuth and apparent velocity determined from slowness analysis match the average values of the aftershocks. For comparison, the ARCES array data are band-pass filtered and analyzed by the beamforming method. The events from the band-passed data are judged by the same criteria. Conventional beamforming detects 513 aftershocks with 181 false alarms; the multichannel Wiener filtered results found 577 aftershocks with 165 false alarms. The MCWF procedure found 10% more events, for which the log 10(amplitude) is between 1.7 and 2, and a 10% lower false alarm rate than the conventional beamforming combined with an appropriate band-pass filter.

The data used in this study were collected as part of NORSAR array monitoring. The NORSAR array data can be obtained from http://www.norsardata.no (last accessed June 2011). Aftershock data used to perform step III was obtained from the bulletin at http://www.norsardata.no/NDC/bulletins/GBF/2008.html (last accessed June 2011). Some plots were made using Generic Mapping Tools version 4.2.1 (www.soest.hawaii.edu/gmt) (last accessed June 2011).

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**References**


