Implementation of Additional Seismological Software for the Determination of Earthquake Parameters Based on MatSeis and an Automatic Phase-detector Algorithm

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INTRODUCTION

Various approaches have been presented during the last few years regarding public-domain seismological software for routine or advanced analysis of earthquake data. The necessity of such software approaches is continuously increasing as the amount of data of permanent and portable seismological networks stored in computer systems is increasing due to the augmentation of networks that use full digital systems with high sampling rates. There is also the additional need for software for the rapid determination of earthquake parameters for high-seismicity areas.

Several software packages have been presented to address these problems, such as Xpirta (Scherbaum and Johnson, 1992), MatSeis (Young et al., 1996), Giant (Riebrock and Scherbaum, 1998), SeisAn (Havskov and Ottemoller, 1999), and Earthworm (EWAB, 2000). All these software packages have an obvious need for relational database management system (RDBMS) support due to the large amount and variety of the information that they must handle. Some of the sample tasks that the RDBMS must take on are the association of the arrivals with origin times and the handling of different event locations. One approach to the database problem is presented in the DataScope software (DataScope, 1997), where a schema file (CSS3.0) describing the tables, records, and fields of the RDBMS is used in order to handle the data through an RDBMS that uses flat-ASCII table files.

The most common problem in the analysis of earthquake waveforms is the determination of phase arrivals. Usually, phase arrivals are picked manually. However, interest in the rapid determination of earthquake parameters has led to the introduction of different approaches for a phase auto-detection system. Most of the approaches concern the P-phase arrival identification. The most common of them compare the short-time average (STA) of a characteristic function with a threshold value, usually the long-time average (LTA) of the same function (Allen, 1978; Goftorl and Herrin, 1981). The auto- and cross-correlation of two or three components may be used in order to identify various phase arrivals through polarization measurements (Magorita et al., 1987; Roberts et al., 1989). Other techniques for automated detection of seismic phases include maximum likelihood (Christofferson et al., 1988; Ruud et al., 1988), fuzzy logic (Chu and Mendel, 1994), and wavelet transform (WT) (Anant and Dowla, 1997; Gendron et al., 2000). For automatic S-phase determination only a few algorithms have been developed (Wang and Teng, 1997; Cichowicz, 1997). The main difficulty with S-phase determination lies in the fact that the P-coda waves are not sufficiently damped when the S wave emerges in the time series. As a result the S arrival is partly "hidden" in the P-coda waves, which makes the identification of the S arrival quite difficult, even for an experienced operator.

In the present study different software tools already developed by other groups are incorporated into a single data analysis system. The software used includes DataScope (DataScope, 1997) as the RDBMS and MatSeis (Young et al., 1996), based on the MatLab software (Mathworks, 1992), as the earthquake analysis software. Additional seismological programs have been used for calculating the earthquake location parameters and the fault-plane solution, such as Hypoellipse2K (Laht, 1999) and FPFIT (Reasenberg and Oppenheim, 1985), respectively. All software was modified, expanded, and merged in order to implement a more complete tool for seismological data analysis. Moreover, a combination of higher-order statistics (HOS) with redundant wavelet transform (R-WT) was used to identify P and S arrivals from a single station seismogram. The system we have developed has been tested with various waveform data recorded in Greece. The evaluation process confirms that the proposed algorithms have high identification accuracy with
EXTENSIONS TO DataScope

DataScope uses a schema file in order to describe the tables, records, and fields of the RDBMS. The form of the CSS3.0 schema file was used in the current approach; that is, an ASCII file and no modifications or additions were implemented in the present work. The tables that comprise the RDBMS were ASCII files so that any user could easily extract the information in any file of the database. For each seismic network, permanent or temporary, separate tables are necessary in order to describe the seismic network through the RDBMS, i.e., network, site, sitechan, wfdisc, etc. In our approach these files are created through a utility, makedb (Figure 1). Initially, a single ASCII file is created by the user that includes all the information of the temporary/permanent seismiological network. Next, makedb is used in order to create the appropriate ASCII table files that describe the seismic network and comply with the CSS3.0 schema file. DataScope as an RDBMS is using unique numbers (ID’s) that describe each relation between entities and information in the database tables. For example, each channel on a site has a unique ID that describes the channel for a specific site. Information like this exists in each table and is used to describe a record in the database and to create links quickly between different tables.

Most of the seismic loggers that are used in temporary seismic networks (e.g., Reftek) export the data as segY waveform files. For this reason a modified version of the segy2css (v. 1.5) (Figure 1) utility of the IRIS software is used in order to transform the segY waveform files into the appropriate data files, which comply with the CSS3.0 waveform data format. It should be mentioned here that several utilities provided with DataScope allow the conversion of waveform files of different types (SAC, Ah, SEED, etc.) to the appropriate CSS3.0 database files. Using the modified version of the segy2css utility the user can add any time series to the data directory and automatically append the information of the waveform files into the database waveform table. However, each time this is
done it is necessary to change/correct the ID’s of the channels in the waveform table. A utility named checkid (Figure 1) was implemented to perform this task, since segy2css does not automatically do so.

After the database files are created, the DataScope software can be used. The user, through a GUI (graphical user interface), can access the database data. Different queries can be easily created and data can be edited in order to modify the database.

**EXTENSIONS TO MatSeis**

MatSeis (v. 1.5) (Young et al., 1996) was used as the main earthquake analysis software. Any additional seismological programs that have been used or implemented were added into MatSeis in order to have a complete tool with different possibilities regarding waveform processing and calculation of earthquake location parameters. MatSeis is based on the MatLab package and directly accesses the CSS3.0 database files in order to handle different information such as waveform data, arrivals, origin times, etc. MatSeis uses two ASCII start-up files where all the appropriate information about the database location, name, and environment variables are set.

In order to interconnect DataScope with MatSeis an additional menu has been implemented in the DataScope GUI to provide the ability to start MatSeis from any window of DataScope. The appropriate start-up files necessary for MatSeis are automatically created, and the database used in DataScope is used directly in MatSeis.

MatSeis handles all processes through a GUI based on MatLab. In Figure 1 a short presentation of the capabilities of MatSeis (v. 1.5) is shown. At first, the user can set/modify the database location. Next, a graphical interface through MatLab can be used so that there is a direct access to the Origin/Waveform/Arrival information in the database. The travel times can be calculated and presented on the screen. Additionally, some signal processing utilities exist, and different waveform analysis procedures can be applied to the time series. A phase detector is available to the user based on the STA/LTA method, as is a trigger tool that can go through the times series and detect phases. Finally, earthquake location software can be used in order to calculate the earthquake parameters. All the above-mentioned tools are already implemented in version 1.5 of MatSeis, which has been the starting point for our approach to the earthquake analysis software.

Initially, an “Overview Window” (Figure 1) is displayed in order to have on the screen a snapshot of the time series data through a wide period of time, where the user can use a drag-and-drop procedure to select time series data for further processing. The above procedure has been implemented in two different ways that are available to the user. The first is a simple data read where all the time series are loaded in the system RAM and discrete points are shown on the screen. Since this is a very memory-intensive process, an alternative was also implemented where only discrete data of the time series are kept in RAM, and each time the user selects from the snapshot window a part of the time series the corresponding data are read from the waveform files.

During phase picking MatSeis allows the phase type to be only P or S. In our approach, through a pop-up menu (Figure 2) additional phase characterizations compatible with DataScope can be added, like the onset quality (ii/c/w), the first

![Figure 2](image-url)  
**Figure 2.** The modified pop-up menu of the phase characterization. The user can define the type of phase (P/S), the onset quality (emergent/impulsive/weak), the first motion for short- (C/D) and long- (u/v) period waves, and the hypo-weight (0/1/2/3/4/9).
motion (C/D for short-period and u/r for long-period waves), and the hypo-weight for later use in Hypoellipse (HWglst 1/2/3/4/9). The user can define graphically the error of the arrival time.

For the evaluation of earthquake parameters the Hypoellipse Y2K (Lafr, 1999) software has been incorporated into MatSeis (Figure 1). The user can set the parameters of Hypoellipse (upper left part of Figure 3) and can select/define the velocity model (upper right part of Figure 3) and the phases to be used in the calculation of the earthquake parameters (lower part of Figure 3). The results are printed in a new window and the predicted phases are marked in the main window with a different gray tone (Figure 4). The user can modify his primary arrival selections where appropriate and recalculate the earthquake parameters. A simple map with the station positions and the epicenter is generated through the GMT3.0 software (Wessel and Smith, 1995).

Focal mechanisms are evaluated using FPfit (Figure 1) (Reasenberg and Oppenheimer, 1985). In order to run FPfit the user must set different parameters such as the minimum magnitude of earthquake to be used, the minimum number of P first motions, searching for multiple or for best fault-plane solution, etc. A GUI (Figure 5) is available to the user to set/modify the default parameters. All parameters are checked, and different alert messages notify the user of the possible errors. Furthermore, the best or all possible fault-plane solutions appear on the screen depending on the selection of the user, and the user can print any of the results. In Figure 5 a sample solution is presented for a local earthquake. In the inset figure the various possible P and T axes compatible with the data (as determined by FPfit) are presented. Finally, after the user finalizes the earthquake location parameters, the origin time and arrival information can be saved in the database, and the user is prompted if the focal mechanism has not been estimated. All parameters can be saved and retrieved in the database, which can be accessed through either MatSeis or DataScope.

**IMPLEMENTATION OF PHASE AUTO-PICKERS**

Our first approach to an automatic P-phase picker relies on the usage of a combination of R-WT and HOS (Saragiotis et al., 1999).

The wavelet transform (WT) is a signal-processing tool that performs a decomposition of a signal, i.e., the seismic trace, into various frequency bands called "scales." In our approach the WT is used for noise suppression, making the reasonable assumption that the accurate picking of the phase arrival onset is limited by the high-frequency noise which is present in the seismic trace. Therefore, after the seismic signal decomposition the frequency scales that describe the highest frequency components are discarded and the signal is reconstructed by inverse WT, using its lowest frequency components, in order to enhance the seismic signal and suppress the noise. However, the WT typically uses downsampling in order to reduce the computational complexity and discard
Figure 4. Time series window with arrival information.

Figure 5. GUI with the parameters for focal mechanism calculation (determined internally using FFFIT) along with the best solution calculated.
redundant information. In applications where high accuracy is an important issue, such as phase-arrival identification, this causes unwanted loss of time resolution. This need is met by the use of the R-WT, which does not downsample the data. In this way, more computations are performed but the original time resolution is kept.

The main idea behind the usage of the HOS for phase detection relies on the identification of a non-Gaussian signal (seismic signal) in a normally or a generally symmetrically distributed background signal (noise). Normally distributed signals have zero-valued HOS, such as for skewness (third-order statistic) and kurtosis (fourth-order statistic), while signals with asymmetric or heavy-tailed distributions (such as the initial part of P or S waves) have high values of skewness and kurtosis (Nikias and Petropulu, 1993).

The skewness, \( \hat{\gamma}_3 \), and kurtosis, \( \hat{\gamma}_4 \), parameters for a finite time series \( x(i) \) are calculated as

\[
\hat{\gamma}_3 = \frac{\sum (x(i) - \hat{m}_x)^3}{(N-1)\hat{\sigma}_x^3}, \quad \hat{\gamma}_4 = \frac{\sum (x(i) - \hat{m}_x)^4}{(N-1)\hat{\sigma}_x^4} - 3,
\]

where \( N, \hat{m}_x, \) and \( \hat{\sigma}_x \) are the length (in samples), the mean, and the standard deviation of the time series, respectively (Nikias and Petropulu, 1993).

The P-phase picker works as follows: The R-WT is calculated for the three (one vertical and two horizontal) components of a seismic trace. Then the skewness and kurtosis parameters are calculated in sliding time windows for the scales that describe the lower frequencies; thus two new vectors, one for the skewness and one for the kurtosis, are produced for each scale. When the sliding time window contains the part of the vector when the P phase arrives, the distribution of the R-WT coefficients is asymmetrical and more heavy-tailed than the distribution of the vector that contains only noise. For the P-phase this results in high values for these two parameters. Thus, the two vectors have local maxima at the time of the P arrival. In order to enhance the maxima, the cross-product of the vectors for the three components for each scale of the R-WT is calculated (P-RWTHOS) (Figure 6).

In order to estimate the S-phase arrival after the P-arrival estimation, the covariance matrix of the three-component seismogram for a time window close to but after the P arrival is calculated. If \( x, y, z \) describe the two horizontal compo-

![Figure 6](https://example.com/figure6.png)

**Figure 6.** Vertical component (top) presented with the calculation of the HOS parameters, kurtosis (middle) and skewness (bottom), using the first approach (R-WT and HOS). The vertical line crossing all plots denotes the P-arrival characterization from the operator at trace 2461. The maximum values for kurtosis and skewness are at traces 2483 and 2485, respectively. The recording is from the permanent seismological network of the Geophysical Laboratory of the University of Thessaloniki (sampling rate of 50 Hz).
nents and the vertical component respectively, the covariance matrix, \( M \), is defined as

\[
M = \begin{bmatrix}
\text{cov}(x,x) & \text{cov}(x,y) & \text{cov}(x,z) \\
\text{cov}(y,x) & \text{cov}(y,y) & \text{cov}(y,z) \\
\text{cov}(z,x) & \text{cov}(z,y) & \text{cov}(z,z)
\end{bmatrix}
\]

The eigenvalues and eigenvectors of the covariance matrix are calculated, which correspond to the lengths and directions of the axes of the polarization ellipsoid. Since the polarization ellipsoid characteristics are evaluated, the two horizontal components are being rotated through the angle defined between the vertical axes and the longest axis of the ellipse in order to show the most likely shear-wave characteristics (Magotra et al., 1987). Then the skewness and kurtosis parameters are again calculated in order to identify the \( S \)-phase arrival.

Application of the above method to seismic traces with great variety in hypocentral distance and earthquake magnitude has shown that for the \( P \)-arrival evaluation there is good agreement between the onsets estimated by the system and the ones marked by the operator. However, the automated \( S \)-phase picker has satisfactorily estimated the \( S \)-phase arrival only in seismic traces in which the \( S \) phase arrives when the \( P \)-phase coda level is sufficiently damped so that the \( S \)-phase characteristics are not “buried” in the \( P \)-phase coda.

In order to overcome this problem the WTST-NST (Wavelet Transform-based STaRionary–NonSTaRionary) filter (Hadjileontiadis and Panas, 1997) is applied to the seismic trace. The WTST-NST filter is a nonlinear filter based on the wavelet transform that separates the nonstationary part of a signal from its stationary component. In our case, the seismic trace segment from the \( P \)-arrival identification (either manually or automatically phase picked) until the highest value of the seismic trace was selected. In this way, due to the change of the statistical properties of the seismic trace at the arrival of the \( S \) phase, the WTST-NST filter considers the \( P \)-phase and its coda as the stationary part of the seismic trace segment. It processes and discards it, so that essentially only the \( S \) phase is left.

The kurtosis and skewness parameters are then calculated on the “filtered” signal in order to find the maxima that denote a possible \( S \)-phase arrival. Finally, in both \( P \)- and \( S \)-arrival identification a correction is evaluated using an algorithm in which the arrival is not marked at the maximum value of skewness or kurtosis but at the maximum slope of these parameters before they reach their maximum values. This correction is justified by the fact that the skewness and kurtosis parameters achieve maximum values when only a sufficient fraction of the time window in which they are calculated contains the \( P \) or \( S \) phase. Since the aim is to determine the arrival times, i.e., the first instant of the \( P \) and \( S \) phases, it is natural to mark the instants where the skewness and kurtosis vectors start to increase abruptly and not at the instant where they present maxima. This final approach to the phase auto-detect problem is called ASPIS (Automatic Seismic Phases Identification System) (Saragiotis et al., 2000). A comprehensive block diagram that describes this system is given in Figure 7. ASPIS was applied to waveforms from many different earthquakes and compared to other phase auto-detect systems.

**EVALUATION OF THE PHASE AUTO-PICKERS**

Both algorithms described in the previous section (P-RWTHOS and ASPIS), as well as Allen’s (1978) algorithm, were incorporated in the graphical waveform-management interface of MatSeis in order to allow the potential user to use a variety of auto-phase pickers. Using these algorithms, now built into MatSeis, we performed tests on two different data sets in order to evaluate their efficiency for automatic phase identification. The first test was applied on waveform data collected from the permanent network of the Geophysical Laboratory of the Aristotle University of Thessaloniki, Greece. The network runs sixteen seismological stations with a maximum aperture of approximately 400 km using a recording sampling rate of 50 Hz. A small set of ten earthquakes with forty-four waveforms was used for the test. The ASPIS algorithm, our first approach (P-RWTHOS), and Allen’s (1978) algorithm were initially applied to the data for \( P \)-arrival auto-picking, and the obtained results were compared with the manual phases that are routinely picked by the network operator. A comparison between the different algorithms is presented in Figure 8 and is summarized in Table 1. In Figure 8 the difference (number of samples) between the \( P \) phase detected by each algorithm and the operator’s pick is plotted for each of the tested waveforms. In general, the automatic phase-picking algorithms tend to pick the \( P \) phase slightly later than the manual picks. This “delay” suggests that phase auto-pickers cannot identify the slight change in the waveform characteristics that occurs right at the beginning of a \( P \)-phase arrival. However, as can also be seen in Table 1, it is obvious that the proposed approach (ASPIs algorithm) exhibits very good results and has a smaller “delay” (\(-0.1 \pm 0.2 \text{ sec}\)) compared to Allen’s (1978) algorithm (\(-0.2 \pm 0.2 \text{ sec}\)). Moreover, Allen’s algorithm failed to pick a \( P \) phase in five (\(-11\%\)) of the waveforms, which was not the case for the ASPIS algorithm for this data set.

For the \( S \)-arrival evaluation the ASPIS and a simple STA/LTA algorithm were applied to the data. The observed differences (in number of samples) between the \( S \)-phase auto-pickers and the operator’s \( S \)-phase selection for each waveform are presented in Figure 9 and are also summarized in Table 1. The superiority of the ASPIS algorithm compared to the simple STA/LTA algorithm is obvious. In the inset plot of Figure 9 the results obtained from the ASPIS algorithm only are plotted, showing that about 80% of the traces exhibit a difference of less than ten samples (i.e., 0.2 sec).

An important issue in the application of the ASPIS algorithm is the length of the window used for the HOS computation. Very large windows usually result in large phase-
Figure 7. Block diagram of ASPIS. x, y, and z denote the two horizontal and vertical components of the seismic trace, respectively, and the HOS vector blocks correspond to either the calculated skewness or kurtosis.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>P Phase</th>
<th>S Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Perc</td>
<td>Δt (sec)</td>
</tr>
<tr>
<td>Allen (1978)</td>
<td>89</td>
<td>0.25</td>
</tr>
<tr>
<td>STA/LTA</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>P-RWTHOS (Skewness)</td>
<td>100</td>
<td>0.69</td>
</tr>
<tr>
<td>P-RWTHOS (Kurtosis)</td>
<td>100</td>
<td>0.65</td>
</tr>
<tr>
<td>ASPIS (Skewness/Kurtosis)</td>
<td>100</td>
<td>0.12</td>
</tr>
</tbody>
</table>
picking errors, while very small windows increase the picking accuracy but also often tend to pick "outliers" such as small spikes, etc., and to miss the true P-phase arrival. In order to check the effect of the window length on the efficiency of the ASPIS algorithm compared to Allen's algorithm, which does not depend on a similar window definition, we performed an additional test. The second data set used in order to evaluate the efficiency of the developed algorithms came from a local experiment near the city of Thessaloniki (northern Greece). Recordings of 64 local events from eight portable stations with a sampling rate of 200 Hz were used. An additional rea-

\begin{table}
\centering
\begin{tabular}{|c|c|c|}
\hline
Algorithm & P Phase & S Phase \\
\hline
& Perc & $\Delta t$ (sec) & $\sigma_f$ (sec) & Perc & $\Delta t$ (sec) & $\sigma_f$ (sec) \\
Allen (1978) & 55 & 0.02 & 0.21 & — & — & — \\
ASPI(Skewness)–Allen success & 95 & 0.01 & 0.28 & — & — & — \\
ASPI(Kurtosis)–Allen success & 96 & 0.03 & 0.31 & — & — & — \\
ASPI(Skewness)–Allen fail & 62 & 0.40 & 1.00 & — & — & — \\
ASPI(Kurtosis)–Allen fail & 60 & 0.60 & 1.12 & — & — & — \\
ASPI(Skewness)–All data & — & — & — & 98 & 0.24 & 0.71 \\
ASPI(Kurtosis)–All data & — & — & — & 98 & 0.36 & 0.74 \\
\hline
\end{tabular}
\caption{Statistical Properties of the Differences between the P and S Phases Determined by the Auto-picking Algorithms and the Corresponding Phases Picked Manually by the Network Operator}
\end{table}

Son to use the specific data set was to test the algorithm's efficiency on waveforms from local (aperture of 50–100 km) rather than regional (aperture 500–1,000 km) networks. Calculations for the P-arrival estimation were applied using different time window lengths, $W$, ranging from 0.125 sec (25 samples) to 2 sec (400 samples).

The final results for P arrivals are presented in Figures 10 and 11, while the corresponding statistical properties are summarized in Table 2. Allen's (1978) algorithm was able to detect P arrivals in 55% of the examined cases (Figure 10A). For the same cases where Allen's (1978) algorithm was successful, the ASPIS algorithm (using either skewness or kurtosis)
Figure 10. Time residuals (sec) from the comparison of various $P$ auto phase-detecting algorithms with the operator’s manual picks using data from a local seismological network (sampling rate is 200 Hz): (A) Allen’s (1978) method, (B) ASPIS (skewness window length 0.25 sec), (C) ASPIS (skewness window length 0.75 sec), (D) ASPIS (kurtosis window length 0.25 sec), and (E) ASPIS (kurtosis window length 0.75 sec).
ysis) was able to pick the P arrival automatically in almost all cases (~95%). Using different windows, \( W \), as previously described showed that the best results were obtained for a time window of \( W = 0.25 \text{ sec} \), 50 samples (Figures 10B and 10D). For large time windows (up to 2 sec), better accuracy was observed for the ASPIS algorithm using the kurtosis criteria, as can also be seen for the results obtained for \( W = 0.75 \text{ sec} \), where the ASPIS-kurtosis results "cluster" around the value of 0 sec (Figure 10E), whereas the ASPIS-skewness results show a more or less systematic bias of ~0.4 sec (Figure 10C).

For the waveforms where Allen's (1978) method failed to mark a P arrival, which must be considered as the most difficult cases in the examined data set, the ASPIS algorithm was able to pick a P phase in ~60% of the cases and produced quite good results (Figure 11). In almost 50% of these cases the algorithm was able to identify a P arrival within 0.5 sec of the operator's choice, although large "outliers" were also obtained, as can be seen in Figure 11 and the corresponding errors in Table 2. In general, the ASPIS algorithm exhibited similar accuracy for the examined data set with Allen's algorithm and was able to also pick P phases in a large number of cases where Allen's algorithm failed, although with a lower accuracy.

The S phases, for which Allen's (1978) method cannot be applied, also showed a good accuracy when the ASPIS algorithm identified them. All S arrivals were automatically picked using small windows (\( W = 0.25-0.5 \text{ sec} \)), since for larger windows (\( W = 1 \text{ sec} \)) several S arrivals were misidentified. Since the applicability of the ASPIS algorithm relies on filtering performed by the WTST-NST filter, it was important to test the effect of the parameter F (Hadjileontiadis and Panas, 1997), which controls the filter behavior. The parameter F is used to define the threshold of the different wavelet classes that are kept in order to reconstruct the filtered waveform during the application of the WTST-NST filter, typically ranging from 2 to 4. The results are presented in Figure 12 for two F values (2.5 and 3.5), as well as in Table 2. In general, the results show that for an F value of 2.5 the lowest time residuals between the predicted and the operator's S phases were found for both skewness and kurtosis versions of the ASPIS algorithm.

**SUMMARY AND DISCUSSION**

The need for an "efficient and complete" seismological software program for routine waveform analysis (phase picking, event location, focal mechanism estimation, presentation of results, appropriate storage, etc.) is obvious. Large amounts of time series data are collected every day at acquisition centers where earthquake parameters are regularly calculated. The approach presented here is a solution based on a complete software package and an automatic phase-detector algorithm for the fast determination of earthquake parameters. The package is based on an RDBMS engine (DataScope) and Mat-Set, while other seismological software such as Hypoellipse2K and FPFIT is also incorporated. Modifications, extensions, and merging were undertaken where necessary in order to implement a complete software package. Our approach is expandable and very easy to use since the MatLab software is the basis of the system and all the operations are handled within a graphical user interface.

In order to automate and speed up the process of determining earthquake parameters, different approaches to the problem of phase auto-detect systems are presented. The first one is based on high-order statistics and the redundant wavelet transform and shows good results for the P-arrival identification compared to the commonly used Allen's (1978) method. However, for the S-arrival identification the results
Figure 12. Time residuals (s) defined from the comparison of ASPIS S-phase auto-detecting algorithm (skewness at the top; kurtosis at the bottom) with the operator’s manual S-phase picks, using the same (as for Figures 10 and 11) local network data set (sampling rate of 200 Hz). Results are presented for an F value (controlling the WTST-NST filter used to isolate the S phase) of 2.5 (left) and 3.5 (right).

were not satisfactory. Our favored approach (ASPIIS) includes the usage of an appropriate filter, WTST-NST (Hadjileontiadis and Panaia, 1997), to extract the P-coda waves for better evaluation of the S arrival. The phase auto-detect algorithms presented here were tested on two data sets of both regional and local scale. The superiority of the ASPIS approach compared to the commonly used STA/LTA method and its variants, as well as to our initial approach, is quite evident.

For the permanent network data the ASPIS software resulted in automatic P-phase evaluation with a residual less than 0.34 and 0.32 sec for the skewness and kurtosis versions of the algorithm, respectively, in 67% of the cases. Also, 67% of the automatic S-phase evaluations with ASPIS have a residual of less than 0.4 sec compared to the operator’s manual phase pick. For the same data set using the STA/LTA algorithm 67% of the arrivals have residuals up to −4 sec. Finally, when ASPIS was applied to the data of the local network, 83% of the cases out of the 480 examined S-phase arrivals have a residual less than 1 sec. Several tests were performed for the optimization of the controlling parameters of the ASPIS algorithm, namely the examined window length and the controlling parameter F of the WTST-NST filter used in the S-phase determination. The results suggest an optimal value of 0.25 sec (50 samples) for the window length and an F parameter equal to 2.5, using skewness and kurtosis versions of the ASPIS algorithm.

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