Automatic Picker Developments and Optimization: A Strategy for Improving the Performances of Automatic Phase Pickers

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INTRODUCTION

Modern seismic networks, either permanent or temporary, can nowadays easily produce such large volumes of data that manual analysis is not possible. Effective and consistent automatic procedures for the detection and processing of seismic events are required to homogeneously process large datasets and to provide rapid responses in near real time.

One of the first modular components of the automatic analysis chain is generally a tool for the identification of seismic phases on the recorded seismic waveforms and the determination of their onset time, a process known as phase arrival picking. A variety of procedures for the automatic picking of phase arrivals have been proposed and successfully implemented during the last decades; almost all of these methodologies are based on the analysis of variations in amplitude, frequency, particle motion, or a combination of these. They typically deal with the first arriving *P* phase; less frequently they are able to detect secondary arrivals.

Most of the picking algorithms can be classified into three main families: energy methods, autoregressive methods, and neural network approaches.

The family of the energy methods is probably the largest, and includes the algorithms of Allen (1978) and Baer and Kradolfer (1987). In this class of algorithms a possible pick is declared when the ratio between a short-term average (STA) of the signal (or of a characteristic function of the signal) and its long-term average (LTA) exceeds a certain threshold parameter (for this reason they are often also called "STA/LTA" algorithms).

The algorithms of the second class, the autoregressive methods, determine an optimal pick time after an arrival has been already detected (*e.g.*, by an energy method). These algorithms study the variation of the statistical properties of the signal, trying to find the point in time that best separates the signal from the noise (Sleeman and Van Eck 1999; Leonard and Kennet 1999; Leonard 2000).

In the third family of methodologies, a neural network is trained to recognize and pick phase arrivals. The analysis can be performed directly on the signal (Dai and MacBeth 1995, 1997; Zhao and Takano 1999) or on selected signal features (Gentili and Michelini 2006).

Though in many ways the most basic class of picking algorithms, energy methods are nowadays also the most widely used. Based on simple mathematical operations, they require little computation and are therefore suitable for the analysis of very large datasets and for real-time implementation; furthermore, they need to process few or no samples after the phase arrival, an essential requirement for time-critical applications, like earthquake early warning. The main drawback of energy methods with respect to autoregressive and neural network approaches is that they demand significant a priori knowledge of the signal properties to correctly set the operational parameters (*e.g.*, triggering thresholds, time-average windows, validation parameters).

Finding an optimal setup for an energy-based picker can be difficult. A clear trade-off exists between sensitivity and the rate of false picks. Also, the influence of each parameter has to be carefully assessed. This operation is frequently carried out by a trial-and-error approach. General "recipes" for improved picking parameters exist (*e.g.*, Pechmann 1998, 2006), but they do not apply equally well to all the circumstances (different frequency bands, microseismicity, teleseismic events).

In this paper we introduce an optimization scheme for choosing the most appropriate set of parameters for a picking algorithm by using real picks and data acquired by a specific seismic network. The optimal model is chosen through searching in the global parameter space of the maximum of an objective function that depends on the comparison between automatic picks and manual picks performed on a dataset representative for a seismic network. The idea of optimizing the parameters of an automatic picker through a global optimization method was first introduced by Olivieri *et al.* (2007). Here we further develop the methodology by: (1) defining an advanced objective function that integrates different metrics in the comparison of automatic and reference manual picks, and

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(2) using seismic noise alongside earthquake recordings in the optimization process.

We show applications to two STA/LTA algorithms: the Allen (1978) picker and the new FilterPicker algorithm (Lomax *et al.* 2012, this issue).

ENERGY-BASED PHASE PICKING

In the energy-based class of algorithms, at each sample, the current value of the signal, or of a characteristic function (CF) of the signal, is compared with the value that can be predicted from the analysis of the previous samples. If the ratio between the current value and the predicted one is greater than a certain threshold, then a possible trigger is declared. Generally the current and the predicted values are respectively obtained through a short-term average (STA) and a long-term average (LTA) of the signal or of the CF. Many algorithms require extra validation on the declared trigger to discriminate true phase arrivals from noise spikes and to improve the time estimation of the arrival (Allen 1978; Baer and Kradolfer 1987; Ruud and Husebye 1992; Earle and Shearer 1994; Lomax *et al.* 2012, this issue).

One of the first and most widely used methods for automatic picking is the algorithm developed by Allen (1978, 1982). The method is based on comparison between the STA and the LTA of a characteristic function of the signal. The characteristic function is based on a combination of the signal and its time derivative at successive samples; this makes the algorithm sensitive to both the amplitude and the frequency of the signal. The STA and LTA are continuously calculated in two consecutive moving time windows: a short-time window (STA) that is sensitive to seismic events, and the long-time window (LTA), which provides information about the temporal amplitude variation of noise in the signal. When the STA/LTA ratio exceeds a preset value, a possible trigger is declared. At this point the algorithm performs several analyses on the signal to distinguish between the "true" triggers associated to earthquake arrival phases and the triggers related to the presence of seismic noise. In the first case the triggers are accepted, while in the second case they are rejected and declared to be "noise." A trigger is only accepted as a seismic phase if some constraints applied to the durations and amplitudes of peaks, the number of zero crossing of the signal, and the end of event, are verified. Several parameters control these extra checks, and they play an important role in the correct declaration of picks and in avoiding excessive triggering during acquisition of a noisy signal that may contain gaps and spikes.

The FilterPicker algorithm is thoroughly described in Lomax *et al.* 2012 (this issue). Here we remark that it is a broadband phase detector and picker algorithm especially designed for real-time operations. The algorithm, loosely related to the Baer-Kradolfer (1987) picker and to the Allen picker (Allen 1978, 1982), is characterized by a small number of critical operating parameters (five) and is designed to avoid excessive picking during large events and produce a realistic time uncertainty on the pick.

OPTIMIZATION METHOD

The determination of optimal picker parameters is based on the maximization of an objective function defined through a comparison between automatic and manual picks performed on real seismic traces. A global search for the optimal parameters set in the multidimensional parameter space is carried out using the genetic algorithm (Holland 1975; Goldberg 1989), a search technique well adapted for solving nonlinear problems. For the search for the best parameter set, we assume that a well-calibrated picker reproduces the same picks as a manual operator, for recordings of seismic events and ambient seismic noise.

Fitness Function

The definition of the fitness function is critical for any optimization method since it quantifies the quality of a solution. Given a set of reference traces containing manually picked events (one manual pick) and ambient seismic noise (no manual pick), we search for the optimal parameter values that satisfy three requirements:

1. automatic picks must be as close as possible to manual picks;
2. excessive triggering during the seismic events must be avoided;
3. triggering on ambient seismic noise must be limited.

From these conditions, the fitness function used during the optimization is defined as:

$$\text{Fitness} = \frac{1}{W}\sum_{i=1}^{M} g_i \tag{1}$$

where M is the number of traces, W is a normalization constant, and g_i is a function of the ith trace defined from the number of automatic picks N_i^a and of manual picks, N_i^m (N_i^m = 0 or 1), in one of the following ways:

- if $1 \le N_i^a \le P$ and $N_i^m = 1$:

$$g_i = \exp\left(-\frac{\left(t_{i,best}^a - t_i^m\right)^2}{2(\sigma_i^m)^2}\right) \tag{2}$$

where $t_{i,best}^a$ is the automatic pick closest in time to the manual pick t_i^m and σ_i^m is the associated manual pick uncertainty; P (Penalty number) is an integer ≥ 1 that represents the number of admissible automatic picks for traces containing event recordings.

- if $N_i^a > P$ and $N_i^m = 1$:

$$g_i = \frac{1}{1+\left|N_i^a - N_i^m\right|}\sum_{k=1}^{N_i^a}\exp\left(-\frac{\left(t_{i,k}^a - t_i^m\right)^2}{2(\sigma_i^m)^2}\right) \tag{3}$$

where $t_{i,k}^a$ is the kth automatic pick of the ith trace, and t_i^m is the corresponding manual pick.

- if $N_i^a = 0$ and $N_i^m = 1$:

$$g_i = 0, \tag{4}$$

- if $N_i^m = 0$:

$$g_i = \left(\frac{1}{N_i^a + 4}\right)^{N_i^a+1}. \tag{5}$$

Following the previous definitions, the value of normalization constant W in Equation 1 is defined as:

$$W = 0.25N_N + N_E \tag{6}$$

where N_N is the number of traces without manual picks and N_E is the number of traces with manual picks used during the optimization. For our inversion, a penalty in fitness function is introduced only when the picker produces more than $P = 4$ picks in the analyzed trace.

The function g_i measures the quality of a set of pick parameters on the individual ith trace. The values that g_i can assume depend on the manual and automatic picks obtained for the trace using the picker parameters of the considered model. The minimum and maximum values of g_i are respectively 0 and 1, indicating the worst and best solution quality for the given trace. If the trace is a recording of an earthquake with a manual pick, the value of the g_i function will be high when the picker gives a number of picks less than or equal to the number of admissible automatic picks P and when the best automatic pick approximates in time the manual pick as suggested by Equations 2 and 3. The value of g_i will be zero when, for the given trace, there is a manual pick but no automatic picks (Equation 4). Finally, for recordings of ambient seismic noise without manual picks, the function g_i increases when the number of automatic picks decreases, and it assumes the maximum value of 0.25 when the number of automatic picks is zero (Equation 5).

TEST CASE

We used the data acquired by the stations of the Irpinia Seismic Network (ISNet; Weber *et al.* 2007) to test and validate the optimization method described above. The network is installed in the Apennine chain, southern Italy, to study and monitor the active fault system responsible for the 23 November 1980 *Ms* 6.9 Campania-Lucania earthquake (Iannaccone *et al.* 2010). ISNet covers an area of about 100 × 70 km^2 and is composed of 24 stations, each of which is equipped with a strong-motion accelerometer and with either a short-period velocimeter or a broadband seismometer (Figure 1B).

We tested two energy-based algorithms for automatic picking: the Allen (1978) picker (hereinafter PICK_EW), implemented in the Earthworm real-time seismic software (Johnson *et al.* 1995) and the new FilterPicker algorithm (Lomax *et al.* 2012, this issue; hereinafter FP).

The optimization is based on a dataset of 105 vertical-component velocity traces from ISNet seismometers, composed of 70 traces of local and regional earthquakes (Figure 1D) and 35 traces with recordings of seismic noise. The selected events reflect the current seismicity of the area, characterized by many earthquakes of small magnitude ($M_L < 2.5$) located inside the network and a few events having higher magnitude ($M_L > 4$) located outside the network (Bobbio et. al. 2009). The first P arrivals have been manually picked, and the pick uncertainty (see Equations 2 and 3) has been attributed according to the four different classes described in Table 1.

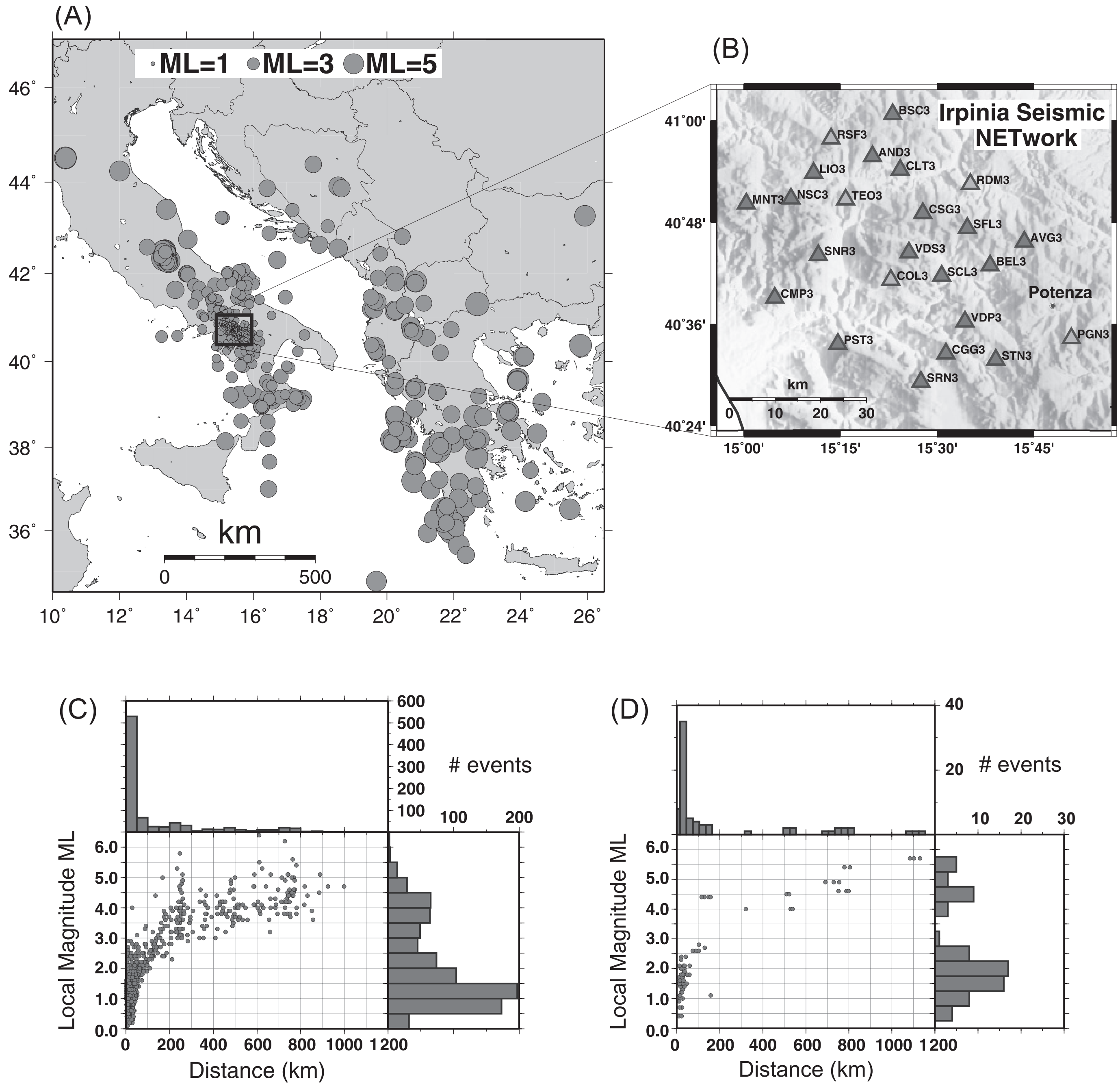
We performed a preliminary inversion to understand, for each automatic picker, how the parameters that regulate the algorithm are resolved by the fitness function. For PICK_EW, we found that, for seven of the 18 parameters (see Table 2), the fitness function is weakly dependent on the parameter value and the resulting distribution is almost flat. We therefore fixed them to their default values and focused the subsequent optimization process on the determination of the remaining 11 parameters. In the case of FP we verified that the fitness function significantly depends on all five parameters (see Table 3).

The search interval for the time constants used in the calculation of STA and LTA of PICK_EW was fixed at the whole allowed interval [0;1]. For the other inverted parameters of PICK_EW and for the five parameters of FP, the search interval has been centered on the default value, with the search interval ranging between zero and twice this value.

The optimization has been performed by the genetic algorithm technique using a crossover probability of 0.85 and a variable probability of mutation between 0.0005 and 0.25. In each generation the size of population has been fixed at 200 for PICK_EW and at 100 for FP, given the different numbers of parameters to optimize. The search is interrupted when the fitness function becomes stable between one generation and another. Figure 2 shows the convergence history of the optimization process for PICK_EW and for FP. In both cases the fitness function monotonically grows with the generation number, with a rapid increase during the first steps of search and a weaker growth during the last steps, up to a stable final value. The convergence of the fitness function is very rapid in the case of FP, where the maximum of fitness is already obtained after about 120 generations. In the case of PICK_EW, the convergence is slower and the maximum was obtained after about 650 generations. In both cases the final value of the fitness function is very similar: 0.69 for PICK_EW and 0.68 for FP. Table 2

TABLE 1
Quality Classes for Manual Picks and Associated Picking Uncertainty in s.

Class	Manual Picking Uncertainty σ^m
0	$\sigma^m \le 0.05$ s
1	0.05 s $\le \sigma^m \le$ 0.1 s
2	0.1 s $\le \sigma^m \le$ 0.2 s
3	0.2 s $\le \sigma^m \le$ 0.5 s



▲ **Figure 1.** (A) Location of the events selected to validate the optimized sets of parameters and (C) the corresponding magnitude/distance distribution. (B) ISNet seismic network (dark gray stations are equipped with short-period velocimeter and light gray stations have a broadband sensor). (D) Magnitude/distance distribution of the event subset used for the parameters optimization.

shows the optimized parameters obtained using PICK_EW and Table 3 shows the optimized parameters of FP.

Validation of Parameters

We tested and validated the optimized parameters for PICK_EW and FP on a larger dataset composed of 5,048 traces of local and regional seismic events (Figures 1A and 1C) and of 948 traces with high seismic noise. All the traces were recorded by vertical components of ISNet velocimeters during the period between December 2007 and December 2009. We compared the results with those obtained by the PICK_EW picker with parameters suggested by Pechmann (1998, 2006).

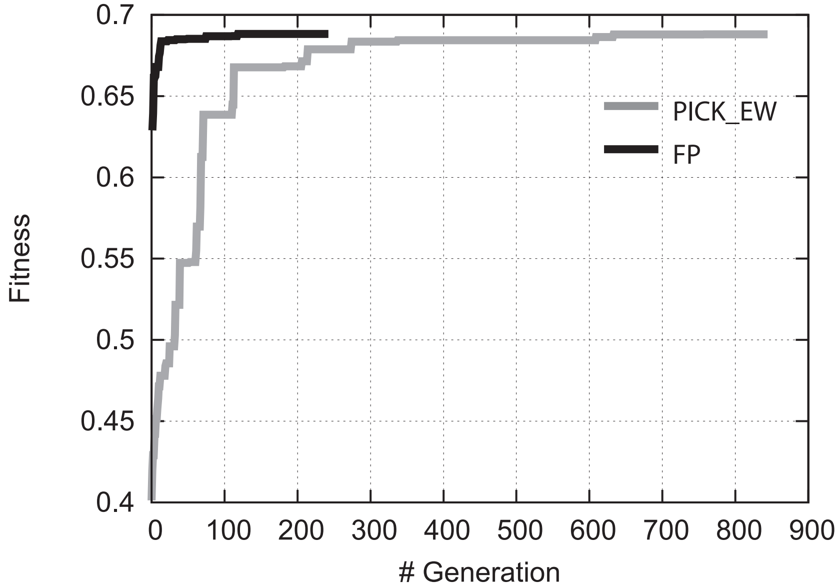
The main part of the selected earthquakes is formed by local events of small magnitude ($M_L < 2.5$) detected either by an automatic procedure or by manual operator and located inside the network. The remaining part is formed by a selection of regional events with a distance from the network's center smaller than 1,000 km and mainly located around the

TABLE 2
Earthworm Picker (PICK_EW) Parameters. For a detailed explanation of the various parameters see Mele *et al.* (2010).
Italics indicate parameters that were not optimized.

Parameter	Short Description	Suggested Value	Optimized Value
Itr1	Parameter used to calculate the zero-crossing termination count	3	5.15
MinSmallZC	Defines the minimum number of zero-crossings for a valid pick	40	75.35
MinBigZC	*Defines the minimum number of big zero-crossings for a valid pick*	*3*	*3*
MinPeakSize	Defines the minimum amplitude (digital counts) for a valid pick	20	13.43
MaxMint	*Maximum interval (in samples) between zero crossings*	*500*	*500*
i9	Defines the minimum coda length (seconds) for a valid pick	0	0.473
RawDataFilt	Filter parameter that is applied to the raw trace data	0.985 or 0.939 for broadband sensor	0.979
CharFuncFilt	Sets the filter parameter that is applied in the calculation of the characteristic function (CF) of the waveform data	3	0.0162
StaFilt	Filter parameter (time constant) that is used in the calculation of the short-term average (STA) of CF	0.4	0.15
LtaFilt	Filter parameter (time constant) that is used in the calculation of the long-term average (LTA) of CF	0.015	0.021
EventThresh	Sets the STA/LTA event threshold	5	2.34
RmavFilt	*Filter parameter (time constant) used to calculate the running mean of the absolute value of the waveform data*	*0.9961*	*0.9961*
DeadSta	Sets the dead station threshold	1200	2056
CodaTerm	*Sets the normal coda termination threshold (counts)*	*49.14*	*49.14*
AltCoda	*Defines the noisy station level at which pick_ew should use the alternate coda termination method*	*0.8*	*0.8*
PreEvent	Defines the alternate coda termination threshold for noisy stations	1.5	1.64
Erefs	*Used in calculating the increment to be added to the criterion level at each zero crossing*	*5000*	*5000*
ClipCount	*Specifies the maximum absolute amplitude (in counts zero-to-peak) that can be expected for the channel*	*2048*	*2048*

TABLE 3
FilterPicker (FP) Parameters

Parameter	Short Description	Suggested Value	Optimized Value
T_{filter}	Longest period for a set of filtered signals from the differential signal of the raw broadband input trace	300Δt	0.865 s
T_{long}	Time scale used for accumulating time-averaged statistics of the input raw signal	500Δt	12 s
S_1	Trigger threshold used for event declaration. A trigger is declared when the summary CF exceeds S_1	10	9.36
S_2	A pick is declared if and when, within a window of predefined time width, T_{up} after the trigger time, the integral of the summary CF exceeds the value $S_2 \cdot T_{up}$	10	9.21
T_{up}	Time window used for pick validation	20Δt	0.388 s



▲ **Figure 2.** Convergence history of the optimization process: fitness value as a function of the number of generations. Light gray: optimization of the PICK_EW picker. Black: optimization of the FP picker.

Apennine chain (central and southern Italy) and in southern Greece (Figure 1A). We manually picked the first arrival for earthquake traces, and we defined the pick quality according to the schema in Table 1. The manually picked dataset is composed of 4,034 short-period (SP) traces (acquired by S13J sensors) and 1,014 broadband (BB) traces (acquired by Trillium 40; CMG-40T and KS2000EDU sensors). This distribution of data reflects the availability of BB sensors among the velocimeters of ISNet (Figure 1B). The noise traces do not have manual picks, and we introduced them into the dataset to evaluate the correct behavior of optimized pickers on traces without seismic events.

In the following we will use the labels "PICK_EW_OPT" and "FP_OPT" to indicate the optimized versions of the two picking algorithms, while "PICK_EW" will indicate the algorithm used with the parameters suggested by Pechmann (1998, 2006).

On the selected dataset we retrieved 17,679, 13,032, and 13,062 automatic picks for PICK_EW, PICK_EW_OPT, and FP_OPT, respectively. The distributions of the number of picks per trace for the three different cases are shown in Figures 3A and 3B. The distributions give an understanding of how the optimized pickers meet the conditions imposed for the optimization. Moreover, these distributions help us to quantify the number of false picks (other phases than the first arrival) produced by each picker, as these can often confuse association algorithms that follow the pickers in an automatic analysis chain. For the traces with manual picks, the number of traces having more than four picks (the number of admissible automatic picks) is 530 and 330 for PICK_EW and PICK_EW_OPT, respectively, and 358 for FP_OPT. Thus, both of the optimized pickers obtained more than four picks only on 7% of the dataset containing event recordings. These results are better than those obtained by PICK_EW, which obtained more than four picks on 10% of the traces. For the recordings of ambient seismic noise, PICK_EW and PICK_EW_OPT provided more picks than FP. For this case the number of traces with more than four picks is 299 (32% of the whole dataset) and 287 (30%) for PICK_EW and PICK_EW_OPT, respectively, and only 56 (6%) for FP_OPT. Then, the FilterPicker better respects the conditions imposed for the optimization of the parameters.

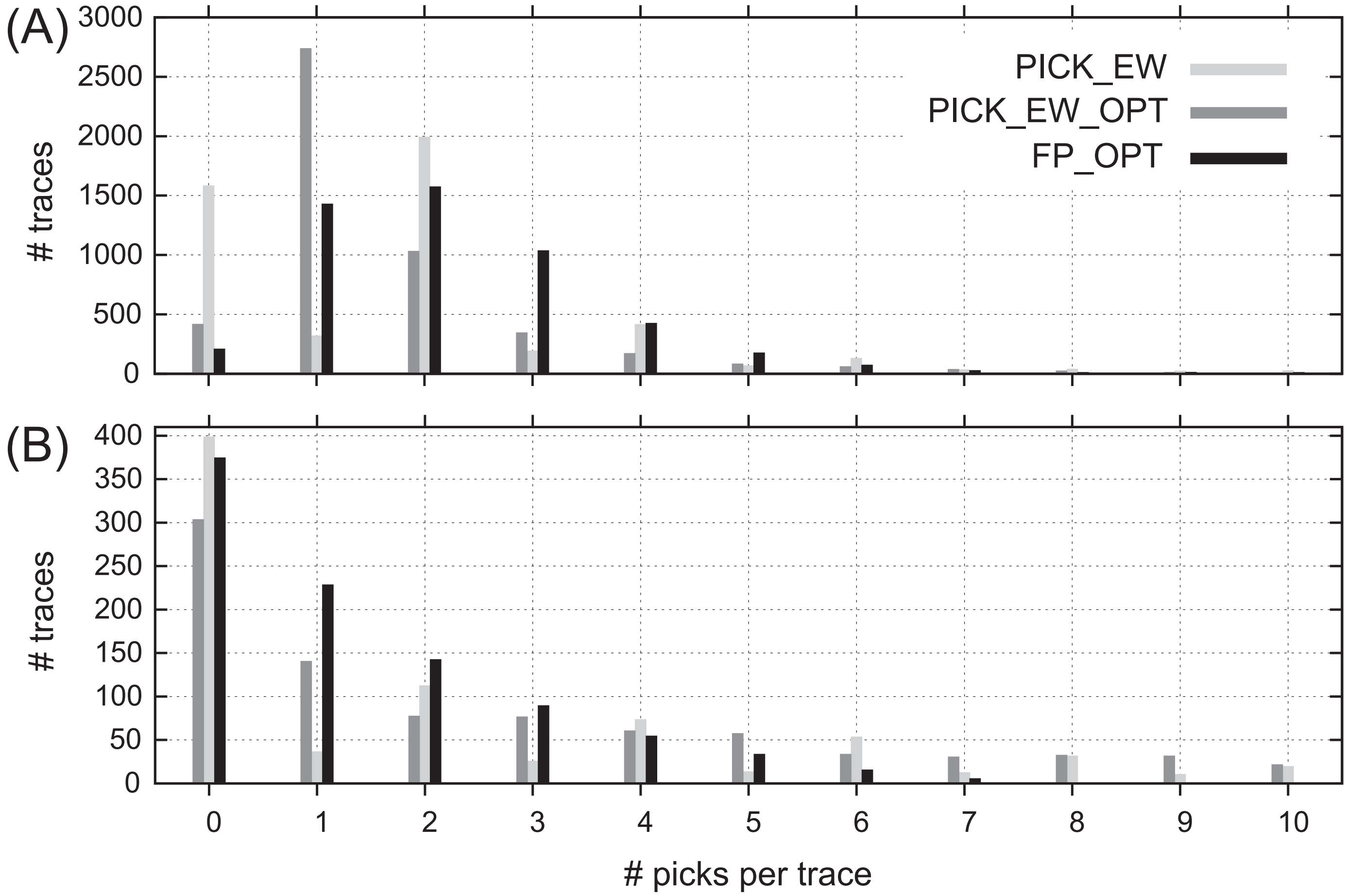
In the following we subdivide the analyzed traces into four different categories:

1. traces picked manually only (*i.e.*, missed automatic picks),
2. traces picked automatically only (*i.e.*, false automatic picks),
3. traces picked both manually and automatically (*i.e.*, correct automatic picks),
4. traces with neither automatic nor manual picks (*i.e.*, noise traces with no picks).

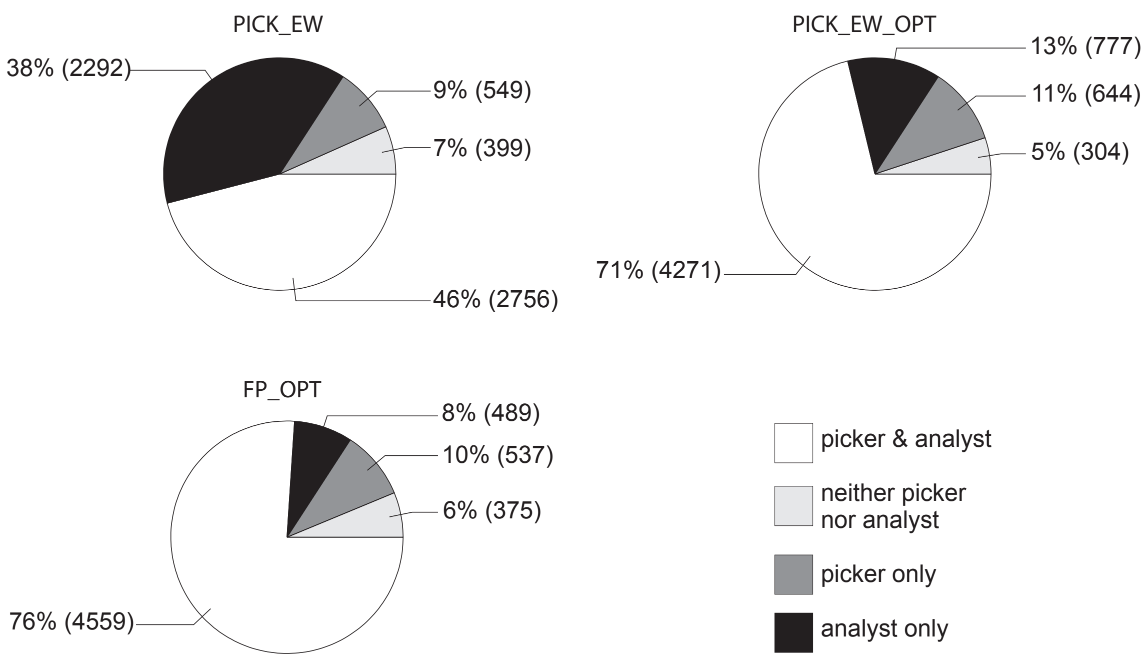
Only the traces where the time difference between the closest automatic and manual picks is less than 2 s are encompassed in the third category. This large time window is needed to fully explore the tails of the pick-error distributions.

Following this schema, a quantitative analysis of the pickers' performance is shown in Figure 4. The pie diagrams show that the optimized parameters used with both the pickers give, with respect to suggested parameters of PICK_EW, a higher number of traces picked manually and automatically (category 3) and, as consequence, a lower number of traces picked by analyst only (category 1). Moreover, FP_OPT, with respect to PICK_EW_OPT, gives a higher number of traces with neither automatic nor manual picks (category 4) and a lower number of traces picked only automatically (category 2). This means that FP_OPT gives a greater number of correct picks and reduces the number of false picks.

We analyzed the performance of the pickers on the different types of velocimetric sensors installed in ISNet. The results, synthesized in Table 4, show the percentage of BB and SP automatically picked traces in category 3 for the three ana-



▲ **Figure 3.** Number of automatic picks per trace containing manually picked events (A) and ambient seismic noise (B). Light gray: number of automatic picks per trace obtained using PICK_EW with the parameters proposed by Pechmann (1998, 2006); Dark gray: number of automatic picks per trace obtained using PICK_EW_OPT; Black: number of automatic picks obtained by FP_OPT. In order to make the figures clear, only data up to 10 picks per trace are shown.

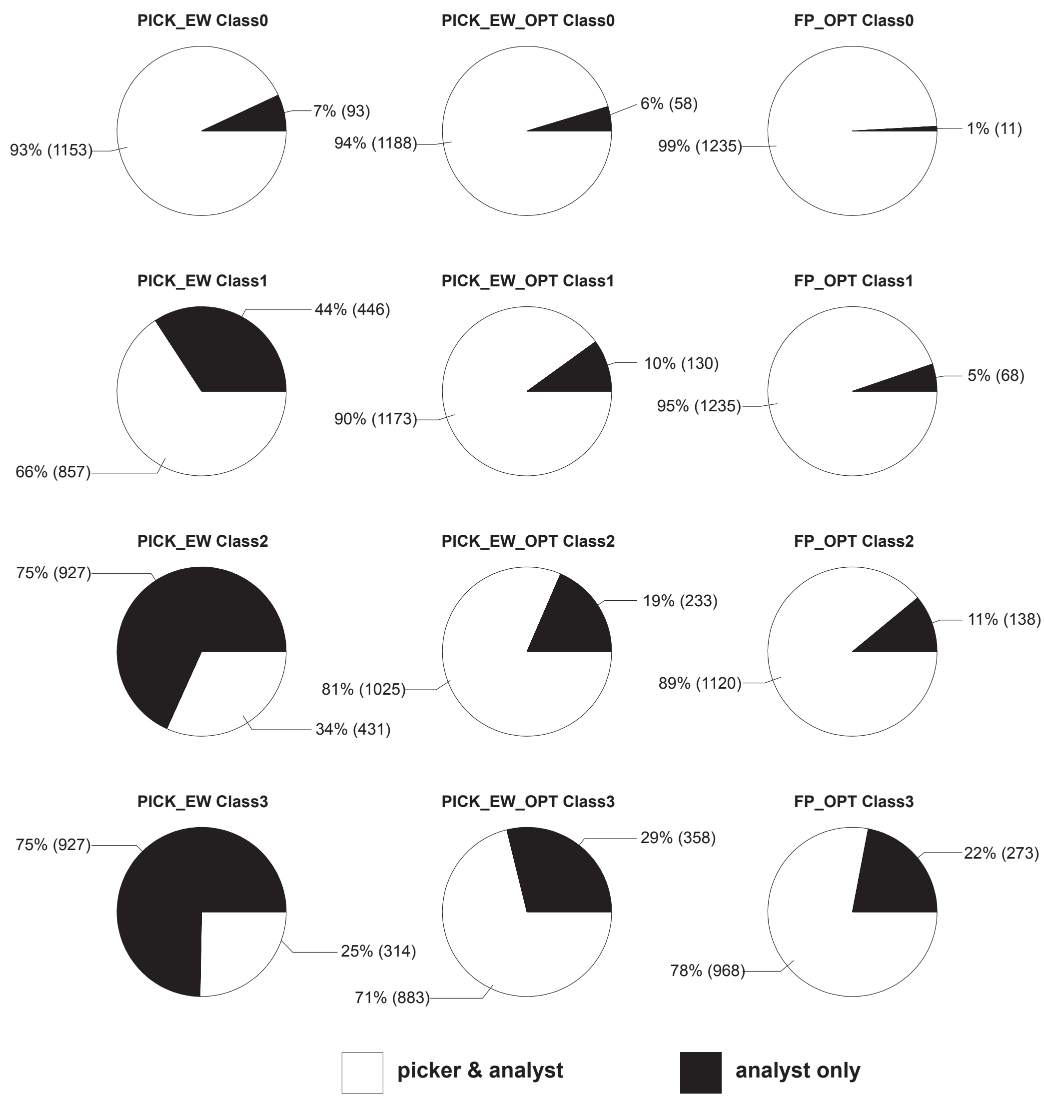


▲ **Figure 4.** Quantitative performance of the automatic pickers.

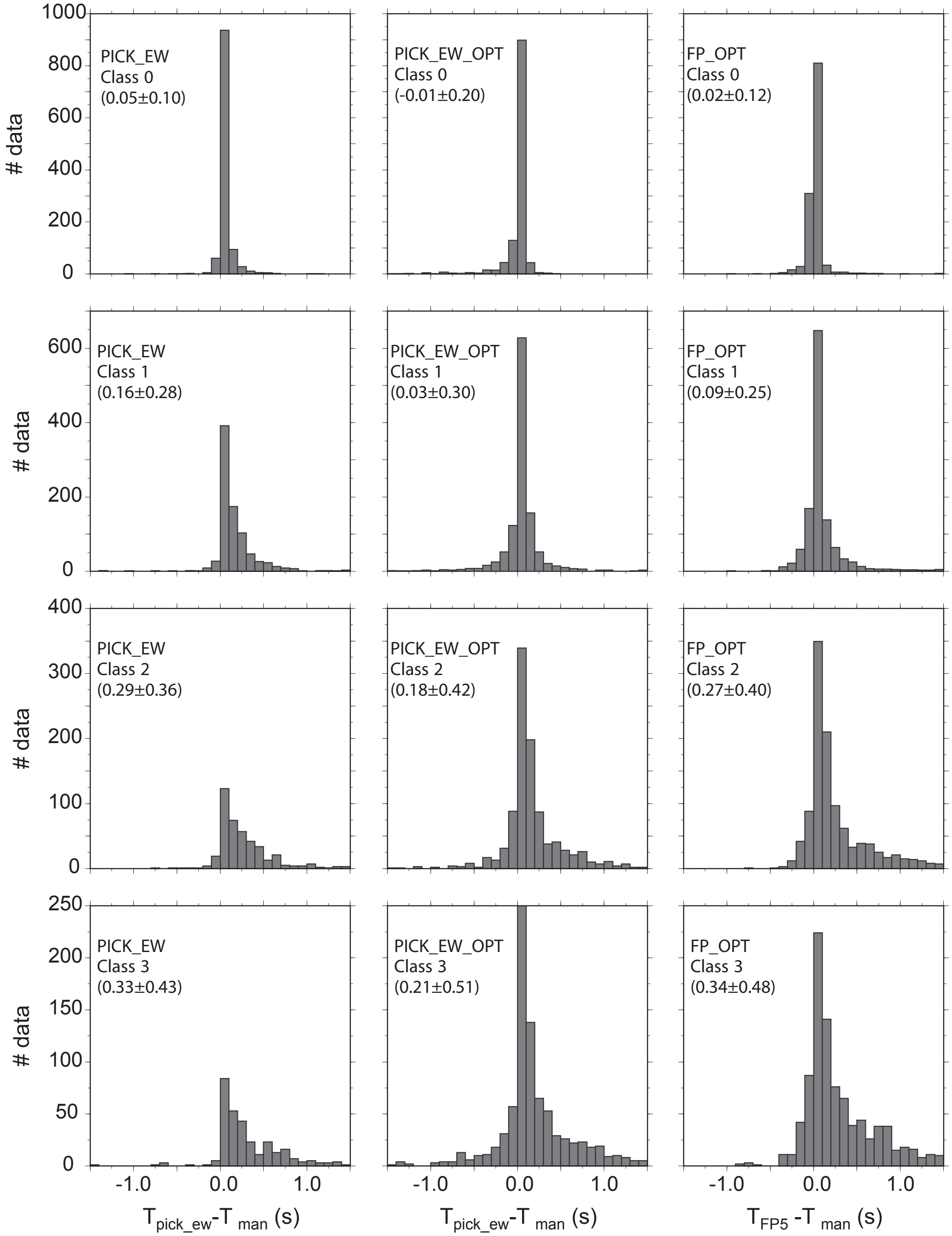
TABLE 4 Short-period and broadband picked traces (as a percentage) in category 3 for the PICK_EW, PICK_EW_OPT, and FP_OPT pickers		
	Percentage of correctly picked traces (category 3) for different sensor types	
Picker	% of automatically picked BB traces	% of automatically picked SP traces
PICK_EW	59	53
PICK_EW_OPT	74	87
FP_OPT	90	90

lyzed cases. With respect to PICK_EW, the optimized pickers picked correctly a significantly greater number of traces in both the BB and SP categories, and the FP_OPT performance is better than that of PICK_EW_OPT, especially for BB data. PICK_EW_OPT picked a greater number of SP traces than it did BB, while FP_OPT produced the same results in both categories, as it picked correctly 90% of data. We verified that the distributions of the residuals computed by PICK_EW, PICK_EW_OPT and FP_OPT, as compared to those of the associated manual picks, are very similar for both SP and BB data. This shows that, for the three different cases, the quality of automatic picks is independent of the type of sensor. For this reason, in the following, we will show the results for the whole dataset, without discriminating between the SP and the BB subcategories.

The pie diagrams in Figure 5 show the percentage of traces belonging to category 1 and 3 with respect to the total number of manually picked traces. The diagrams are organized according to the four pick-quality classes of Table 1. We interpret the pick-quality class as a marker of the signal-to-noise ratio of the first arriving *P* wave. For both pickers the number of automatic picks decreases with the decrease of signal-to-noise ratio. In all cases the percentages of traces picked by optimized parameters is higher than the percentages relative to PICK_EW with suggested parameters, and these differences appear more pronounced with the decrease of signal-to-noise ratio. This means



▲ **Figure 5.** Quantitative performance of the automatic pickers on traces organized by manual picking-quality classes (see Table 1).



▲ **Figure 6.** Distributions of time differences, in seconds, between automatic picks and corresponding manual picks within each class of manual picking-quality (see Table 1).

that FP_OPT and PICK_EW_OPT are more able to pick the first arrival, especially in cases of noisy recordings where the signal-to-noise ratio of the first arrival is low.

Figure 6 shows the distributions of residuals (manual time minus automatic time) within each class of picking accuracy. In all three cases, for each trace the automatic pick that is closest to the manual pick is used for the evaluation of residuals. The mean value and the standard deviation for each picking class (reported in figure legends) are in all three cases comparable. The dispersion of distributions increases with the decreasing accuracy of manual picks, as expected. The mean values of distributions are near zero for the traces with manual pick in class 0 and 1, while they are greater than zero for the traces with picks in class 2 and class 3. In these latter cases the distributions obtained by PICK_EW and by FP_OPT are not symmetric with respect to the zero value, and they present a positive coda indicating delayed picks with respect to the manual readings.

Figure 7 shows examples of traces relative to a regional earthquake (2009/04/06 Aquila, Italy; *Mw* 6.3; Maercklin *et al.* 2011) and to a local event (2009/05/18 Colliano, southern Italy; M_L 2.5) with manual and automatic picks from PICK_EW_OPT and FP_OPT. Each trace shows 10 s of signal, aligned with respect to the manual pick (located for all traces at 2 s). On each trace the black and gray vertical bars are the automatic picks by FP_OPT and PICK_EW_OPT, respectively. For the regional event (Figure 7A), FP_OPT tends to give a multiple of automatic picks after the manually picked first arrival, probably associated with secondary arrivals. For this event the differences between automatic and manual picks are, on average, of the order of a few tenths of a second for the traces with clear first arrival, while the differences increase for the more noisy traces or for first arrival with an emergent character. For the local event (Figure 7B) the results are very similar for both pickers, and the differences between automatic and manual picks are of the order of a few hundredths of a second for all the traces.

Test Using Phase Association

In typical seismic network operations, automatic phase picks are used to detect and locate seismic events through the association of picks recorded at different stations. The phase association criterion can be as simple as a time coincidence or can include more advanced checks on the compatibility between the arrival times at the stations and the possible location of the source, given the velocity model. This latter approach is generally more robust, since it prevents random time coincidences of noise energy from being declared as events. The phase association acts as a filter on the picked arrivals, removing all those arrivals that cannot be explained in terms of a common seismic source. For example, an automatic picker set to high sensitivity might produce several spurious picks for noise or later arrivals. An effective association algorithm can then successfully filter out these extra picks. For this reason, the performances of an automatic picker targeted at event detection have to be evaluated in connection with the phase association algorithm.

Here we use Earthworm's phase association module, named "binder" (Dietz 2002), which is based on a grid search for the most likely common hypocenter that explains a set of arrivals. We test the number of events detected using PICK_EW and FP and the binder configuration currently operational at ISNet (Iannaccone *et al.* 2010). In this configuration an event can be declared when at least five *P*-arrival times are available.

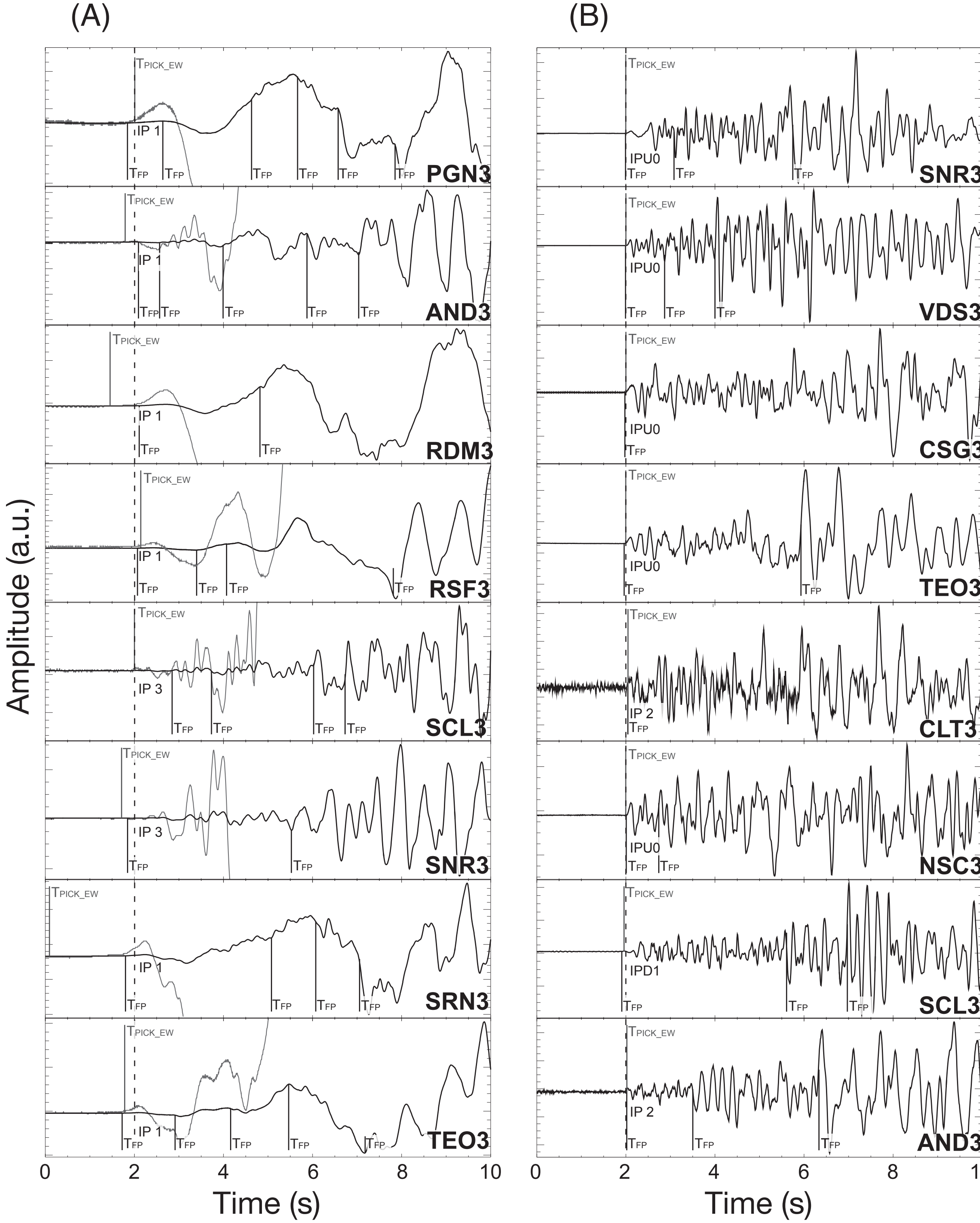
For our test, we created three separate datasets composed of recordings of events inside the network, events outside the network, and false events.

The first dataset is composed of the recordings of 301 events that occurred within the ISNet network between December 2007 and November 2009. We extracted these from the ISNet bulletin (http://isnet.na.infn.it/cgi-bin/isnet-events/isnet.cgi), selecting only events with at least six vertical recordings and with at least five manual picks. Thirty-nine percent of the events in this selected dataset have been manually detected, since the automatic procedure originally failed due to non-optimized picking parameters and/or temporary station failures.

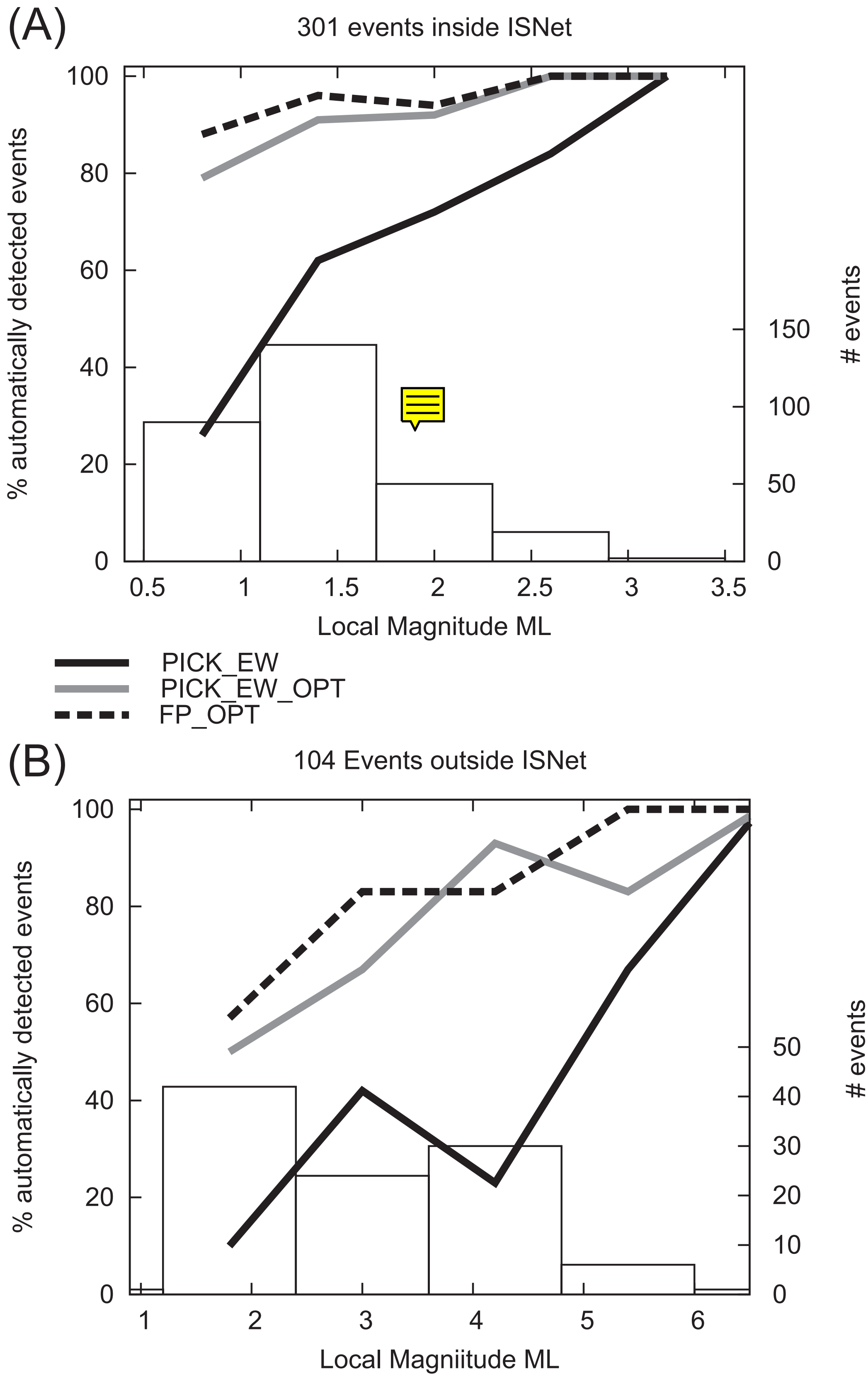
We picked automatically each trace using PICK_EW, PICK_EW_OPT, and FP_OPT. Then we associated all the automatically picked arrivals without making any kind of pick selection, and we detected the events using the binder. An event is declared *automatically detectable* only when the binder associates five or more automatic picks. Using FP_OPT, we obtained 282 detectable events (corresponding to 94% of total events); with PICK_EW_OPT the retrieved detectable events were 265 (84% of total events), and using PICK_EW we obtained 164 events (55% of total events). We organized all the events into classes of magnitude using a binning width of 0.6 and we computed, for each class, the percentage of detected events; Figure 8A shows the results of this analysis. With respect to PICK_EW with the suggested parameters, both the optimized pickers lead to a higher percentage of declared events in all the magnitude classes. This difference increases when the local magnitude decreases. All events with magnitude greater than 2.5 are detected using both the optimized pickers, while for the events with magnitudes less than 2.5, the percentage of detected events obtained by FP_OPT is higher than that obtained using PICK_EW_OPT. The greatest difference between the two percentage levels is observed for events with magnitude between 0.5 and 1.1, with about 90% of events detected by FP_OPT and about 80% of events detected by PICK_EW_OPT.

The second test uses earthquakes that occurred outside the ISNet. We selected 104 events with at least six traces and within 1,000 km from the network center. Sixty-two percent of these events have been added to the ISNet bulletin from external sources and have not been originally detected by the network. On this dataset, FP_OPT obtained 76 detectable events (corresponding to 73% of total events), PICK_EW_OPT retrieved 71 detectable events (68% of total events), and using PICK_EW with suggested parameters we obtained 26 events (25% of the total number of events). Figure 8B shows the percentage of detectable events organized by magnitude class using a binning width of 1.2. In this case also, the pickers with optimized parameters retrieve a higher percentage of declared events for all the examined magnitudes. The percentage of detected events obtained by FP_OPT is on average higher than that obtained using PICK_EW and PICK_EW_OPT; moreover, using FP_OPT we obtain 100% of detected events for magnitudes higher or equal to 5.5, while using PICK_EW and PICK_EW_OPT we obtain the same percentage only for events of magnitude 6.5.

Finally, we tested the pickers on a dataset of 49 false events produced by the simultaneous occurrence of spurious noise on channels of different seismic stations. These events have been detected by the automatic procedures of ISNet during stormy days with high wind pressure fluctuation between December 2007 and November 2009. Applying PICK_EW using the suggested parameters we obtained 23 false events (about the 47% of the whole dataset); PICK_EW_OPT retrieves 31 false



▲ **Figure 7.** Example traces and automatic picks for (A) the 2009.04.06 Aquila (Italy) *Mw* 6.3 and (B) the 2009.05.18 Colliano (southern Italy) M_L 2.5 earthquakes recorded at stations of ISNet. The PICK_EW and FP automatic picks obtained with optimized parameters are compared with the manual picks. On each trace the black and gray bars are the FP_OPT and PICK_EW_OPT automatic picks, respectively, while the dashed bar at 2 s is the manual pick. T_{PICK_EW} is the automatic PICK_EW_OPT pick; T_{FP} is the automatic FP_OPT pick. The four-character code for the manual pick identifies the features of the manually picked arrival. The first letter defines the phase onset (emergent or impulsive); the second letter (*P*) defines the type of wave; the third letter (not always present) indicates the phase polarity (up or down); the last number is the quality of manual picks defined according to Table 1. To better show the early phase arrivals, the first seconds of the traces in (A) are also represented with amplitude increased by a factor of 10 (gray curves).



▲ **Figure 8.** Results of statistical analysis performed using the optimized picker on recordings of events inside (A) and outside (B) the network. The lines indicate the percentage of automatically detected events by PICK_EW (black line), PICK_EW_OPT (gray line), and FP_OPT (black dashed line) as a function of the local magnitude M_L. The distributions show the number of events used in relation to the local magnitude.

events (about 63% of the whole dataset) and FP_OPT produces only 10 false events (about 20% of the whole dataset).

DISCUSSION AND CONCLUSIONS

In this paper we proposed an optimization scheme for improving the performances of automatic seismic phase pickers by using real manual picks and data from a specific seismic network. The strategy is based on the comparison between manual picks and automatic measurement of arrival times retrieved by automatic picker on a dataset representative of the seismic network. The dataset is composed of signals of seismic events and traces of seismic noise. The optimal choice of picker parameters is performed following a fitness function that quantifies the goodness of a parameter-set in reproducing the manual picks and not producing picks on traces with only seismic noise. We used the genetic algorithm optimization technique to search for the maximum of the fitness function to determine an optimal parameter-set for each automatic picker. The genetic algorithm has been used in many optimization problems, and in our case has shown itself to be a valid tool for a wide exploration of a multi-parametric model space and for finding valid models verified by a posteriori analysis. In this work we have not tested the performances of other optimization techniques; however, global optimization techniques such as Monte Carlo or simulated annealing could be easily introduced into the scheme of optimization as an alternative to the genetic algorithm.

We applied this optimization scheme with the aim of tuning the picker parameters for the picking of high-frequency first-arrival phases of local and regional events recorded by seismometers at the ISNet network in southern Italy. However, the procedure is also applicable to far *S*-wave picking and regional and teleseismic picking where there may be a lower dominant frequency of the picked phases.

The analysis is performed using two different pickers: the classic Allen (1978) picker, as implemented in Earthworm (PICK_EW), and the new FilterPicker (FP; Lomax *et al.* 2012, this issue). In order to test the retrieved best parameter-sets we performed statistical analysis on the automatic picks obtained on a dataset of three years of local and regional data acquired by the network. When compared with standard parameter settings, the tuned pickers produce a higher number of realistic onset times. Indeed, more than 70% of the manual picks were automatically estimated with optimized pickers instead of 46% produced by the suggested parameters. Moreover, the distributions of residuals obtained by comparing automatic and manual picks have a large peak around 0 s and standard deviations comparable to the errors of manual onset time measurements. Finally, we verified the parameter-set using the automatic obtained picks as input of the Earthworm phase association routine. With optimized parameters, we found a number of correctly detected earthquakes significantly higher than the number of earthquakes detected using PICK_EW with suggested parameters. The main differences between optimized and standard parameter settings are observed for events of low energy having relative low signal-to-noise ratio and emergent first arrival. For these traces PICK_EW with standard parameters is unable to pick enough arrival times to enable them to be located.

The proposed optimization scheme is also a useful tool in comparing the performances of different pickers applied to the same dataset. In our analysis the two pickers with the optimized parameters generally provided similar performances with some small differences. FP with respect to PICK_EW provided a higher number of correct picks, especially when the first arrival is noisy, and it did not trigger excessively on the traces with seismic noise. This means that FP, compared to PICK_EW, is better able to identify local events of small energy, and it produces fewer declarations of false events.

DATA AND RESOURCES

Seismic data used in this study were collected by ISNet (Irpinia Seismic Network) managed by AMRA Scarl (Analisi e Monitoraggio del Rischio Ambientale). The data are available online at the Web site http://seismnet.na.infn.it; data availability is subject to registration. The figures are made by the following software packages: Generic Mapping Tools (http://gmt.soest.hawaii.edu/), Seismic Analysis Code (http://www.iris.edu/software/sac/), Gnuplot (http://www.gnuplot.info/), and Ploticus (http://ploticus.sourceforge.net/doc/welcome.html). Data analysis and processing are made by using the modules PICK_EW and BINDER_EW of Earthworm (http://folkworm.ceri.memphis.edu/ew-doc/). The FP phase detector and picker is available in the Java program SeisGram2K (http://alomax.net/seisgram) under the option "Pick->FilterPicker" and as an Earthworm module; Java and C source for FP are available at http://alomax.net/FilterPicker/. The optimization code is available on request from the corresponding author.

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