

# Users Guide for MPX Picking System

by

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# Contents

1	Introduction	3
<b>2</b>	Basic Concept of MPX	3
3	Compilation of Reference Data Set	4
4	Calibration Procedure4.1Adjustment of Search Windows4.2Calibration of the Automated Quality Assessment	<b>5</b> 6 10
	4.3 Assessment of Calibration Scheme	13
<b>5</b>	Examples of Production Modes	15
	5.1 Application to the Alpine Region	15
6	Cookbook Example: MDA via SPSS Software	16
Bi	bliography	20

# 1 Introduction

The MannekenPix (MPX) software of Freddy Aldersons allows the automated (re-)picking of seismic phases from the original waveform data. This users guide represents a helpful extension to the original MPX users guide of *Aldersons* (2005). It gives gives a short introduction to the basic concept of MPX, explains the main parameters, and illustrates how MPX is calibrated towards a specific waveform data set. A detailed description of the fundamental concept of MPX and its application to the Dead-Sea Region and Italy can be found in *Aldersons* (2004) and *Di Stefano et al.* (2006). Furthermore, *Diehl et al.* (2008) applied the MPX software to the greater Alpine region. They demonstrated how the performance of MPX can be further improved for a regional data set.

In the first section, we give a brief overview on the basic concept of MPX. In the second part, we describe the parameters and how to calibrate these (calibration procedure). In the third section we specifically focus on the applications to the Alpine Region. In the last section we provide a cookbook example on how to perform the MDA with the SPSS software.

It should be mentioned that this guide refers to MPX-version 2.0.11 (December 2005). Furthermore, we thank Freddy Aldersons for providing us with the MPX software and his 'any-time' help and support.

# 2 Basic Concept of MPX

The MPX system combines a picking algorithm with an automatic quality assessment, which is able to adopt the weighting procedure of a human picker. However, it is important to know that the MPX picking algorithm requires an initial (or guiding) pick for each seismogram. Since MPX is usually used for repicking of known and identified local and regional earthquakes, a routine pick (e.g. from the routine analysis of an agency) or a predicted pick (theoretical arrival time derived from a catalogue location and a standard velocity model) can be used for this purpose. The automated quality assessment is accomplished by estimating the quality-class membership from a set of discriminant waveform characteristics or 'predictors' (signal-to-noise ratio, etc.) measured at (and around) the automatic pick. The mapping of the predictor-values to discrete quality classes is done via weighting factors (Fisher coefficients) for each predictor. The Fisher coefficients have to be calibrated with a (hand picked) reference data set in order to adopt the error assessment of the seismologist. Multiple-Discriminant-Analysis (MDA) can be used to find appropriate Fisher coefficients for the reference data set. Figure 1 summarizes the basic concept of MPX. The kernel of the system is its Wiener-Filter (WF) routine. The WF is used to determine the thresholds for the picking engine, but also for measuring some of the waveform characteristics used for the quality assessment. In addition, it can also be used for waveform filtering. Basically, the WF compares the characteristics of the seismogram in two search-windows located around the initial pick. In the ideal case, the 'earlier' window contains just noise and the 'later' contains noise+signal characteristics. The picking engine implemented in MPX is based on the Baer-Kradolfer algorithm (*Baer and Kradolfer*, 1987) extended by a delay correction as described e.g. in *Aldersons* (2004) or *Di Stefano et al.* (2006). The MPX-Workflow can be divided into four main steps:

- Setup reference data set: consistent manual picks for representative subset of waveform data set (tectonic region, magnitude, depth, network, etc). Divide reference data set in two subsets. Part I is used for calibration. Part II is used for testing calibration scheme (see section 3).
- Calibration-Procedure: adopt automatic picking and quality assessment to reference data part I (see section 4).
- Test-Procedure (optional): Apply calibration scheme to reference data part II and assess performance.
- Production-Procedure: Initial picks necessary for all seismograms in waveform data set. Apply calibration scheme to complete waveform data set (see section 5).



Figure 1: Basic concept of MPX. The Wiener-Filter routine represents the kernel of the picking system. It is used to derive thresholds for the picking engine and wave-form characteristics for the quality assessment engine. Optional, it can be used for waveform filtering.

# **3** Compilation of Reference Data Set

Since the reference data set should present a cross section of waveforms expected in the complete data set (production stage), we have to extract a representative selection of earthquakes and recording stations. Possible criteria are: location (different tectonic regions, different networks), magnitudes (e.g. not only the strongest) and depth (important e.g. in subduction zones). In general one can tend to higher magnitudes, since these earthquakes are recorded over larger distances and therefore, they will contain a broad spectrum of qualities. In addition, they will include strong and clear later arrivals such as Pg and PmP phases. During the calibration and test procedure we have to ensure that MPX never picks a later arrival as the first arrival. The number of picks depends on the dimension of the study area. However, we suggest at least 1000 picks for calibration and testing.

The picking procedure itself should be performed as consistent as possible, since these picks will be used to calibrate the automatic picker. Therefore, the manual picker should define some general rules for picking and error assessment. In any case, we recommend the picking of the uncertainty intervals for each phase, which later allows a flexible quality (error) class definition. We assign an additional weight for the uncertainty of the phase identification. For more details on reference picking see 'Users Guide for Consistent Phase Picking' by *Diehl and Kissling* (2008) or *Diehl et al.* (2008).

## 4 Calibration Procedure

The calibration of the automatic picking system is based on the comparison between reference picks and automatic picks. Since we want to imitate the manual picker we have to assume, that the reference picks are located at the 'true' position and the assigned reference weights represent the 'true' uncertainty interval. The picking and quality assessment of MPX is controlled by a set of parameters (summarized in Table 1), which have to be calibrated in the following procedure. The calibration procedure is divided in 6 major steps:

- 1. Step: Estimate the accuracy of initial picks (predicted from velocity model or routine picks) by calculating difference between reference and initial picks as demonstrated by *Diehl et al.* (2008).
- Step: Adjustment of search windows. Choice of initial safety gaps depends mainly on the accuracy of initial picks (analyzed in previous step). Use suggested values as a first guess for the remaining parameters (see 4.1 for details).
- 3. Step: Apply MPX to the reference data set. For the initial MPX run, default Fisher coefficients have to be used, since Fisher coefficients appropriate for our reference data set still have to be calculated. For a set of default Fisher coefficients see e.g., *Di Stefano et al.* (2006) or *Diehl et al.* (2008). Use the output of MPX (export-file) and calculate appropriate Fisher coefficients via MDA (e.g. with SPSS). For details on the automatic quality assessment via pattern recognition and MDA see 4.2 and 6.

- 4. Step: Apply MPX to the reference data set with updated (appropriate) Fisher coefficients and/or adjusted search windows.
- 5. Step: Check of performance by comparison of MPX output with reference data set. See section 4.3 for details.
- 6. Step: The calibration procedure is an iterative process. If result of step 5 is not satisfactory, repeat step 2+4+5, 3+4+5 or 2+3+4+5 till satisfactory performance is achieved.

Figure 2 summarizes the MPX calibration procedure described above.



Figure 2: Flow chart illustrating the MPX calibration procedure.

## 4.1 Adjustment of Search Windows

The search window adjustment controls the picking accuracy, the hit rate and even the phase identification. In the pre-picking stage MPX evaluates the spectral density in a noise (NW) and in a signal+noise (SNW) window via the Wiener Filter routines. The position of these windows are controlled by the initial pick (routine or predicted arrival  $t_{pred}$ ), the length of the windows ( $L_N$ )

MPX Parameter	Achieved by	Dependencies	Example from Alpine Reference Data Set
Fisher coefficients (Predictors x Classes)	MDA, Test with reference data	Waveform characteristics of data set & errors of picking engine	Not shown here
Length of analysing windows $L_N$ and $L_S$ (Wiener Filter length) (sec)	Test with reference data	Frequency content of signal	$L_N = L_S = 2 \text{ s}$
Set of safety gaps $g_N$ and $g_S$ for predicted pick (sec)	Test with reference data	'Scatter' of predicted picks <sup>†</sup> & frequency content	2.5 s, 1.25 s, 0.5 s, 0.08 s
Set of safety gaps $g_N$ and $g_S$ for routine pick (sec)	Test with reference data	Scatter of routine picks & frequency content	Not used
Lower frequency threshold (Hz) (Frequencies below threshold are not considered for SNR determination)	Test with reference data	Frequency content of signal	0.50 Hz

<sup>†</sup> Predicted arrival time depends on simple structural model (usually 1D velocity model). True 3D structure results in 'scattering' of true arrival times around predicted pick. Furthermore, imprecise initial hypocenter (usually taken from bulletin information) can cause additional 'scattering' on predicted arrival.

 Table 1: Summary of MPX parameters which have to be calibrated during the calibration procedure.

and  $L_S$ ), and the width of the safety gaps ( $g_N$  and  $g_S$ ), which separates NW from SNW as shown in Figure 3.

After this spectral density analysis the picking algorithm is applied to the waveform (picking stage). The MPX picking engine is based on the method of *Baer and Kradolfer* (1987), who calculate a characteristic function CFi from



Figure 3: Search window adjustment: The search windows NW and SNW are centered around the initial pick (here predicted  $t_{pred}$ ) and are separated by safety gaps  $g_N$  and  $g_S$ .

the envelope of the waveform. The onset is accepted as a pick for a value of CFi larger then a pre-defined Threshold1 for a certain amount of time (TupEvent). Threshold1 is automatically determined by MPX based on the spectral analysis done in the pre-picking stage, while TupEvent is an *a priori* value defined within MPX (depends on the characteristic frequency of the signal). This procedure of pre-picking and picking is iteratively performed 4 times with wide safety gaps in the first iteration and steadily refining (shrinking) safety gaps for the following iterations. This method allows a very high accuracy of the automatic picking. In order to achieve a satisfying hit-rate and accuracy, we have to adjust the following search window parameters:

### Window length $L_N$ and $L_S$ for Wiener filter (seconds)

The length of  $L_N$  and  $L_S$  is depending on frequency content of noise and signal. The shorter the better the localisation effect. On the other side, short windows may underestimate lower frequencies. Thus, we have to deal with trade off between localisation and reliability. The signal frequency is mainly driven by epicentral distance (attenuation of higher frequencies).

User Guide Suggestions (Aldersons, 2005):

### Set of 4 safety gap parameters $g_N$ and $g_S$ (seconds)

The safety gap is necessary to separate the signal and signal+noise window.

<sup>-</sup> Local approx. 1-3 s. For epicentral distance  $\Delta < 150$  km:  $\approx 1$  s.

<sup>-</sup> Regional: approx. 2-5 s. For  $150 < \Delta < 500$  km:  $\approx 2.0-2.5$  s

During the picking process, the gap is iteratively reduced. Therefore, we have to define four windows. The first gap value, which is used for the first iteration of the picking process, has to be chosen according to the expected error between initial pick (routine pick or predicted pick) and the true signal. If the difference between initial pick and actual signal is much larger than this gap, the picking engine may not be able to detect the onset properly as shown in Figure 4b. However, if we use a very wide first safety gap, miss-picks of



Figure 4: Safety gap adjustment: Trade-off between hit-rate and accuracy. For consistent automatic picks we have to use narrow safety gaps in combination with initial (predicted) picks close to the actual phase onset as shown in a). Initial picks far off the actual phase onset in combination with narrow safety gaps result in no or inconsistent automatic pick (b). Wide safety gaps increase probability of picking impulsive later phases (c).

later phases become more likely as demonstrated in Figure 4d. Therefore, it is necessary to reduce the error between initial and actual phase arrival as much as possible. This can be achieved by improving predicted arrivals (minimum 1-D model + station corrections + improved locations) as demonstrated by *Diehl et al.* (2008) or the use of reliable routine picks. To estimate the order of this error, we have to calculate the standard deviation and the maximum deviations between initial and reference picks. The fourth and last gap value is used for determination of the final pick and it is suggested to be between 40 and 80 ms. The range of its value is limited by two boundary conditions. In theory, a small gap improves the accuracy of the picking. On the other side, in combination with a low frequency wavelet, the picking may get unstable in this case, since a very narrow gap is not able to separate noise and signal+noise properly anymore. Therefore the fourth gap value has to be a compromise between target accuracy and frequency content of the signal. Furthermore, it should not be smaller than the actual sampling rate. Once we found values for the first and the last gap values, we chose the second and the third value such that the step size from one gap to another is equally distributed. We have to define a set of gap parameters for both types of guiding picks (routine or predicted), since their errors can be rather different.

User Guide Suggestion (Aldersons, 2005):

 $1^{st} \Rightarrow$  expected error between initial and actual onset (predicted-reference)

 $2^{nd} \Rightarrow$  equally distribution of step size (e.g. half of  $1^{st}$ )

 $3^{rd} \Rightarrow$  equally distribution of step size (e.g. 60 - 120 ms)

 $4^{th} \Rightarrow$  compromise between frequency & accuracy: 40 - 80 ms

#### Lower frequency threshold (Hz)

The lower threshold for maximum of signal amplitude spectrum. Frequencies below this threshold will not be used in the calculation of the signal to noise ratio. It could be interpreted as a pseudo high-pass filter, without effecting the shape of the waveform.

#### User Guide Suggestion (Aldersons, 2005):

The 'Lower frequency threshold' should be set about half the lowest frequency expected for the first onset (0.5 - 2.0 Hz).

### 4.2 Calibration of the Automated Quality Assessment

### Quality Classification via Pattern Recognition

Let us define an *a priori* quality weighting scheme of *L* classes for reference picking. Each of these classes is associated with a specific uncertainty interval. The automatic classification of the pick is realised by correlating a set of *N* discriminating variables (predictors) to a certain criterion group *j* (quality class). The mathematical objective of this so called 'discriminant analysis' is to weight and linearly combine the predictors  $P_i$  (i = 1, ..., N) in a way that maximizes the differences between groups while minimizing differences within groups (*Fisher*, 1936, 1938). The weighting coefficients  $F_{ij}$  are called the Fisher coefficients. Thus, the linear discriminant function  $D_j$  for class *j* can be written as

$$D_j = F_{0j} + F_{1j} \cdot P_1 + F_{2j} \cdot P_2 + \ldots + F_{Nj} \cdot P_N, \text{ with } j = 1, \ldots, L - 1 \quad (1)$$

 $F_{0j}$  represents the constant term and is also called 'independent term'. Thus we have to specify M = N + 1 Fisher coefficients. MPX determines N = 9predictors for each automatic pick, including parameters like signal to noise ratios, etc. For a detail list of predictors used in MPX see e.g., Aldersons (2004) or *Di Stefano et al.* (2006). Subsequently, MPX calculates the *L* discriminant functions for a given set of  $M \times L$  Fisher coefficients. Since  $D_j$  has to be maximized we assign the quality class j, which is related to the largest  $D_j$ . Figure 5a illustrates the automatic quality classification of MPX: a set of (appropriate) Fisher coefficients applied to the predictor values will return the MPX quality class  $W_{MPX}$  of the pick. A set of appropriate Fisher coefficients is derived from the reference data set as described in the following sections.

#### a) MPX Quality Classification:



Inverse problem solved through MDA

Figure 5: Concept of phase-quality classification with MPX. a) The quality class  $W_{MPX}$  of a phase pick is estimated from predictors measured around the pick weighted by Fisher coefficients. b) An appropriate set of Fisher coefficients is derived via MDA from the reference data set (training set).

#### Appropriate Fisher Coefficients via MDA

The principle of the MDA is summarized in Figure 5b. To calibrate the quality assessment towards a specific data set, we use the predictor values derived by MPX for a subset of reference picks (training set). The MDA then determines Fisher coefficients, which classify the predictors as good as possible towards the reference classes (classification target). The MDA procedure via the statistic package SPSS is described in section 6 in more detail.

It should be mentioned that misclassification costs are not symmetrically distributed. We rather accept downgrading of picks than upgrading of low qualities. Therefore the application of the MDA to our problem is not straightforward. Since the predictors are strongly related to the waveform characteristics, the result of the MDA significantly depends on the filter used prior to the picking. Thus, the determination of Fisher coefficients for a stable and high accurate weighting scheme strongly depend on the data set used for the MDA. For the Alpine region, it seems to be affected by the epicentral distance of the data, the magnitude range and the used waveform filter as described in *Diehl et al.* (2008).

#### Assessment of Absolute Timing Error with MPX

Since the pattern recognition described by *Aldersons* (2004) is mainly based on signal characteristics in the close neighborhood of the pick, it cannot account directly for the absolute timing error of the extended Baer-Kradolfer picker. However, if we assume that the majority of the reference picks are at the 'true' position, an effective automated quality assessment has to account also for the deviation between automatic and reference pick. Figure 6 illustrates such an apparent misclassified MPX weighting. Although MPX assigns the right



Figure 6: Example for an apparent misclassified weighting. The automatic pick is determined at the later impulsive phase. In contrast, the reference pick is located at the ramp-like first arrival phase. The error  $\varepsilon_{Pick}$  between automatic and reference pick is larger than the automatic assigned error  $\varepsilon_{MPX}$  corresponding to quality class  $W_{MPX} = 1$ . Considering the uncertainty of the later impulsive phase independent from the misidentification as first arriving phase, MPX assigns the correct weighting class  $W_{MPX} = 1$ .

quality class  $W_{MPX}$  to the (later) automatic pick  $P_{MPX}$ , it does not account for the absolute picking error  $\varepsilon_{Pick}$  between reference  $(P_{Ref})$  and automatic pick  $(P_{MPX})$ . If we adjust the MDA towards pure waveform classification, the performance of MPX will always be biased by the error between automatic and reference pick  $\varepsilon_{Pick}$ .

Based on the assumption that  $\varepsilon_{Pick}$  is strongly affected by the waveform characteristic (i.e., error of picking algorithm is smaller for impulsive first arrivals), *Di Stefano et al.* (2006) introduced the concept of 'TrueWeights'. The 'TrueWeight'  $W_{true}$  represents the quality class corresponding to the picking error  $\varepsilon_{Pick}$ . In order to account for  $\varepsilon_{Pick}$  in the automatic classification, they used  $W_{true}$  instead of the reference weight  $W_{Ref}$  as classification target in the MDA. However, the assumption above may not always be valid. Considering the picking algorithm determines an onset close to the reference pick for a low quality phase by accident. In such a case, the characteristics of a low quality onset would be mapped to a high quality  $W_{true}$ , although the reference weight  $W_{Ref}$  would indicate a low quality phase. This will lead to an increase of low quality picks upgraded to higher quality classes by MPX.

To avoid such contamination, we have to consider not only the picking error  $\varepsilon_{Pick}$  but also the the reference weight  $W_{Ref}$  for the 'TrueWeight' determination. The picking error  $\varepsilon_{Pick}$  is only used as  $W_{true}$ , if  $\varepsilon_{Pick}$  is larger than the reference error  $\varepsilon_{Ref}$ . Otherwise, we use the reference weight as  $W_{true}$ . The determination of  $W_{true}$  in our approach can be summarized in the following way:

If 
$$\varepsilon_{Pick} \leq \varepsilon_{Ref} \Rightarrow W_{true} = W(\varepsilon_{Ref}) = W_{Ref}$$
  
If  $\varepsilon_{Pick} > \varepsilon_{Ref} \Rightarrow W_{true} = W(\varepsilon_{Pick})$   
 $W(\varepsilon_{Pick})$  is the quality class that includes the error  $\varepsilon_{Pick}$ .

Considering  $\varepsilon_{Pick}$  in Figure 6, the 'TrueWeight' for the automatic pick is  $W_{true} = 3$ . As a consequence, waveform attributes of rather impulsive phases (like the later phase in Figure 6), will be mapped to lower quality classes during the MDA. Therefore, the MDA based on  $W_{true}$  instead of  $W_{Ref}$  will downgrade more of the rather impulsive phases, but on average, it will provide a higher accuracy in terms of absolute errors. The application to the Alpine region data set shows, that we have to deal with a strong trade-off between accuracy and MPX classification (*Diehl et al.*, 2008).

## 4.3 Assessment of Calibration Scheme

To assess the performance of the automatic picking and quality classification for a specific calibration scheme, we have to compare the automatic picks with the reference picks. We have to consider the following errors (see also Fig. 7):

- $\Rightarrow$  Timing-Error between reference and automatic pick:  $\varepsilon_{Pick}$
- ⇒ Classification-Error between reference weighting  $(W_{Ref})$  and automatic weighting class  $(W_{MPX})$ .

If we assume that the reference pick represents the 'true' first phase onset, a satisfying calibration is achieved if:

- The timing error  $\varepsilon_{Pick}$  between reference and automatic pick is within the automatic assigned error interval  $\varepsilon_{MPX}$  for most of the automatic picks (standard deviation  $\sigma_{ij}$  of all  $\varepsilon_{Pick}$  should be within automatic assigned error interval  $\varepsilon_{MPX}$ , where *i*: Reference weight  $W_{Ref}$ , *j*: MPX weight  $W_{MPX}$ ).
- Low reference quality picks are not upgraded to highest quality class by MPX quality assessment. A maximum classification-error between reference weighting  $(W_{Ref})$  and automatic weighting class  $(W_{MPX})$  of 2 classes  $(W_{Ref} - W_{MPX} \leq 2)$  for upgrading towards higher classes is

tolerated. However, the downgrading of picks is much less critical. Even for an ideal weighting scheme downgrading of higher qualities is required, since automatic picks far off the reference pick should get a lower weight (see also 'Absolute Timing Error' in section 4.2).



Figure 7: Errors that define performance of automatic picking and quality classification. The uncertainty of the reference pick  $P_{Ref}$  is represented by the error interval  $\varepsilon_{Ref}$  and its corresponding quality class  $W_{Ref}$ . Based on predictor values and Fisher coefficients the automatic pick  $P_{MPX}$  is classified as quality class  $W_{MPX}$ . The corresponding error interval is represented by  $\varepsilon_{MPX}$ . The deviation between reference and automatic pick is described by  $\varepsilon_{Pick}$ .

Usually we have to dial with a trade-off between these two conditions as discussed in 'Absolute Timing Error' of section 4.2. To assess the performance of MPX classification  $W_{MPX}$  and the picking error  $\varepsilon_{Pick}$  simultaneously, we introduced the 'TrueWeight'  $W_{true}$ . If we compare the weighting classes derived by MPX ( $W_{MPX}$ ) with the true weights  $W_{true}$  derived from the picking error and the reference class we can assess the picking error and the onset quality classification at once.

To assess the calibration for the complete reference data set, we compare the results of MPX with the reference data set in the so-called 'Classification-Matrix' as shown in Figure 8. In the case of an ideal calibration (and picking), all reference class '0' picks would be recovered as class '0' by MPX. The same would be valid for class 1,2,3, and 4. The 'Classification-Matrix' would be populated only on the diagonal elements as illustrated by grey squares in Figure 8b. For real data, we observe a smearing of quality classes by MPX. However, we accept downgrading of picks and also moderate upgrading of classes, as long as  $\sigma_{ij}$  remains within the error interval of the upgraded class. We do not accept upgrading of poor picks (e.g. class 3 or 4) to highest quality classes (0,1) as indicated by the black squares in Figure 8b and we require downgrading of picks far of the corresponding reference pick ( $\varepsilon_{Pick} > \varepsilon_{Ref}$ ).



Figure 8: The Classification-Matrix: Smearing of quality classes and standard deviation  $\sigma_{ij}$  of  $\varepsilon_{Pick}$  for each element.

## 5 Examples of Production Modes

Di Stefano et al. (2006) used MPX for the re-picking of first arriving P-phases from the Italian National Network (INGV) and demonstrated the improvement in terms of consistency of the phase data. The successful application of the calibrated MPX towards a large data set requires the following: Accurate initial picks, reliable phase identification, and the detection (and removal) of low quality waveform data (non-seismic signals like spikes, etc.). The following case study will describe solutions for the these problems in detail. For further description see also *Diehl et al.* (2008).

### 5.1 Application to the Alpine Region

The application of MPX to the greater Alpine region is described in detail by *Diehl et al.* (2008). The main conclusions of this study are:

- Stable and reliable automatic picking requires accurate initial picks. In case of heterogeneous data sets consisting of waveform data from several seismic networks, only predicted arrival times can be used. To improve accuracy of predicted arrivals, the iterative use of automatic picker and minimum 1-D models is necessary as demonstrated by *Diehl et al.* (2008). Precise predicted arrival times reduce the number of phase misidentifications significantly.
- The performance of MPX can be improved by the use of a distance-

dependent calibration scheme. In the case of the Alpine region, we used different sets of Fisher coefficients and waveform filters below and above an epicentral distance of 100 km. By splitting the data set into two distance ranges and by using a regional minimum 1-D model, we achieved a first order discrimination between Pg and Pn phases.

- To further improve the performance of MPX, an automatic assessment of the various phase onsets will have to be included in the picking algorithm, since the MDA cannot account for it directly. As any other such algorithms, MPX picks the earliest well-defined signal as the first arriving phase. However, beyond the crossover distance the first arriving Pn is often less well-defined than secondary arriving phases such as Pg or PmP. To correctly identify the picked phase multiple picking approaches, as suggested by *Bai and Kennett* (2000), have to be considered. They propose the use of attributes provided by short-term to long-term average ratios, autoregressive modeling and polarization analysis to pick and identify series of P- and S-phases.
- Low-quality waveform data (e.g., spikes, data gaps, step functions, etc.) have to be identified and removed prior to the automatic picking. See *Diehl et al.* (2008) for details on how these non-seismic signals can be automatically identified.

# 6 Cookbook Example: MDA via SPSS Software

We have seen in section 4.2 that we have to evaluate appropriate Fisher coefficients from the reference data set in order to calibrate the automatic quality classification scheme. This calibration is performed by a *Multiple Discriminate Analysis* (MDA). Basically, the MDA compares the classes assigned to reference picks with the corresponding predictors evaluated by MPX (for the automatic pick). However, the timing of the automatic pick  $P_{MPX}$  usually deviates from the reference pick  $P_{Ref}$ . The error between automatic and reference pick is  $\varepsilon_{Pick}$ . Hence, we have to dial with a trade-off between the timing and weighting scheme calibration: we cannot correlate the predictors of an automatic pick with its corresponding reference weight  $W_{Ref}$  without considering the error of the automatic pick  $\varepsilon_{Pick}$ . Therefore, we have to evaluate the 'true' weighting class  $W_{true}$  for  $P_{MPX}$ .  $P_{MPX}$  can be determined by three different methods as described in section 4.2:

- 1. Mainly  $\varepsilon_{Pick}$  is used for true weight determination (*Di Stefano et al.*, 2006).
- 2. Both  $\varepsilon_{Pick}$  and  $W_{Ref}$  are used for true weight determination (*Diehl et al.*, 2008). We recommend this method to account for absolute timing errors.

3. Another mixture between 1. and 2., which is not used so far.

After assigning the true weights to the automatic picks, we perform the MDA to correlate predictors to the target weighting classes by evaluating the best set of Fisher coefficients for each class. The target classes will be represented by the true and not by the reference weights!

In a first step, we apply MPX to our reference data set (or subsets of it) with adjusted search window setup (see 4.1) and a set of arbitrary default Fisher coefficients. The MDA via the statistic package SPSS uses the output of this (initial) MPX run. Once we estimated a new set of Fisher coefficients via the MDA, we have to update the according values in the MPX command-file and perform another MPX run.

The MDA is practically performed via Excel macros and SPSS in the following way (recommended by F. Aldersons):

- Import MPX export-file to an empty MS-Excel spreadsheet. Import has to start with row 13 and you have to set separators for the first columns by hand. Be sure the importing process was performed correctly (last column has to be labelled as 'AW'). If class definition starts from different values (e.g., from 1 in MPX and from 0 in reference data) you have to adapt this now.
- Open the MS-Excel template spreadsheet (includes certain macros) provided by F. Aldersons ('MPX2ImportYourDataW0 4.xls'). Be careful, if you use different error classes you have to modify the macro. Error intervals used for reference picking are also specified in the macro!
- Be sure spreadsheet of empty 'MPX2ImportYourDataW0 4.xls' is labelled as 'Sheet1'. Copy & paste the whole (eventually modified) spreadsheet (including two header lines) to the template. In the next step you have to execute the macro:  $\Rightarrow$  Tools  $\Rightarrow$  Macro  $\Rightarrow$  Macros...  $\Rightarrow$  'PrepareDataForMDA'. This will create two new spreadsheets: 'MPX2Export' (contains original export-file) and 'ForMDA' (contains data necessary for MDA: weights, predictors). The macro calculates 'true' weights with three different methods described above. The 'true' weights will be labeled as 'TrueWM1', 'TrueWM2', and 'TrueWM3' (M1  $\Rightarrow$  Method 1, etc.).
- In the next step, you have to open the SPSS template '*ReadyForImport-MDA.sav*' provided by F. Alderson. Of course, this step requires a installed version of SPSS. Then, copy the content of the Excel 'For MDA' spreadsheet (without the two header lines) and paste it to the SPSS '*ReadyForImportMDA.sav*' template.
- Now, we can perform the MDA within SPSS. Select from the SPSS menu: 'Analyze'  $\Rightarrow$  'Classify'  $\Rightarrow$  'Discriminant...'. We have to set some parameters for the MDA in the pop-up window (see Fig. 9). First, choose the

target for the MDA ('Grouping Variable'). In our case, it will be the true weight, determined with one of the three methods (TrueWM1-3). We recommend method 'TrueWM2'. We mark this data column in the upper left window of the pop-up menu with the left mouse button and accept this selection by pushing the 'add-arrow' next to the 'Grouping Variable' field. Then, we have to define the range of the 'Grouping Variable' with the 'Define Range...' option. In our example the 'Grouping Variable' ranges from 0 to 4 (class 0 to class 4). Subsequently, we have to define the set of predictors ('Independents') by selecting the nine parameters ('wfilston'-'cfnoidev') from the upper left window of the pop-up menu and add them to the 'Independents' field. Enable the 'Enter independents together' option (if not already enabled). The settings in the main window should agree with the menu shown in Figure 10. Additionally, we have to fix some settings in the sub-menus 'Statistics...' and 'Classify...'. In 'Statistics...' we have to enable all options (see Fig. 11), the settings for sub-menu 'Classify...' are presented in Figure 12.

• Now, we can execute the MDA by pushing 'OK' button in the main MDA menu. The results will be displayed in the SPSS viewer. You can extract the Fisher coefficients determined by the MDA from the 'Classification Function Coefficients' table. The group prediction of this set of coefficients can be seen in the 'Classification Result' table.

After evaluating this set of new Fisher coefficients via the MDA, we insert them in the MPX command-file and perform another MPX run. Subsequently, we have to analyse the export-file again. We have to ensure that our weighting scheme (see also section 4.3):

- Separates the classes properly (dominance of diagonal elements). If not, merging unresolved classes.
- Does not upgrade lowest quality picks to highest quality classes (smearing).
- Errors  $\varepsilon_{Pick}$  fall within assigned error intervals (trade-off between weighting and timing).

filenr	Grouping Variable:
autop	Þ
refep	(Defee Dense)
refew	Define Kange
abserr	Independents:
truewm1	
# truewm2	4
truewm3	
# wfilston	
# gpdlston	<ul> <li>Enter independents together</li> </ul>
# gpdlampr	O Use stepwise method Method
Statistic	cs) Classify) Save
Select	
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	Grouping Variable:	
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	# gpdlampr	
	¥ Spinner	
	<ul> <li>Enter independents together</li> </ul>	
	O Use stepwise method Method	
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Selection V	ariable:	
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	Valuetin	
Decet     Decet	Cancel OK	
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Figure 9: Main SPSS pop-up window to perform MDA (default).

Figure 10: Settings in main SPSS pop-up window to perform MDA.

Discriminant Analysis: Statistics					
Descriptives					
Means					
🗹 Univariate ANOVAs					
🗹 Box's M					
Matrices					
Within-groups correlation					
🗹 Within-groups covariance					
Separate-groups covariance					
🗹 Total covariance					
Function Coefficients					
✓ Fisher's					
 ☑ Unstandardized					
? Cancel Continue					

Figure 11: Settings in sub-menu 'Statistics...'.

Discriminant Analysis: Classification				
Prior Probabilities				
<ul> <li>All groups equal</li> </ul>				
Compute from group sizes				
Use Covariance Matrix				
Within-groups				
Separate-groups				
Display				
☑ Casewise results				
Limit cases to first:				
🗹 Summary table				
Leave-one-out classification				
Plots				
🗹 Combined-groups				
Separate-groups				
🗹 Territorial map				
Replace missing values with mean				
? Cancel Continue				

Figure 12: Settings in sub-menu 'Classify...'

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