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SINGLE-TRACE DETECTION AND ARRAY-WIDE COINCIDENCE ASSOCIATION OF LOCAL EARTHQUAKES AND EXPLOSIONS

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Abstract—Local earthquakes and explosions can be recognized automatedly for the Bochum University Germany (BUG) small array by a sequence of knowledge-based approaches performed in the field and in the central hub. In single-trace detection, the recognition is based on sonogram patterns adapted for a wide variety of noise conditions on all array sites. The adaptation is performed by two steps: first each pattern is adjusted to the actual signal energy, second all those weaker phases that are below the new detection threshold are excluded. In the hub, a rule-based approach performs the coincidence evaluation. It is described by its 14 rules and the implicit assumptions.

This scheme was tested on 1 month of data. The knowledge base consisted of 12 seismograms transformed automatically into the detector's internal knowledge representation of sonograms. The results show excellent performance for noise rejection and quarry blast recognition; for earthquakes clustering, a 85% success is achieved. The network success—usually below the best single performance—could be improved above any single-station optimum. Results of the rule-based approach are compared to the routine processing of the same data by Walsh-detection and the '2 of 4' coincidence voting.

Key Words: Event detection, Coincidence association, Seismic small array, Discrimination of explosions.

INTRODUCTION

When the large seismic arrays such as LASA or NORSAR were installed some 10 years ago, it already was obvious that the seismologists faced huge amounts of online data. Handling these data by automated seismogram analysis is of moderate complexity because the great efforts in measurements pay off by simple and robust procedures to extract the necessary event parameters: detection is enhanced by beamforming, phase identification can just discriminate on slowness, whereas associating phases to complete events can be controlled via the test on common azimuths. Another more simple situation for signal processing arises in dense seismic networks. Once again, the large technical expenditure allows for simple signal processing: coincidence tests are a reliable event criterion; further analysis can rely on adjacent stations, their good S/N ratio makes P-onset picking robust. This information is sufficient to get a hypocenter guess, other phases are not mandatory.

The situation gets far more complex, if we are concerned with single-trace data and once again need human-like performance. Those situations arise from the analysis of sparse network data, either because of limited number of sites or because of weak events when only adjacent stations can resolve the seismogram. Another application are tripartite arrays such as BUG (Joswig, 1993). Here online detection is performed by voting as in a seismic network because of the inhomogeneous site conditions. For weak events, all the traditional detectors either miss or produce numerous false alarms. A more reliable solution is by knowledge-based programs which code known patterns in grammars (Anderson, 1982), character strings (Liu and Fu, 1983), or images (Joswig, 1990). Once this path is gone, the detection messages supply more information than just timing. Any subsequent rule-based system such as the one here introduced, COASSEIN, thus can perform a more sophisticated event recognition than just voting.

SINGLE-TRACE DETECTION

The detector approach presented here utilizes the fact that a great fraction of all detected signals is caused by some few, recurrent types of seismic events and noise burst sources. They can be recognized by known patterns of the sonogram-detector (Joswig, 1990). When we developed this single-trace algorithm, our initial impetus was to copy as closely as possible the behavior of seismologists when examining helicorder records of a single seismometer for event detection. One weakness of our initial method was in the tedious process of pattern extraction that needs a fair understanding of the selected PR algorithm. In contrast, seismologists think in seismograms, so the aim for detector enhancement is to hide the internal knowledge representation done by spectral images (see Fig. 1). We achieved this goal by automated pattern adaptation which restricts the knowledge engineering to the simple collection of seismograms.

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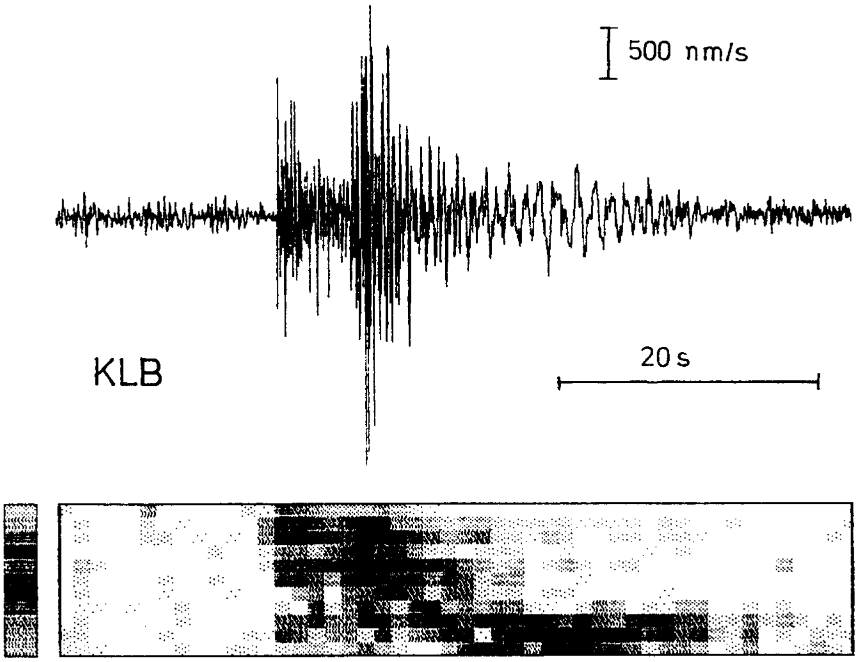
The basic idea of pattern adaptation is explained by the synthetic example in Figure 2. Suppose, we take a strong event as the pattern and have to decide on weaker signal energy in the data. At first glance, we associate and compare the prominent phases by their relative timings, spectral contents and amplitudes. This type of seismogram correlation can be done equally well on sonograms. The pattern adaptation is needed to correct for the lack of smaller phases and code details in the weak event. For this purpose, we have to rescale the given pattern to the actual data amplitude which will cancel all those pattern details that are below the actual noise level in the data segment. In the subsequent PR, we can test on the existence of significant energy spots and the *predicted* absence of weaker phases.

For the stationary noise periods, the sonogram images do not show any contrast. The necessary result of *nonidentification* by any recognition process can as well be achieved by simpler approaches such as STA/LTA (Short-Term-Average to Long-Term-Average). So the application of the sonogram-detector can be




```
C  29.03.1988 08:00:26 h
C  Ml = 2.0   Az = 052 deg   R = 039 km
Hamm
5,0.4,35 {prerun, detec thres, min# samp}
C
 d|-----jihggghged................
 e|-----nmljknmiihghhgfffgefef.gf.
 g|-----qpnnmoqomljkliigji..hh.hhg
 i|-----nnlnosppmkk.jjj..i....i.j.
 h|-----oonnorqpoonlkik.iki.ij....
 i|-----oonloqoopmonkll...i.......
 j|-----.mn.noQQoloolkl.kk.....j..
 h|-----j.nilomjNOklkllih.ilk.ihkk
 f|-----kkljjonjmnmklmlMMkNkjmmlkk
 g|-----kjgiiglgijlkelmmOMONmmkljk
 e|-----ghhfhjhf..hkkklimnnlkjgiih
```

log f

t

Figure 1. Internal knowledge representation of pattern event for *Hamm* region: in ASCII-file, last 11 lines represent pattern matrix, left of bars is noise variance. All values except symbolic minus signs are greater than zero and can be coded to letters via 1 = a, 2 = b, ... Capitals represent same value as lowercase letters but mark those samples used for median filtering to determine P_{ref}. Period stands for samples that are changed to zero not to influence calculation of *fit*. Matrix correpond to sonogram except that image displays prewhitened energy.

restricted to those data segments of limited duration that include some nonstationary signal energy. In this configuration, the sonogram-approach acts as postdetector on windows that are preselected by STA/LTA. The latter can be set extremely sensitive not to miss any possible event; the high false alarm rate will be compensated effectively by the subsequent pattern recognition.

The sonogram-detector starts by determining the power spectral density matrix $\mathbf{A}(f, t)$ with

$$\mathbf{A}(f, t) = \sum_{half\text{-}octave} X(f)X(f)^*. \tag{1}$$

For the examples presented here, 2.56 sec time segments $x(\tau)$ are transformed by FFT to $X(f)$ with a segment overlap of approximately 50%. With a sampling frequency of 100 Hz, the resulting time increment t between consecutive windows is 1.25 sec. Prior to FFT, a tapering function of $\sin^2 \tau$ is applied. In the frequency domain, the energy is summed up in half-octave-wide passbands from 0.4 to 19 Hz. The achieved $\mathbf{A}(f, t)$ is transformed to logarithmic scaling via

$$\mathbf{C}(f, t) = \log_2 \mathbf{A}(f, t). \tag{2}$$

The detection process demands images that discriminate on temporary signal energy as well as possible, but sonograms of Equation (2) are not suited for this task (Joswig, 1991). Instead of the unbiased energy image, we want to display signals only, where *signal* is the fraction of actual energy that significantly differs from stationary noise induced by the ground motion. For the quantitative description, the noise in $\mathbf{A}(f, t)$ is assumed to consist of log-normal distribution samples (Lacoss, 1972; Swindell and Snell, 1977) whereas in $\mathbf{C}(f, t)$ the noise windows have Gaussian distribution given by mean $\mu(f)$ and variance $\sigma(f)$. In our images, we care for best robustness and will calculate the median $M(f) = M_{50}$ instead of mean and $S(f) = M_{75} - M_{50}$ instead of variance, once again determined per frequency band and for a period of pure noise. Additionally, $S(f)$ is restricted to plausible limits by $0.5 < S(f) < 1.5$. So we get the final image matrix $\mathbf{D}(f, t)$ of detectable signal energy by

$$\mathbf{D}(f, t) = \begin{cases} \log_2[\mathbf{A}(f, t) - 2^{M(f)}] & \mathit{if}\ \mathbf{A}(f, t) > 2^{M(f)+S(f)} \\ - & \mathit{else} \end{cases}. \tag{3}$$

The minus sign in the lower row is symbolic only to blank nonsignificant energy; it will later be replaced by actual values. Related to $\mathbf{D}(f, t)$, the vector $N_D(f)$

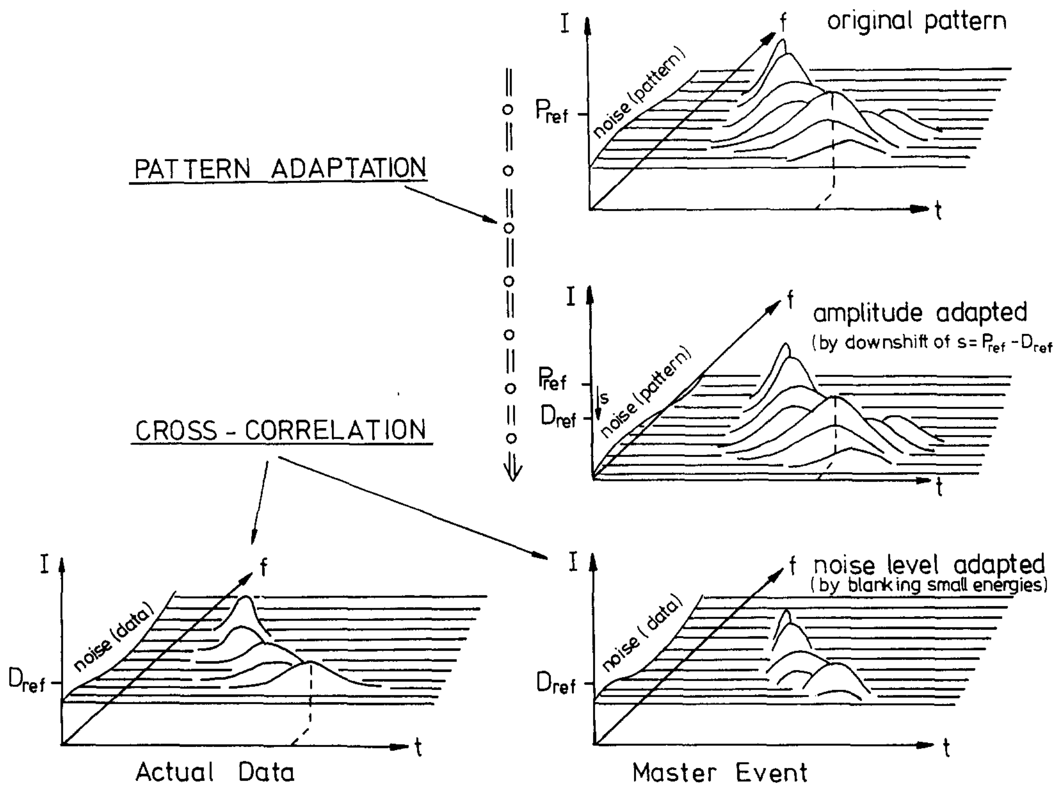


Figure 2. Artificial example intended to explain basic idea of adaptive pattern recognition: master event and actual data are displayed as PSD-'mountains' over 'highlands' of stationary noise levels in time–frequency plane. As seismologist can predict which coda details remain visible in changing noise, detector can by (i) adjusting pattern amplitude P_{ref} of some reference point to actual data energy D_{ref} and (ii) transposing actual noise level of data sonogram onto pattern. All parts of pattern sonogram will be cancelled which are downshifted below new noise level. Finally, pattern fit is calculated by cross-correlation.

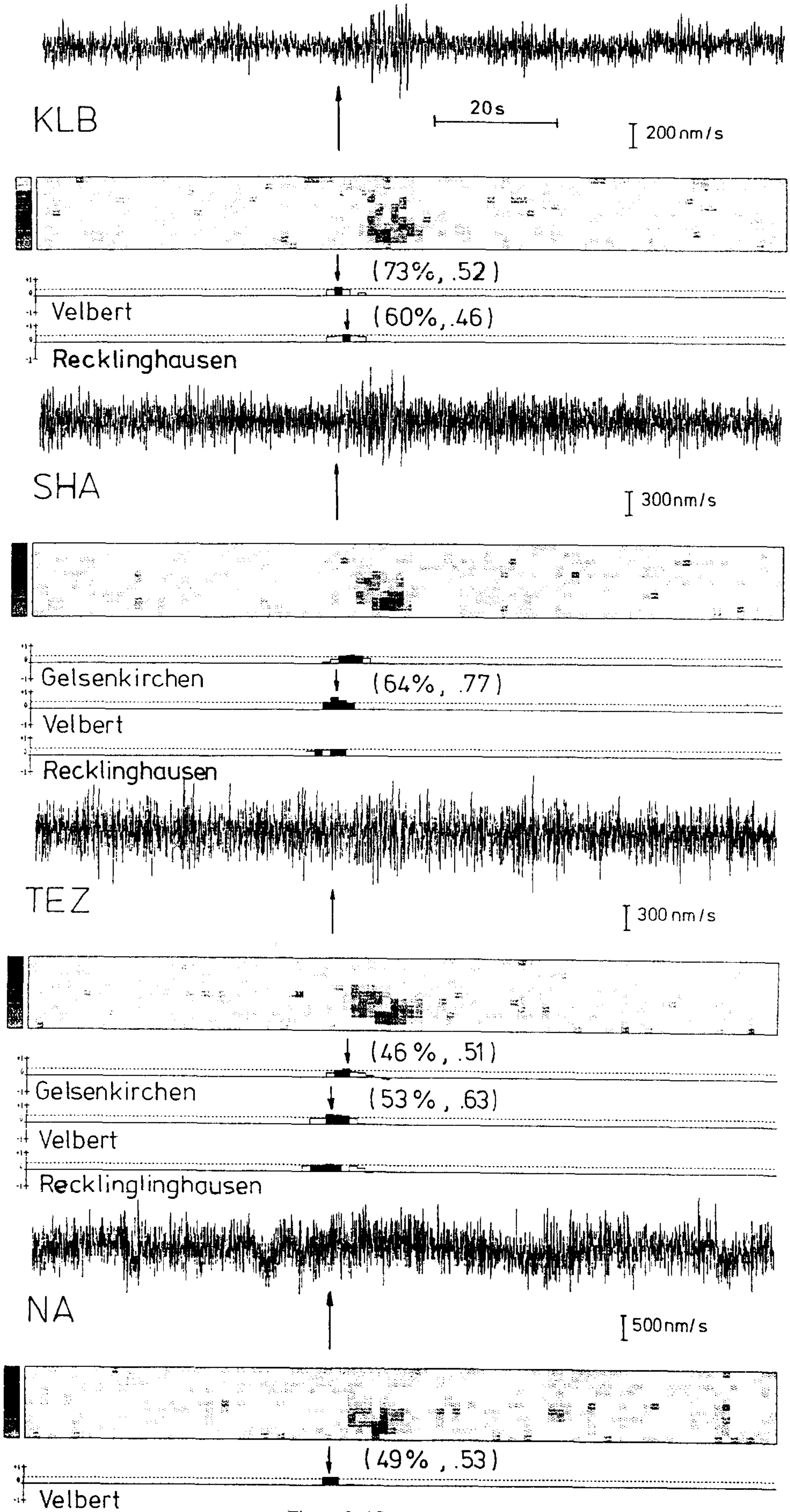


Figure 3. (*Caption opposite*).

will describe the log noise variance in the actual data, it is defined by

$$N_D(f) = \log_2[2^{M(f)+S(f)} - 2^{M(f)}]. \quad (4)$$

$\mathbf{D}(f, t)$ and $N_D(f)$ are rounded to nearest integers to suppress fine grain amplitude differences less than $\sqrt{2}$ [corresponding to the log base of 2 for the energy in Eq. (2)].

In pattern recognition, we need the explicit definition of desired signal patterns. Fortunately here, matrix $\mathbf{D}(f, t)$ of a single seismic event can be taken immediately as the pattern $\mathbf{P}(f, t)$ due to the selected correlation technique. The only constraints are (i) the selection of a sufficiently large event for good S/N ratio and (ii) the definition of an inverse area of symbolic minus signs before the P-onset. In the final calculation of pattern fit, this inverse area results in an edge conversion which will enhance the onset timing.

Adapting a given pattern to the actual S/N ratio is described best by C-code and a numerical example given in Appendix 1. It represents data and pattern in the f–t plane by $3 * 9$ matrices with their associated noise variances left of the vertical bars. Firstly, the pattern amplitude is adjusted based on the median of some reference samples marking an area of stable energy. Once both matrices have the same amplitude, the next step for a matched comparison is to harmonize the noise levels by transposing the noise variance of the data onto the pattern. Obviously, this also will affect the detectability of pattern energy. Although the dominant features remain valid, some weaker details are modified by the two *masking criteria* in "*Adapt Pattern Noise* . . . " (see Appendix 1). By the first criterion we test if down-scaled pattern energy can be detected in the actual noise, else we demand *no energy*. The second clause seeks for those samples of detected energy in the data that are below the pattern noise; their significance is unknown for the subsequent recognition process and thus the equivalent pattern sample is set to zero.

The calculation of the pattern fit $fit(t)$ is based on prewhitened matrices by which we stress the contents of the whole image and do not focus on maximum amplitudes only. Prior to this step, those areas must be defined that display *no energy* by the symbolic minus signs. Their weights are adjusted in two *balance conditions* which cause $fit(t) = 0$ per frequency band if either pattern or data consists of random noise only. The final comparison between pattern and data calculates as a cross-correlation. The values of $fit(t)$ are normalized to $[-1, +1]$; they oscillate around zero for stationary noise, so 0.4 usually is a good detection threshold.

Figure 3 displays the event identification in the four BUG small array stations based on the pattern set of Figure 4. Although compiled into one image, the detection process is performed at each site independently. Taking every threshold surpass (the black boxes) of any pattern as detection, SONODET would cause many false alarms. Instead, we restrict the significance of recognized patterns to a global maximum assuming just one event in the sufficiently short data segment. If $fit > 0.6$ and $valid\_pattern > 60\%$, this identification is assumed to be PROBABLE; only the one global maximum per data segment is reported by pattern type and onset time. For even higher agreement ($fit > 0.9$, $valid\_pattern > 80\%$), we characterize the results as DEFINITE assuming that no errors will be likely then. On the other hand, if one or both conditions for PROBABLE do not hold, the highest identification is taken as POSSIBLE and a second selection—if any—is reported as POSSIBLE too, representing the next highest threshold surpass of another pattern. Finally, if none of the patterns triggers at all (i.e. $fit < 0.4$) but the signal energy exceeds a sufficiently large threshold, an event beyond the existing knowledge base must be assumed and will be announced by the message 'WARNING—significant signal energy of unknown type'.

ARRAY-WIDE COINCIDENCE EVALUATION

The rule-based reasoning on trigger coincidence presented here is termed COASSEIN for *Coincidence Association in Seismic Networks.* Because of its limited complexity, the system was coded in C instead of an AI-language such as LISP or prolog but the main characteristics of knowledge-based systems such as the separation of knowledge base and inference engine have been preserved. The principal idea of COASSEIN is straightforward: all the SONOGRAM-messages are taken as *station events* (SE) with detection time, type, and quality of recognition; those within a reasonable time window are collected and combined to hypothetical *network events* (NE) with one identification per station only. The rules of COASSEIN start the reasoning about all the created NEs and try to select the most appropriate one as the final conclusion. Of course, the most obvious rule is that we can not allow for contradicting pattern types in the selected NE. But this restriction alone is too exclusive to guarantee a sufficient system performance as we will see later.

Figure 3. Sonogram-detection on BUG small array traces for weak *Velbert* event: spectral noise at SHA, TEZ, and NA masks signal energy in upper frequencies. Effect can be predicted by evaluating different noise levels (vertical noise bars), it essentially determines pattern adaptation. Quality of detection is PROBABLE for SHA and POSSIBLE for others, suggesting alternative identifications of *Recklinghausen* in KLB and *Gelsenkirchen* in TEZ. All onset times are correct within 1 sec; they are based on whole seismogram signature and thus remain stable even if most of P-onset has disappeared in noise.

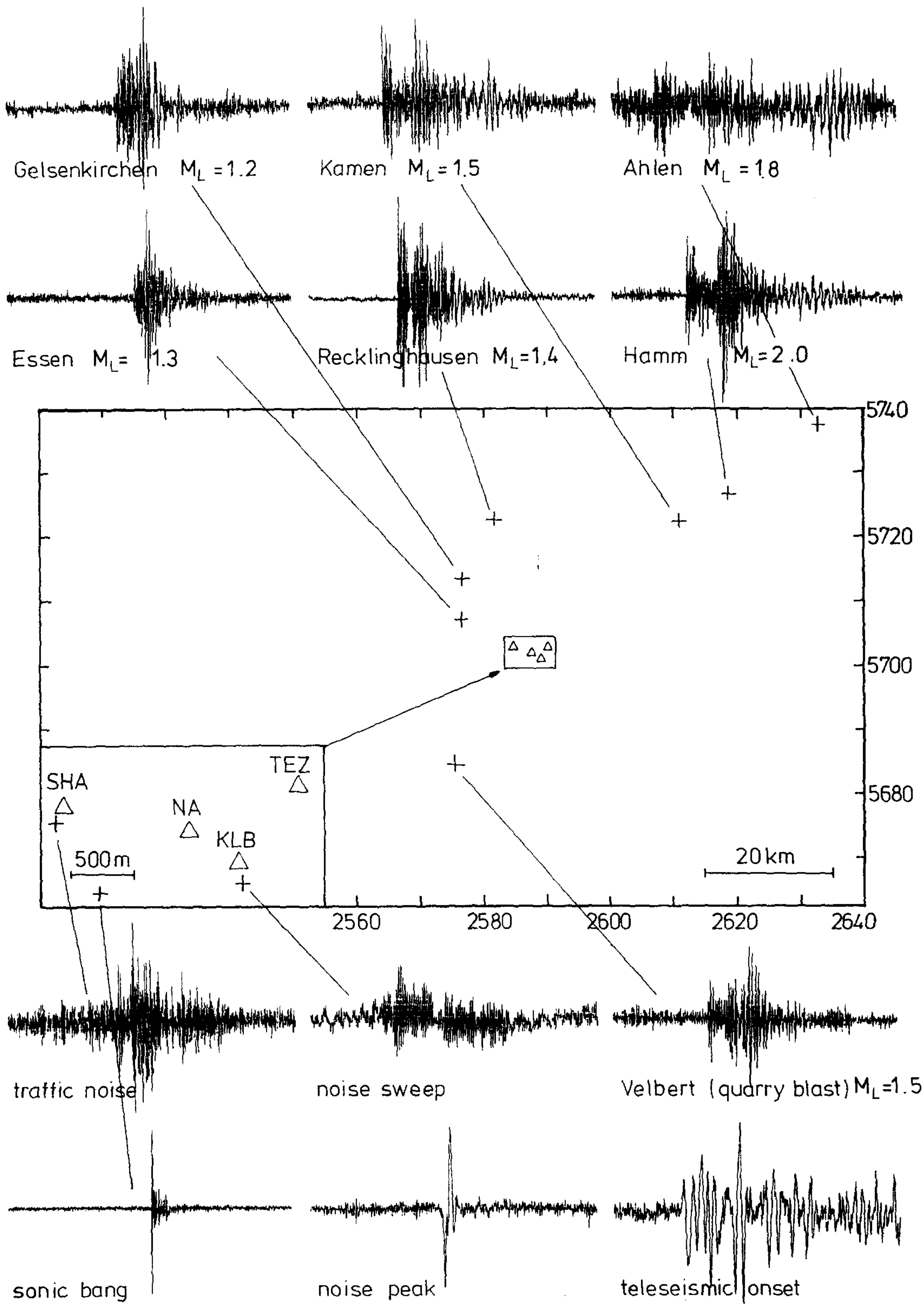


Figure 4. Set of 12 pattern events and their related epicenters: this is knowledge base for reported test run of sonogram-detector and is valid for all array stations. It consists of recurrent seismic events and some typical noise bursts. Conversion from seismograms to internal knowledge representation of spectral images was done automatically, that is it is transparent to seismologist.

Table 1. Cost function of COASSEIN

Recognition Confidence of SONOGRAM-Detector			Cost Function of COASSEIN	
quality	fit	cover	initial cost	additional cost for cluster exchange
DEFINITE	> 0.9	> 80%	0	not allowed
PROBABLE	> 0.6	> 60%	20	+ 20 + f(Station)
POSSIBLE	>thres	>thres	40	+ 10 + f(Station)
				with f(KLB) = 4 f(SHA) = 2 f(TEZ) = 3 f(NA) = 0
either two POSSIBLE recogn. of different type at a time or one PROBABLE / DEFINITE			modific = 0	will set modific = 1

In the actual rule-based system, both the NEs and SEs are organized into doubly linked lists with a *sentinel* as predefined entry at the beginning of each sublist. For the SEs, the sentinels describe the default of *no-detection* per site; the entry *cost* is an integer coding the recognition quality (i.e. POSSIBLE, PROBABLE, DEFINITE, see Table 1). The NE-sentinel has an overall *scost* = -1 (the sum of costs for all referenced SEs) and represents the final *no-solution*. The organization into doubly linked lists was selected to ease list modification whereas the rule execution proceeds. In fact one way to distinguish the general rule types is by the impact they have on these internal listings. According to Appendix 2, we can characterize four fundamental types by *NE-creation rules* to modify the NE-list, *selection rules* which do not change any list, *resolution rules* to modify the SE-lists and the optional *reevaluation rules* which ask for new SEs by hypothesis-guided SONOGRAM-tests.

The main advantage in knowledge-based coincidence evaluation is the reasoning about recognized event types instead of the blind judgment on time differences in any voting scheme. The two extremes easy to handle are the contradiction and the agreement of patterns at all sites. But how do we want to rate an event with agreement in three stations but deviation in the fourth? If stations report different recognitions, do they have the same significance? Are there typical or site-dependent mistakes in event detection that we can foresee and try to compensate?

Some of these questions can be decided easily because the detection messages of the SONOGRAM-detector already contain information about the recognition quality. Other aspects like the interstation weights, a majority voting or error handling could be performed by explicit rules. However, we decided not to create too many rules, instead some of our knowledge is coded implicitly into the appropriate values of *cost* (see Table 1) which will guide the solution ranking. When higher costs are assigned to the less reliable recognitions, the most promising candidates for a joint solution will be placed on top, if NEs are ordered by increasing *scost*. Then the selection rules just have to start at lowest *scost*, loop through the NE-list and stop the evaluation, whenever they determine the first match to fulfill their requirements (e.g. no contradiction). Even if there are other possible solutions, this processing scheme ensures that only one final conclusion is selected, the one with minimal cost and thus highest reliability.

In coding our knowledge to the full rule set of Ap pendix 2, we abstracted from individual patterns to generic terms or *event qualifiers* that allow for a more concise formulation with the implicit knowledge: whereas seismic events are correlated for all array sites, the noise bursts occur at single stations only. Sonic bangs, however, are noise signals and nonetheless recognized at various stations because of the limited array aperture. Quarry blasts cause seismic wave propagation similar to local earthquakes and thus they will be treated the same at this stage of event processing.

COASSEIN performs in consecutive loops always starting by NE-creation with implicit ranking by increased cost (see Appendix 3). If two NEs have the same cost, *#seismic* as the number of SEs that contain seismic patterns in the given NE will serve as the additional ranking criterion. During NE-creation, *#stations* as the number of all detections that contribute to a NE, *#modific* as the number of SEs modified by cluster exchange (see next) and *scost* are calculated also. Then the system will check on each selection rule tested against all NEs. If no conclusion is determined, control proceeds to the resolution rules. Firing any of them will reset the NE-list and thus force NE-creation to be applied immediately (the condition *NEs exist* in every other rule will fail). If neither selection nor resolution rule can fire any more, the *final exit* is reached stating that the given rule set is unsufficient to resolve the reported SEs, so this data set must be counted *undefined* in the statistics given later. The only other exit from this loop of list modifications is reached, when a *conclusion* is determined by any of the selection rules.

There are six *selection rules* to determine the final conclusion. The obvious rule of noncontradiction is only second because we want to improve the handling of those rarer situations when the actual event is not represented by any pattern in the SONOGRAM-detector. This situation is termed *Local* but yields the correct message UNKNOWN-PATTERN of SONODET only for good S/N ratio (at KLB), elsewhere misidentifications take place by different local patterns and recognizing TELESEISMIC-ONSET for the surface waves. This mixture of messages is typical for events from local distance without pattern, so it is utilized in the third selection rule. Selecting a NE without contradiction as final conclusion in the second rule is restricted to the coincidence of at least 3 of 4 stations. The possibility *2of4* is allowed only if the agreement was reached without applying the cluster exchange which in general weakens the conditions for coincidence. If there is only one seismic detection at all, it is ignored by the 4. rule. NEs without any seismic pattern will contain noise detections only and thus are treated as NOT-EVENT in the 5. rule. The last resolution rule explicitly covers a situation that should never arise for any reasonably tuned set of patterns in the SONOGRAM-detector and thus is termed PANIC.

If none of the selection rules was fired, control proceeds to the *resolution rules*. The *cluster exchange rule* describes our knowledge of identification uncertainities caused by similar looking seismograms. There are two situations that contribute to this effect: one is caused by adjacent epicenter regions with similar azimuths to the small array, the other mirrors seismic events from different directions but same epicentral distance which will cause comparable effects in the seismogram duration and energy dispersion. In the map of Figure 5, these connected regions are shown for the local seismicity monitored by the BUG small array. Appendix 2 defines the corresponding exchange pairs with an individually tuned correction time for the P-onset. This modification reflects the general behavior of SONOGRAM-detection which adjusts its pattern fit relative to the seismogram maxima, that is S-phase and surface waves.

Cluster exchange is a powerful tool to refine the initial detection messages for coincidence tuning, thus it should be applied before other resolution rules. They are (i) the ignorance of local noise at one station, if the others report seismicity—probably a coincidence by chance has masked the weaker seismic signal, (ii) the cancelling of any UNKNOWN-PATTERN message that did not contribute to the conclusion of *Local* and (iii) the skipping of a POSSIBLE recognition at the station with worst S/N ratio (here NA).

TEST RESULTS

To report on the detection performance, a test period of 1 month from 18 March to 20 April 1988 was selected. As a front end, the WALSH-detector (Goforth and Herrin, 1981) performs at each site and reports its detection time to the hub which decides by voting. Only the triggered data segments are transmitted from the stations, stored on disk and are thus available for postprocessing or tests of alternative approaches. Table 2 summarizes the detection results of all single stations and for two selections of the voting logic. The data set contains 91 local (below 100 km) and regional events (below 1000 km epicentral distance) and 25 teleseismic earthquakes.

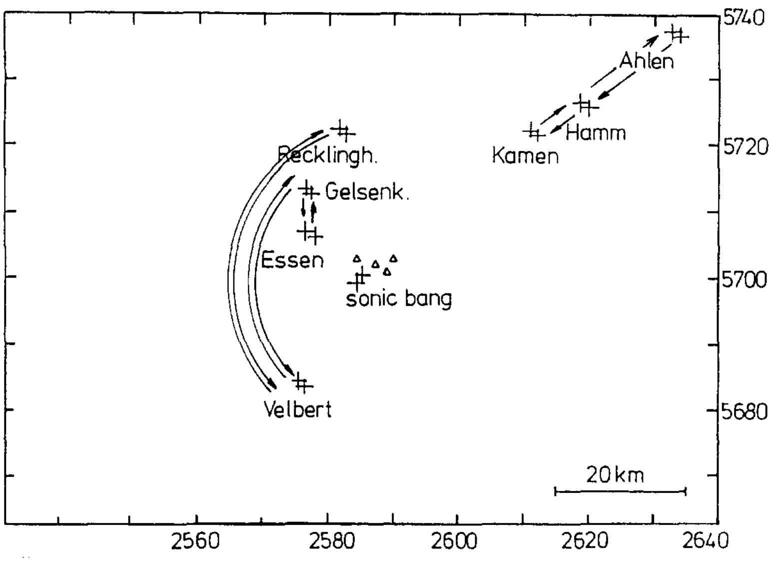


Figure 5. Epicenter map for cluster exchange combinations: SONOGRAM-detector most likely confuses event patterns is they symbolize regions with same epicentral distance such as *Velbert* and *Recklinghausen* or adjacent regions such as *Hamm* and *Kamen*. Cluster exchange rule reflects this uncertainty by performing type conversion in identified patterns whenever solution cannot immediately be determined by COASSEIN.

Table 2. System performance for WALSH/voting

one month of continous data (18.3.1988 - 20.4.1988)	WALSH Detections				VOTING Results	
	KLB	SHA	TEZ	NA	2of4 in 5 sec or KLB	2of4 in 5 sec
116 SEISMIC EVENTS and QUARRY BLASTS were						
- successfully detected	106	98	88	57	111	103
- missed local and regional	4	8	11	40	0	2
- missed teleseismic onsets	6	10	17	19	5	11
sum of events	116	116	116	116	116	116
FALSE ALARMS were caused by						
- local bursts	61	627	213	360	69	14
- sonic bangs	3	5	4	3	5	5
sum of false alarms	64	632	217	363	74	19
SUM of DETECTIONS	168	730	305	420	185	122

The single station performance shows the expected dependency on the local ground noise level (see fig. 1 in Joswig, 1993). The WALSH-detector was tuned for local seismicity by a sequency window correspondent to 1–4 Hz bandwidth, a transformation length of 2.56 sec with 50% overlap, noise statistics on 64 segments and $K = 6$ for the detection threshold. The upper frequency limit reflects the energy increase of noise bursts above 4 Hz; it does not indicate the end of earthquake spectra which extend up to 20 Hz for the P-onset. The remarkably high number of false alarms in SHA is due to traffic noise by trucks on an adjacent, badly paved road. Because seismograms from local earthquakes and quarry blasts are not distinguished at this stage of event analysis, they are counted together in Table 2. Voting is performed in the routine operation of the array by the condition that *2of4* stations report a detection within 5 sec. This delay is significantly larger than the maximum travel time of body waves through the array aperture which calculates to 0.7 sec. The increase is intended to compensate for the uncertainty in onset timing because weak events are recognized more likely by their stronger phases in P-coda or S-phase. Enlarging the time window, however, also increases the probability of casual noise coincidences; for the 1 month test period, it happened 14 times. The remaining five false alarms are the result of sonic bangs; they violate the basic assumption utilized for voting, that is, that signals on more than one station can be caused only by seismicity.

The whole approach described so far yields a detection threshold of $M_L = 1.0$ in 50 km distance. In order to improve the detection probability, we also tried a voting scheme where KLB as the best station can trigger a network detection. Of course, this approach traces every KLB false alarm to the final network statistics but the actual increase of 55 false alarms was tolerable for the 1 month test period. The second selection in voting improved the joint detection by eight events. However, even the *2of4* voting mode missed two less local events than KLB in its single-trace statistics. This effect is typical for cultural noise where even good stations are masked temporarily by some local noise bursts.

The set of seismograms for offline testing consists of 185 data segments with 3 min duration for each of the four small array stations. They start 120 sec before the coincidence trigger and consist of 68 earthquakes mostly induced by mining, 43 quarry blasts, and 74 false alarms. The pattern events in Figure 4 are selected from this data set as those seismograms that have the best available S/N ratio for the individual source regions; some typical noise traces complement the pattern set. All the patterns were derived from KLB registrations, only *traffic noise* and *sonic bang* are based on SHA records. This uniform knowledge base challenges the sonogram detector's capability to adapt its patterns to the extremely different noise conditions within the array.

The results of event identification differ for each cluster and station. All the misidentifications are reasonable and divide into the *Essen–Gelsenkirchen–Recklinghausen* confusion on one side and the *Kamen–Hamm–Ahlen* perturbation on the other. Most of quarry blasts from *Velbert* are well detected although the *Recklinghausen* cluster of induced seismicity at same epicentral distance could confuse the recognition.

Overall, the majority of 111 seismic events and quarry blasts is correctly identified at any station (from 96 at KLB to 67 at NA), most of the predetector's 74 false alarms are rejected (at least 70 at any station). The ability to recognize and reject noise bursts is independent of the noise level, so even without event patterns the sonogram-detector could serve as postdetector for noise bursts to reduce the false alarm rate significantly.

In Table 3, the results of COASSEIN are given for the entire test run, subdivided into each pattern type and complemented by the number of times each rule

Table 3. Results of COASSEIN with full rule set

statistics for coincidence reasoning by COASSEIN					
185	sum of all events	174 right 95%	8 wrong 04%	2 missed 01%	1 undef 00%
69	NOT-EVENT	69 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
5	SONIC-BANG	5 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
43	VELBERT	42 right 97%	0 wrong 00%	1 missed 02%	0 undef 00%
6	ESSEN	5 right 83%	1 wrong 16%	0 missed 00%	0 undef 00%
8	GELSENKIRCHEN	8 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
4	RECKLINGHAUSEN	4 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
3	KAMEN	3 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
15	HAMM	12 right 80%	3 wrong 20%	0 missed 00%	0 undef 00%
3	AHLEN	3 right 100%	0 wrong 00%	0 missed 00%	0 undef 00%
9	LOCAL	6 right 66%	3 wrong 33%	0 missed 00%	0 undef 00%
20	TELESEISMIC-ONSET	17 right 85%	1 wrong 05%	1 missed 05%	1 undef 05%

rule(A):	233 firings of	- create network events
rule(B):	3 firings of	- unknown pattern in KLB, assume LOCAL
rule(C):	105 firings of	- coincidence for network-wide
rule(D):	5 firings of	- contradiction local-teles., assume LOCAL
rule(E):	50 firings of	- recognized local noise burst
rule(F):	21 firings of	- ignore single seismic detection
rule(G):	0 firings of	- panic - contradiction in definite
rule(H):	33 firings of	- cluster exchange for new se's
rule(I):	19 firings of	- cleaning-up se-list
rule(J):	7 firings of	- ignore single noise burst
rule(K):	3 firings of	- ignore unknown pattern
rule(L):	5 firings of	- ignore POSSIBLE identification in NA
rule(M):	51 firings of	- reevaluation for network-wide
rule(Z):	1 firings of	- no solution found in rule base

was fired. The success is remarkably good, only the *Hamm* and *Local* types show poorer performance. This is because of some consistent but untypical seismograms for three *Hamm* events and the unpredictable variety of seismograms by infrequently active sources. Both situations mark the principle limits of knowledge-based approaches at date which can reliably handle routine situations only. The one teleseismic event that was marked *undef* (i.e not covered by the existing rule-set) was extremely weak and recognized by contradicting local patterns at only two stations.

To discuss the overall system performance best, the results of COASSEIN (also with partly masked

Table 4. System performance for SONODET/COASSEIN

185 time windows were preselected by WALSH & VOTING (2of4 or KLB)	SONOGRAM Recognitions KLB	SHA	TEZ	NA	COASSEIN Conclusions all rules applied	mask clus-ex	mask clus-ex & ig-NA
68 SEISMIC EVENTS were							
- successfully recognized	55	44	50	37	58	47	47
- miss-located as wrong event	8	14	12	8	8	5	5
- missed	5	10	6	23	1	1	1
- undefined in rule-set					1	15	15
sum of seismic events	68	68	68	68	68	68	68
43 QUARRY BLASTS were							
- successfully recognized	41	40	39	30	42	40	37
- miss-located as seismic ev.	1	1	1	4	0	0	0
- missed	1	2	3	9	1	1	0
- undefined in rule-set					0	2	6
sum of quarry blasts	43	43	43	43	43	43	43
74 NOISE TRACES were							
- successfully rejected	71	72	73	70	74	72	69
- false alarms	3	2	1	4	0	0	0
- undefined in rule-set					0	2	5
sum of noise traces	74	74	74	74	74	74	74
SUM of TIME WINDOWS	185	185	185	185	185	185	185

rule set) are compiled into Table 4 with the corresponding single-trace results of SONOGRAM-detection. As any coincidence approach, COASSEIN reduces the false alarm rate below the already good values of the SONOGRAM-detector to the theoretical minimum of zero. This result includes all the five sonic bangs and thus shows the first principal advance over the WALSH/Voting combination reported by Table 2.

Coincidence is a stronger criterion than single trace detection, so one would expect some lower detection probability, but higher recognition security for the joint results than for the best single station. This is true for COASSEIN, when cluster exchange as the most powerful resolution rule is masked; the drop in detection probability equals the effect of Voting for the WALSH-detections. With the full rule-set, however, we note the remarkable situation that joint results are in every aspect better or at least equal than any single-trace performance of all the stations. So this marks the second advantage of knowledge-based processing over traditional approaches.

As a minor effect, the power of cluster exchange also can glue together what should stay separate and contradicting; this behavior caused the slight increase from five to eight miss-located seismic events in COASSEIN.

When distinguishing the results by source type, the noise suppression almost is perfect. Quarry blast recognition of *Velbert* is good at single stations, so it is favorable in COASSEIN, whereas real earthquakes yield a 85% success only. This, of course, reflects the obvious fact that earthquakes occur by a wide variety of seismograms, so they need many patterns and rules to be covered exhaustively. As a rule of thumb we determined that 85% indeed is a good estimate for the success that seismology should expect from any automated routine processing at date.

It should be noted that the comparison of single-trace results and joint calculations in Table 4 tends to favor the single sites, because *successfully recognized* for the SONOGRAM-detector can indicate just one right identification out of the two POSSIBLE ones, whereas COASSEIN reports only one solution in any situations. This situation of 'second guess' is true for about 25% of all the SONOGRAM-detections. And why does station TEZ perform better than SHA, although its noise level is higher and thus its WALSH performance (see Table 2) is lower? The reason is in the more stationary behavior of ground noise of TEZ which improves the image quality of sonograms.

CONCLUSIONS

The BUG small array was introduced as an example for seismic monitoring not covered by the pure concepts of array or network design. In common with a many station array, the beam calculation yields azimuth for epicenter determination and slowness for phase identification. The online processing, however, performs similar to a seismic network and utilizes a WALSH-detector per station and the *2of4* voting scheme in the hub.

The online approaches can be replaced by knowledge-based procedures to achieve higher system performance. On the other hand, coding of site specific knowledge into these programs prevents their application to other installations without principal modification: the SONOGRAM-detector requires new patterns which present the typical seismograms; COASSEIN must be inspected for the impact of pattern classification, the influence of site characteristics in the cost function and the typical ensemble of detection messages in the conditional parts of selection and resolution rules.

Once tuned as for the BUG small array, the coincidence association excludes all false alarms and reliably recognizes sources with repeating seismograms such as quarry blasts. Without cluster exchange, the joint recognition is worse than results of the best single station. This decay is typical for coincidence criteria which impose more severe restrictions on the data than single-trace approaches could demand. Utilizing the cluster exchange as knowledge-based variation of the initial SONOGRAM identifications increased the joint results to 85% for earthquake sources which is above any single station performance of the BUG small array.

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APPENDIX 1

This is a numerical example intended to explain the adaptation of given patterns to the actual S/N ratio and the calculation of pattern fit. Suppose, the sonograms consist of three frequency bands, the pattern has nine samples and it is moved to a particular place over the larger sonogram of actual data. Then we can restrict the data to a matrix with the same dimensions 3 × 9. In both matrices, the minus signs act as symbolic placeholders to indicate nonsignificant signal energy; they will be replaced by actual values later. All positive numbers represent energy values calculated by Equations (3) and (4) respectively and are rounded to nearest integers.

Loop Over All Patterns* and *Shift Patterns Over Whole Data Window

PATTERN ADAPTATION — EXAMPLE

Original Data & Pattern Set with Noise Variances

```
data[f][t] = -  no detectable energy   (the minus signs..
pate[f][t] = -  no energy required     ..are symbolic only)
pate[f][t] = 0  don't care for calculation of fit
```

```
nd[f]|data[f][t]     np[f]|pate[f][t]
2|-2-5432--          4|---754--0
3|3-35564-3          3|---656434
3|-3--3476-          3|---045783
```

Determine Amplitude Shift sh *(by Difference of Medians)*

```
(medians are based on samples of stable energy in pate[f][t] )
sh = medi(pate[fi][ti]) - medi(data[fi][ti]);
```

i.e., samples {1;5},{0;6},{0;7}

medi(6,7,6)=6   medi(6,7,8)=7

sh = 7 - 6 = 1

Adapt Pattern Amplitudes by Shift sh

```
for (f,t) { if (pate[f][t] > 0) {
              if (pate[f][t] > sh)  pate[f][t] -= sh;
              else                  pate[f][t] = - ; } }
```

```
2|-2-5432--          3|---643--0
3|3-35564-3          2|---545323
3|-3--3476-          2|---034672
```

Adapt Pattern Noise np[f] *to Data Noise* nd[f]

```
for (f) { for (t) { if (np[f]<nd[f])
            {if (pate[f][t]!=0 && pate[f][t]<nd[f]) pate[f][t]=-;}
     else{if (pate[f][t]==- && data[f][t]<np[f]) pate[f][t]=0;}
            } np[f] = nd[f]; }
```

```
2|-2-5432--          2|---6430-0
3|3-35564-3          3|---5453-3
3|-3--3476-          3|---03467-
```

Determine remaining Part of modified Pattern

```
n = 0;  for (f,t) { if (pate[f][t] > 0) n++; }
```

valid_pattern = 12 / 14 = 86%

Prewhiten Pattern and Data (noise variance remains)

```
for (f,t) { if (pate[f][t]  > 0)  pate[f][t] = pate[f][t] - (dn[f] -1);
            if (data[f][t]  > 0)  data[f][t] = data[f][t] - (dn[f] -1);
            if (pate[f][t] == 0)  data[f][t] = 0;  }
```

--- final set of matrices ---

```
2|-1-4320-0          2|---5320-0
3|1-13342-1          3|---3231-1
3|-1-01254-          3|---01245-
```

Balance Conditions (to replace the symbolic minus signs)

```
for (f) {n=0; s=0; for (t) { if (pate[f][t]==-) n++;
                             else  s+=pate[f][t]; }
     mp[f]=s/n;  md[f]=1/3; }
```

md[f] = [-1/3, -1/3, -1/3]   mp[f] = [-5/2, -5/2, -3/1]

PATTERN RECOGNITION — EXAMPLE

Calculate Cross-Correlation

```
ccf=0;  for (f,t) {
     d=(data[f][t]==-)?md[f]:data[f][t];
     p=(pate[f][t]==-)?mp[f]:pate[f][t];
     ccf+=d*p; }
```

$$\begin{aligned}ccf=\{&{}^1/_3\cdot{}^5/_2 - 1\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 + 4\cdot5 + 3\cdot3 + 2\cdot2 + 0\cdot0 + {}^1/_3\cdot{}^5/_2 + 0\cdot0\\ &- 1\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 - 1\cdot{}^5/_2 + 3\cdot3 + 3\cdot2 + 4\cdot3 + 2\cdot1 + {}^1/_3\cdot{}^5/_2 + 1\cdot1\\ &+ {}^1/_3\cdot{}^3/_1 - 1\cdot{}^3/_1 + {}^1/_3\cdot{}^3/_1 + 0\cdot0 + 1\cdot1 + 2\cdot2 + 5\cdot4 + 4\cdot5 + {}^1/_3\cdot{}^3/_1\}\end{aligned}$$

Calculate Autocorrelation of Data

```
acd=0; for (f,t) { if (data[f][t] == -)
             acd+=md[f]*mp[f];
       else acd+=pow(data[f][t],2); }
```

$$\begin{aligned}acd=\{&{}^1/_3\cdot{}^5/_2 + 1\cdot1 + {}^1/_3\cdot{}^5/_2 + 4\cdot4 + 3\cdot3 + 2\cdot2 + 0\cdot0 + {}^1/_3\cdot{}^5/_2 + 0\cdot0\\ &+ 1\cdot1 + {}^1/_3\cdot{}^5/_2 + 1\cdot1 + 3\cdot3 + 3\cdot3 + 4\cdot4 + 2\cdot2 + {}^1/_3\cdot{}^5/_2 + 1\cdot1\\ &+ {}^1/_3\cdot{}^3/_1 + 1\cdot1 + {}^1/_3\cdot{}^3/_1 + 0\cdot0 + 1\cdot1 + 2\cdot2 + 5\cdot5 + 4\cdot4 + {}^1/_3\cdot{}^3/_1\}\end{aligned}$$

Calculate Autocorrelation of Pattern

```
acp=0; for (f,t) { if (pate[f][t] == -)
             acp+=md[f]*mp[f];
       else acp+=pow(pate[f][t],2); }
```

$$\begin{aligned}acp=\{&{}^1/_3\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 + 5\cdot5 + 3\cdot3 + 2\cdot2 + 0\cdot0 + {}^1/_3\cdot{}^5/_2 + 0\cdot0\\ &+ {}^1/_3\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 + {}^1/_3\cdot{}^5/_2 + 3\cdot3 + 2\cdot2 + 3\cdot3 + 1\cdot1 + {}^1/_3\cdot{}^5/_2 + 1\cdot1\\ &+ {}^1/_3\cdot{}^3/_1 + {}^1/_3\cdot{}^3/_1 + {}^1/_3\cdot{}^3/_1 + 0\cdot0 + 1\cdot1 + 2\cdot2 + 4\cdot4 + 5\cdot5 + {}^1/_3\cdot{}^3/_1\}\end{aligned}$$

Calculate fit(pattern,time_shift)

```
fit = 2*ccf / (acp + acd);
```

fit = 2 · 104.7 / (125.2 + 118.7) = 0.86

***Final Detector Message* (global maximum of fit): PROBABLE 'onset-time' of type 'ABC' (86%, .86)**

APPENDIX 2

The full rule set of COASSEIN is given subdivided into the four different rule types NE-creation, selection, resolution, and reevaluation. Instead of enumerating all pattern combinations, event qualifiers are defined as abstract entities. The cluster exchange is the most powerful resolution rule to dissolve any contradictions in the initial detector messages of SONODET.

```
NE-CREATION RULES: ---------------------(applied only if NE's do not exist)

  * Permutate SE's and rank by  (I)  increasing cost
                                (II) decreasing #seismic
```

```
SELECTION RULES: -----(applied only if NE's exist and no conclusion found)

  * IF     KLB reports UNKNOWN-PATTERN,
    THEN   set conclusion to LOCAL            (i.e. unknown source region)

  * IF     NE exists without Contradiction and
           ( #seismic >= 3  or  (#seismic = 2 and #modific = 0) ),
    THEN   set conclusion to type of actual NE

  * IF     Cluster-Exchange was not already applied and NE exists
           with contradiction local_seismic() to TELESEISMIC-ONSET,
    THEN   set conclusion to LOCAL            (i.e. unknown source region)

  * IF     #seismic = 1,
    THEN   set conclusion to NOT-EVENT        (i.e. ignore single seismic)

  * IF     #seismic = 0,
    THEN   set conclusion to NOT-EVENT        (i.e. recognized un-seismic)

  * IF     NE exists with two SE's of DEFINITE that contradict,
    THEN   set conclusion to PANIC
```

```
RESOLUTION RULES: ----(applied only if NE's exist and no conclusion found)

  * IF     Cluster-Exchange was not applied before,
    THEN   perform Cluster-Exchange by adding new SE's

  * IF     Cluster-Exchange was just applied,
    THEN   clean-up of redunant SE's

  * IF     NE exists with #seismic >=2 and
           only one SE is local_burst()
    THEN   set this station to NO-DETECTION

  * IF     NE exists with SE of type UNKNOWN-PATTERN,
    THEN   set this station to NO-DETECTION

  * IF     NE exists with POSSIBLE recognition in NA,
    THEN   set NA to NO-DETECTION
```

```
REEVALUATION RULES: ----------------(applied only if conclusion is found)

  * IF     final NE is seismic() and time difference > 2 sec
           or #seismic < 4
    THEN   reevaluate missing/deviating station
```

```
FINAL EXIT: -----------(applied, if last resolution rule was unsuccessful)

  * IF     this point is ever reached,
    THEN   set conclusion to "No solution found in Rule-Base"
```

Event Qualifiers for Pattern Characterization in the Rule Set				
not_event()	is	station_noise()	or	SONIC-BANG
station_noise()	is	local_burst()	or	NO-DETECTION
local_burst()	is	TRAFFIC-NOISE, NOISE-PEAK or NOISE-SWEEP		
network_wide()	is	seismic()	or	SONIC-BANG
seismic()	is	local_seismic()	or	TELESEISMIC-ONSET
local_seismic()	is	quarry_blast()	or	rockburst()
quarry_blast()	is	VELBERT		
rockburst()	is	ESSEN, GELSENKIRCHEN, RECKLINGHAUSEN, KAMEN, HAMM or AHLEN		

```
                         Cluster Exchange Rules

IF      SE has type VELBERT,
 THEN   set to GELSENKIRCHEN        and change time to +4  and
        set to RECKLINGHAUSEN       and change time to +2

IF      SE has type GELSENKIRCHEN,
 THEN   set to VELBERT              and change time to -4  and
        set to ESSEN                and change time to +2

IF      SE has type of ESSEN,
 THEN   set to GELSENKIRCHEN        and change time to +0  and
        set to SONIC-BANG           and change time to +0

IF      SE has type of RECKLINGHAUSEN,
 THEN   set to VELBERT              and change time to -2

IF      SE has type of KAMEN,
 THEN   set to HAMM                 and change time to +0

IF      SE has type of HAMM,
 THEN   set to KAMEN                and change time to +0  and
        set to AHLEN                and change time to +0

IF      SE has type of AHLEN,
 THEN   set to HAMM                 and change time to +0

IF      SE has type of SONIC-BANG,
 THEN   set to ESSEN                and change time to +0  and
        set to GELSENKIRCHEN        and change time to -2  and
        set to VELBERT              and change time to -2  and
        set to RECKLINGHAUSEN       and change time to -4

IF      SE has type of NOISE-PEAK,
 THEN   set to TELESEISMIC-ONSET and change time to +0
```

APPENDIX 3

This example gives a listing of COASSEIN: the reasoning starts by reading in five SEs. Two NEs are created initially but contradict in reported pattern types, so the cluster exchange is fired. The redundant SEs of *Essen* and *Gelsenkirchen* at TEZ are removed, then the permutation creates 36 new NEs. Yet, all NEs show contradiction because of *Traffic-noise* at SHA and the resolution rule must be applied once again. This time the rule for *single noise bursts* fires, it resets the SE-list of SHA to *no-detection*. The final solution is encountered but reevaluation is tried as an hypothesis-guided test on pattern occurrence at SHA to refine the conclusion.

```
processing next event: known solution is GELSENKIRCHEN

firing: 5 se's read in
          se[02]  KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
          se[04]  SHA  : TRAFFIC-NOISE  at 18:43:51   cost=020     modific=0
          se[06]  TEZ  : ESSEN          at 18:43:45   cost=040     modific=0
          se[07]  TEZ  : GELSENKIRCHEN  at 18:43:45   cost=040     modific=0
          se[09]  NA   : VELBERT        at 18:43:41   cost=040     modific=0

firing: 2 ne's created
          ne[02]       : CONTRADICTION  at 18:43:50  #stations=4 #seismic=3
            .                                        scost=120   #modific=0
            .     KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
            .     SHA  : TRAFFIC-NOISE  at 18:43:51   cost=020     modific=0
            .     TEZ  : GELSENKIRCHEN  at 18:43:45   cost=040     modific=0
            .     NA   : VELBERT        at 18:43:41   cost=040     modific=0
          ne[03]       : CONTRADICTION  at 18:43:50  #stations=4 #seismic=3
            .                                        scost=120   #modific=0
            .     KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
            .     SHA  : TRAFFIC-NOISE  at 18:43:51   cost=020     modific=0
            .     TEZ  : ESSEN          at 18:43:45   cost=040     modific=0
            .     NA   : VELBERT        at 18:43:41   cost=040     modific=0

firing: cluster exchange rules give 8 new se's
          se[02]  KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
          se[03]  KLB  : ESSEN          at 18:43:48   cost=044     modific=1
          se[04]  KLB  : VELBERT        at 18:43:42   cost=044     modific=1
          se[06]  SHA  : TRAFFIC-NOISE  at 18:43:51   cost=020     modific=0
          se[08]  TEZ  : ESSEN          at 18:43:45   cost=040     modific=0
          se[09]  TEZ  : SONIC-BANG     at 18:43:45   cost=053     modific=1
          se[10]  TEZ  : GELSENKIRCHEN  at 18:43:45   cost=053     modific=1
          se[11]  TEZ  : GELSENKIRCHEN  at 18:43:45   cost=040     modific=0
          se[12]  TEZ  : ESSEN          at 18:43:47   cost=053     modific=1
          se[13]  TEZ  : VELBERT        at 18:43:41   cost=053     modific=1
          se[15]  NA   : VELBERT        at 18:43:41   cost=040     modific=0
          se[16]  NA   : RECKLINGHAUSEN at 18:43:43   cost=050     modific=1
          se[17]  NA   : GELSENKIRCHEN  at 18:43:45   cost=050     modific=1

firing: cleaning-up removes 2 modified se's
          se[02]  KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
          se[03]  KLB  : ESSEN          at 18:43:48   cost=044     modific=1
          se[04]  KLB  : VELBERT        at 18:43:42   cost=044     modific=1
          se[06]  SHA  : TRAFFIC-NOISE  at 18:43:51   cost=020     modific=0
          se[08]  TEZ  : ESSEN          at 18:43:45   cost=040     modific=0
          se[09]  TEZ  : SONIC-BANG     at 18:43:45   cost=053     modific=1
          se[10]  TEZ  : GELSENKIRCHEN  at 18:43:45   cost=040     modific=0
          se[11]  TEZ  : VELBERT        at 18:43:41   cost=053     modific=1
          se[13]  NA   : VELBERT        at 18:43:41   cost=040     modific=0
          se[14]  NA   : RECKLINGHAUSEN at 18:43:43   cost=050     modific=1
          se[15]  NA   : GELSENKIRCHEN  at 18:43:45   cost=050     modific=1

firing: 36 ne's created
          ... (list of 36 network events) ...

firing: ignore TRAFFIC-NOISE in SHA as single noise burst

firing: 36 ne's created
          ... (list of 36 network events) ...

firing: ******** coincidence found for GELSENKIRCHEN at 18:43:45 ***********
          ne[29]       : GELSENKIRCHEN  at 18:43:45  #stations=3 #seismic=3
            .                                        scost=110   #modific=1
            .     KLB  : GELSENKIRCHEN  at 18:43:46   cost=020     modific=0
            .     SHA  : NO-DETECTION   at 18:43:45   cost=100     modific=1
            .     TEZ  : GELSENKIRCHEN  at 18:43:45   cost=040     modific=0
            .     NA   : GELSENKIRCHEN  at 18:43:45   cost=050     modific=1

firing: reevaluate SHA
          call SONOGRAM-Detector: test on GELSENKIRCHEN at 18:43:45 in SHA
```