Ⓔ

On the Perception of Audified Seismograms

by Lapo Boschi, Laurianne Delcor, Jean-Loïc Le Carrou, Claudia Fritz, Arthur Paté, and Benjamin Holtzman

ABSTRACT

Recordings of the Earth's oscillations made by seismometers, following earthquakes or other geophysical phenomena, can be made audible by simply accelerating and playing them through an audio reproduction system. We evaluate quantitatively the possibility of using such an acoustic display of seismic data for practical applications. We first present to listeners examples of two categories of data, based on geophysical parameters that are not revealed to them. In the first test, the control parameter is the terrain, either oceanic or continental, sampled by the propagating seismic wave. In the second test, it is the geometry of the seismic fault, which can be either thrust or strike slip. The listeners are asked to associate each of a set of audified seismograms, that are presented to them binaurally, to either one of the two categories. At the end of the test, they are asked to define the features of audified signals that helped them in completing their task. The third and final test consists of repeating the fault-geometry categorization exercise after a brief training session. About 35, 27, and 17 listeners participate in the first, second, and third tests, respectively. Both sexes, a wide range of ages, and three different backgrounds (acousticians, geoscientists, and physicists) are represented. Although the number of listeners is too small for a definitive statistical analysis, our results suggest that listeners are able, at least in some cases, to categorize signals according to all the geophysical parameters we had chosen. Importantly, we clearly observe that listeners' performance can be improved by training. Our work opens the way to a number of potentially fruitful applications of auditory display to seismology.

Electronic Supplement: Audified seismograms for different paths and sources.

INTRODUCTION

Auditory display or sonification of scientific data has been applied successfully to research topics in several disciplines (e.g., Cowen, 2015). Seismic data analysis naturally lends itself to audification, a particularly simple form of sonification which consists of accelerating seismic signals (the frequency of which is lower than that of audible sound) before playing them through an audio reproduction system. Auditory display of seismic data was first explored during the Cold War, when the ability to distinguish underground nuclear tests from natural earthquakes acquired a political relevance (Speeth, 1961; Frantti and Leverault, 1965; Volmar, 2013). Audification was eventually discarded, in this context, in favor of seismic-array methods (Volmar, 2013); in recent years, however, it has been revived by seismologists, mostly for purposes of teaching and dissemination (e.g., Dombois and Eckel, 2011; Kilb *et al.*, 2012; Peng *et al.*, 2012; Holtzman *et al.*, 2014; Tang, 2014). Our own experiments (Paté *et al.*, 2016, 2017) convinced us that it is a valuable and inspirational tool for the analysis of seismic data in many contexts. We suggest that it might also soon find more specific, effective research applications.

This study attempts to contribute to the quantitative analysis of the human auditory system's response to audified seismic data. As researchers peruse data via auditory display, the implicit assumption is made that they are capable of recognizing patterns and completing some related tasks by hearing. We question this assumption for the case of audified seismic data and thus begin to evaluate what can be achieved by audification that is not already implemented through traditional techniques in seismic data analysis. Both the early work of Speeth (1961) and the recent efforts by our group (Paté *et al.*, 2016) indicate that listeners can detect meaningful clues in audified seismic signals and thus categorize the signals according to these clues. Paté *et al.* (2016) showed that the categories formed by the listeners can be associated with several geophysical parameters, but listeners could not entirely distinguish the effects of individual parameters (e.g., source–receiver distance, geological properties of the terrain at the receiver and between source and receiver, etc.) from one another. We present here a different approach to the analysis of audified data: listeners are asked to complete a constrained-categorization task, rather than a free-categorization one, on two sets of data, each controlled by a single geophysical parameter (Earth structure in the area where the recorded seismic waves propagate; focal mechanism of the source). The listeners' performance in auditory analysis is compared with their performance in a similar task, completed via visual analysis of analogous data. We consider the visual analysis of a plot to be a traditional task that most individuals with some scientific background are, to some extent, familiar with. Visual analysis serves here as a reference against which results of auditory tests can be compared, and, accordingly, its results are not analyzed in as much detail. Listeners are then briefly trained and the auditory

doi: 10.1785/0220170077

test repeated after training, with a general improvement of test scores. Finally, listeners are asked to explain the criteria they followed to categorize the data, and their description is compared with quantitative parameters computed from the data.

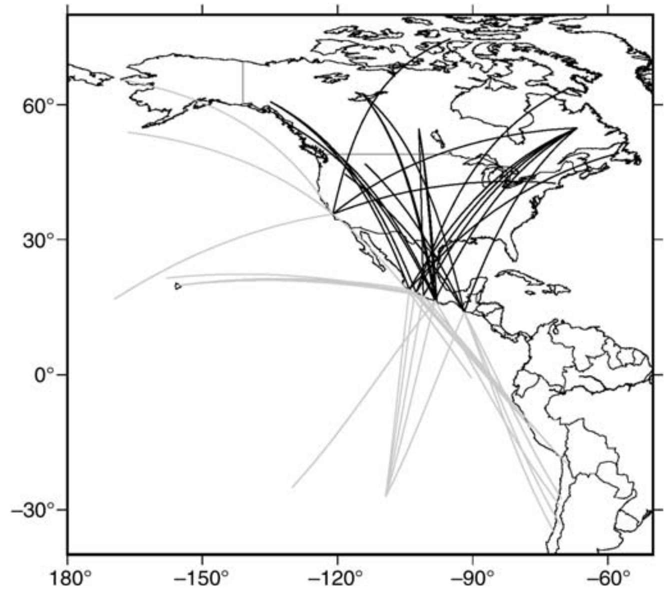
DATABASE

The work of Paté *et al.* (2016) evidenced the difficulty of disentangling the influences of different physical parameters on the seismic signal (e.g., source–receiver distance, properties of the source, geology at the receiver location, and geology between source and receiver). We compiled two new audified seismic data sets, each designed to emphasize the role of one specific parameter. Both data sets only included events of magnitude between 6 and 8, with focal depths estimated by Incorporated Research Institutions for Seismology (IRIS) between 20 and 40 km and recorded at epicentral distances between 4000 and 6000 km. The scale lengths under consideration are therefore different from those of Paté *et al.* (2016), who used recordings of a magnitude 5.5 event made no more than a few hundred kilometers from the epicenter. All events contributing to either data set occurred between 9 August 2000 and 18 April 2014.

The first data set (DS1) is limited to source mechanisms of the strike-slip type, with magnitude between 6 and 7, and the propagation path (approximated by an arc of great circle) is required to lie entirely within either a continental or oceanic region. Figure 1 shows that events in DS1 are located along the Pacific coast of Mexico and in California, whereas stations can be located in North America (continental paths), on ocean islands throughout the Pacific ocean, and in Chile or on the Alaskan coast (oceanic paths). It is well known that a seismic waveform is affected in many ways by the properties of the medium through which the wave propagates before being recorded. For example, based on the work of Kennett and Furumura (2013) and Kennett *et al.* (2014) on waveform differences across the Pacific Ocean, we anticipated that the bulk properties of oceanic versus continental crust and lithosphere would result in profoundly different seismograms and audified signals. We expected this ocean–continent dichotomy to be far more important than other parameters in characterizing traces in DS1, and we assumed that it would also guide the subjects' response to the corresponding audified signals.

The second data set (DS2) is limited to continental propagation paths but includes both strike-slip and thrust events of magnitude between 6 and 8 (Fig. 2). We expected differences between signals generated by strike-slip and thrust events to be more subtle and harder to detect, whether visually or aurally. Again, all sources contributing to DS2 are in southwestern North America; stations are distributed throughout Canada and the United States, and, in one case, in the Caribbean. Earthquake mechanisms were obtained from the Global Centroid Moment Tensor Project (see Data and Resources).

Approximately 500 seismograms meeting the requirements of DS1 and DS2 were downloaded from the IRIS database (see Data and Resources). Only traces showing, at a visual analysis, a relatively high signal-to-noise ratio (SNR) were kept. Traces vis-

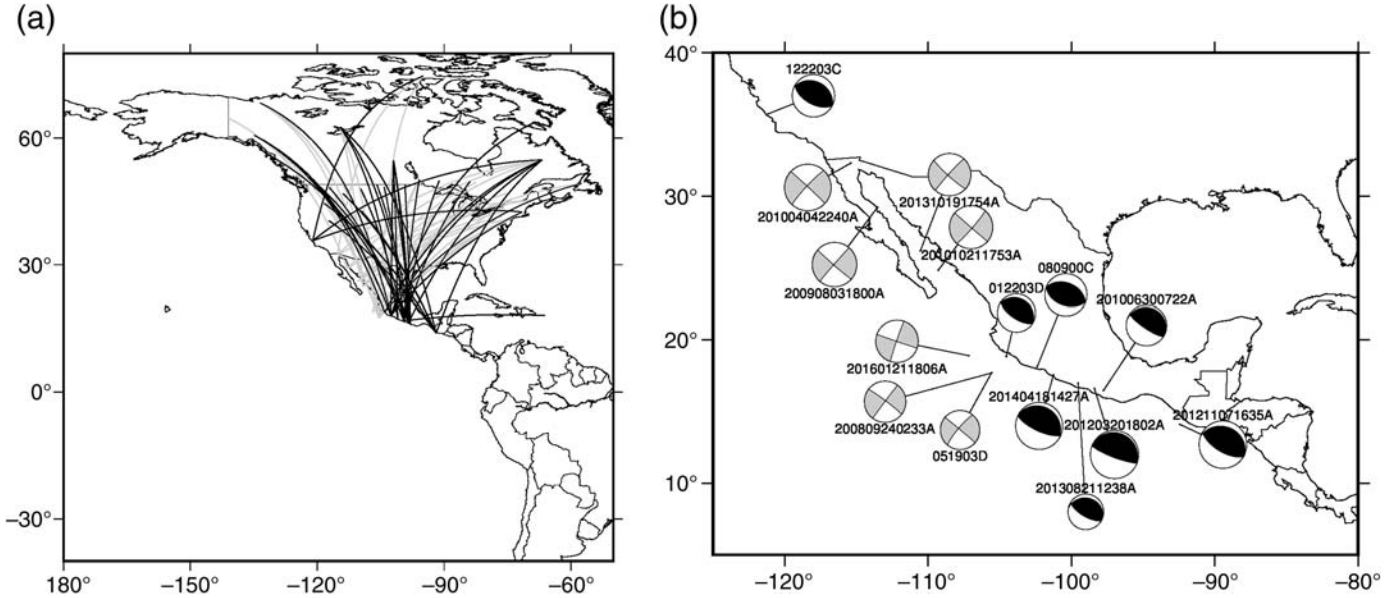


▲ **Figure 1.** Surface projections of ray paths associated with audified data set DS1. DS1 consists of recordings of events occurring along the west coast of Mexico, made at stations at epicentral distances of 4000–6000 km; recordings made at North American stations correspond to ray paths only traversing continental terrain (black lines), whereas stations along the Pacific coast or on ocean islands result in purely oceanic paths (gray lines).

ibly containing signal from more than one seismic event were likewise discarded. As a result, DS1 includes 23 continental and 23 oceanic signals, whereas DS2 includes 52 strike-slip and 52 thrust signals. No filtering or instrument-response correction was applied to the data. The sampling rate of all downloaded seismic traces is 50 Hz. The duration of traces to be audified is 8000 s, starting 1800 s before the *P*-wave arrival as found in the IRIS catalog and including the most significant seismic phases and most or all of the coda. Time is sped up by a factor of 1200, selected so that all frequencies present in the seismic traces are mapped into the audible range (Holtzman *et al.*, 2014). Each sonified signal was normalized with respect to its maximal value. The resulting, audified 6-s-long signals are turned into Waveform Audio File Format (WAV) files via the MATLAB function audiowrite (see, Data and Resources). Their spectra show most energy between 20 and 600 Hz.

EXPERIMENTS

All experiments (Table 1) were conducted in an acoustically dry room (i.e., not entirely anechoic but with very little reverberation of sound). The subjects played audified seismic signals on a laptop computer via a MATLAB-based software interface and listened to them through an audio card and closed headphones with adjustable volume (see, Data and Resources). Some tests involved the visual, rather than acoustic display of the signals, which was also implemented with the same interface: seismograms were plotted in the time domain as in Figure 3 (albeit



▲ **Figure 2.** (a) Same as Figure 1, but for data set DS2, which only includes recordings made at stations within the North American continent of either strike-slip (gray ray path curves) or thrust (black) events. Their epicenters and focal mechanisms (Ekström *et al.*, 2012) are shown in (b) using the same color code.

with a longer time window, extending from ~0 to ~20, 000 s), and subjects had no way to modify the plots' size or format. We provided each subject with all necessary instructions at the beginning of the test so that the subject would be able to take the test autonomously. The subjects knew that the signals were recordings of earthquakes; at the beginning of the test, they were told that all signals would belong to one and only one out of two possible families, named A and B. By assigning neutral names to data families and providing no information as to their nature, we minimize the bias that might be caused by a specialized (geophysical) knowledge/understanding of the data. After each test, subjects were asked to briefly explain the criteria they had followed in responding to it. They typed their answers on the computer used for the test.

Table 1
Summary of Listening Experiments

Data Set	Number of Waveforms	Subjects A	Subjects G	Subjects P	Audio	Visual	Training
DS1	40	18	9	8	Yes	Yes	No
DS2	40	15	5	7	Yes	Yes	No
DS2	36	10	3	4	Yes	No	Yes

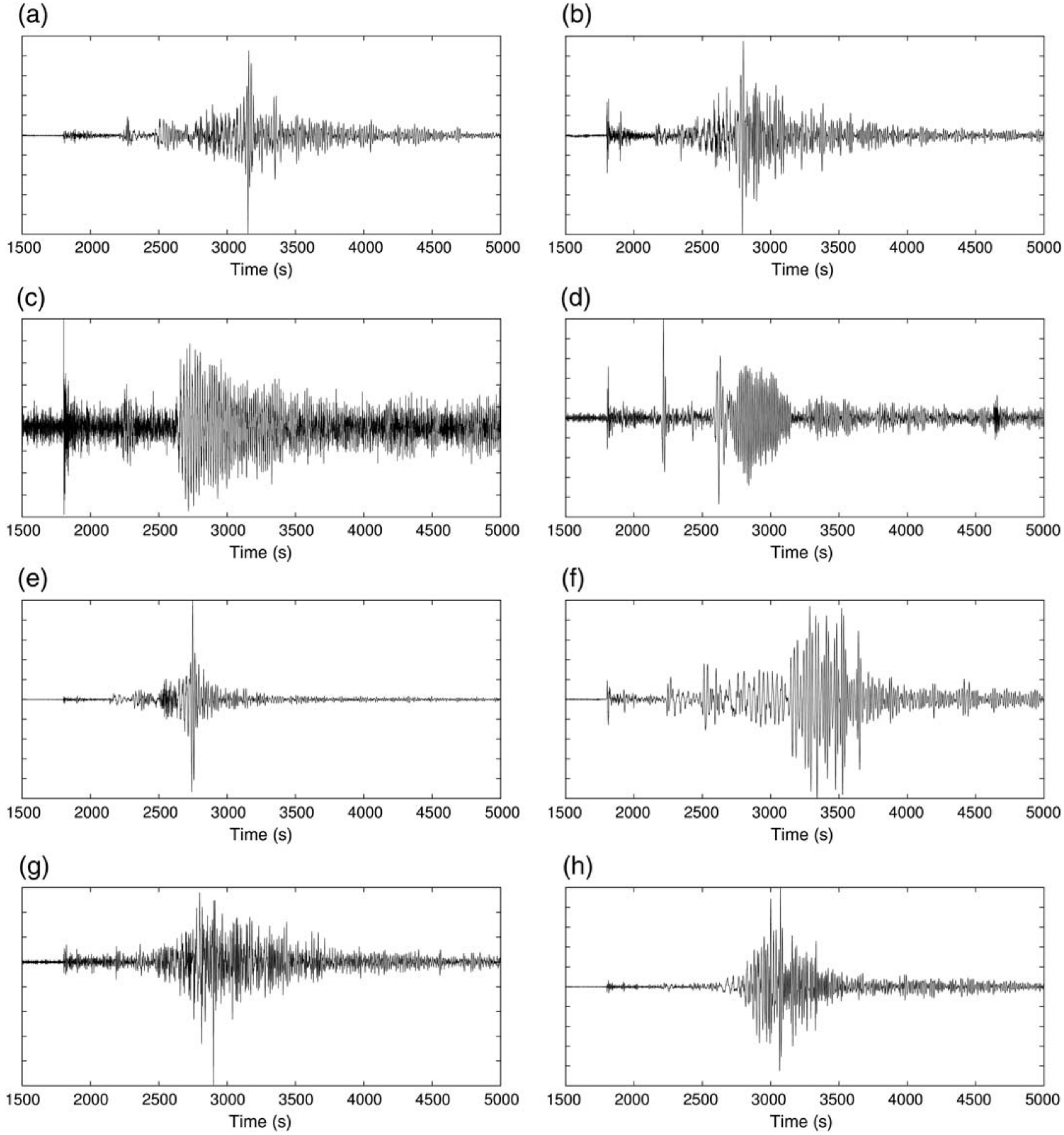
The first two columns to the left indicate how many signals from which data set were presented to the subjects. The letters A, G, and P stand for acousticians, geoscientists, and physicists, respectively; audio and visual indicate which type(s) of data were provided to the subjects; training refers to whether subjects were trained before taking the test.

All subjects were researchers, faculty, and graduate and undergraduate students with backgrounds in Earth Sciences (hereafter, geoscientists), room or musical acoustics (hereafter, acousticians), or applied physics/engineering (hereafter, physicists).

Constrained Categorization without Training

In the first suite of experiments, families A and B were each defined by three examples that subjects listened to or looked at before starting the test. Each of the three example audified signals could be listened to three times at most. Visual examples were plotted on the screen and could be looked at for no more than 3 min before starting the test. All subjects were given the same examples. The subjects were then exposed to 40 unknown signals; after listening to/looking at each signal, they selected whether it belonged to family A or B; no other answer was possible. Each auditory signal could be listened to three times at most; plots were visible on the screen for 5 s. The subjects' selections were recorded by the software interface.

Importantly, this approach is profoundly different from that of Paté *et al.* (2016), who asked subjects to form as many categories as they wanted according to their own criteria (Gaillard, 2009). It is also different from paired comparison, where a subject is presented with two stimuli and must choose which one belongs to which of two categories. We explored the latter approach in preliminary tests with few subjects, who all obtained extremely high scores; this strengthened our hypothesis that the geophysical parameters we had selected (propagation path and orientation of the fault) do map into audible acoustic properties of the corresponding audified signals. We considered, however, that a paired-comparison test does not resemble any real task in



▲ **Figure 3.** Examples of seismograms used in our study. (a,b) DS1, continental paths; (c,d) DS1, oceanic paths; (e,f) DS2, thrust faults; (g,h) DS2, strike-slip faults. Data are velocity recordings from Incorporated Research Institutions for Seismology, with no instrument-response correction nor filtering. The vertical axis is not labeled because we systematically normalize all seismograms (both visual and audio). In our visualization experiments, the horizontal axis was less exaggerated and the time span much longer, so that in principle the exact same information was provided to subjects in visualization and listening tests. The image files used in experiments are available in the Ⓔ electronic supplement to this article.

seismic data analysis and discarded this approach in our subsequent experiments.

Auditory and Visual Display of DS1 (Oceanic vs. Continental Paths)

In the first experimental session, 35 subjects (13 women and 22 men), aged between 18 and 61, took two tests involving data from DS1. The group included 18 acousticians, 9 geoscientists, and 8 physicists. Forty signals were evaluated visually in one test, and their audified counterparts were listened to in another.

As explained in the Database section, we made the hypothesis that data belonging to DS1 would tend to be categorized according to the terrain sampled by the propagation paths. Signals corresponding to oceanic propagation paths were presented as examples of family A and continental signals as examples of B. In the following, we loosely speak of correct answer whenever a subject associates with family A an oceanic signal or with family B a continental one. Exactly half of the signals in this experiment correspond to oceanic propagation paths and the other half to continental ones. The signals were the same for all subjects, but their order was random, changing at each realization of the experiment.

The average percentage of correct answers (average score) in this first experiment amounts to 78% for the visual test and 63% for the auditory one. All scores are summarized in the histograms of Figure 4a,b. We suspect that the very low scores of two outliers (one per test) to have been caused by a misunderstanding of the instructions, which resulted in the subjects swapping families A and B.

For the sake of comparison, we consider the case of entirely random answers, that is, the human subject is replaced by an algorithm that generates random yes/no answers, or answers are given by tossing a coin. In this null hypothesis, test scores are controlled by the cumulative binomial distribution (e.g., Press *et al.*, 1992): each signal listened to can be treated as an independent trial, with a success probability of 50%. Figure 4a shows that in the first auditory test, about one out of three subjects scored above the 99% confidence level as defined through the cumulative binomial distribution; in other words, the probability that a subject would obtain (at least) such a score by giving random answers is less than 1%. It is thus probable that some of the best-scoring subjects identified a real difference between signals that they classified as belonging to families A and B. Given how we constructed the two families (see the Database section), it is also reasonable to infer that the auditory clues identified by the subjects are directly related to the effects, on seismic waveforms, of wave propagation through oceanic versus continental crust.

Our data are not numerous enough for the histograms in Figure 4a,b to clearly suggest specific statistical distributions. By visual inspection of Figure 4a, one might speculate that the distribution of auditory test scores is bimodal, with one peak around 50% corresponding to the null hypothesis and another peak around 70% reflecting the performance of subjects who did find meaningful clues in the signals.

Scores in the visual test (Fig. 4b) were generally quite high and higher than for the auditory test. This indicates that, at this point, visual analysis of the data might be a more effective way to complete the task of categorizing DS1 data.

Auditory and Visual Display of DS2 (Thrust vs. Strike-Slip Faults)

Of the subjects who took part in the experiment described in the Auditory and Visual Display of DS1 (Oceanic vs. Continental Paths) section, 27 (15 acousticians, 7 physicists, and 5 geoscientists; 7 women and 20 men) also participated in the second session, involving 40 signals from DS2. Half of the signals originated from the strike-slip faults, and the other half from the thrust faults shown in Figure 2b. Again, each subject took an auditory and a visual test, with average scores of 52% and 62%, respectively. The results of both auditory and visual tests are illustrated in Figure 4c,d.

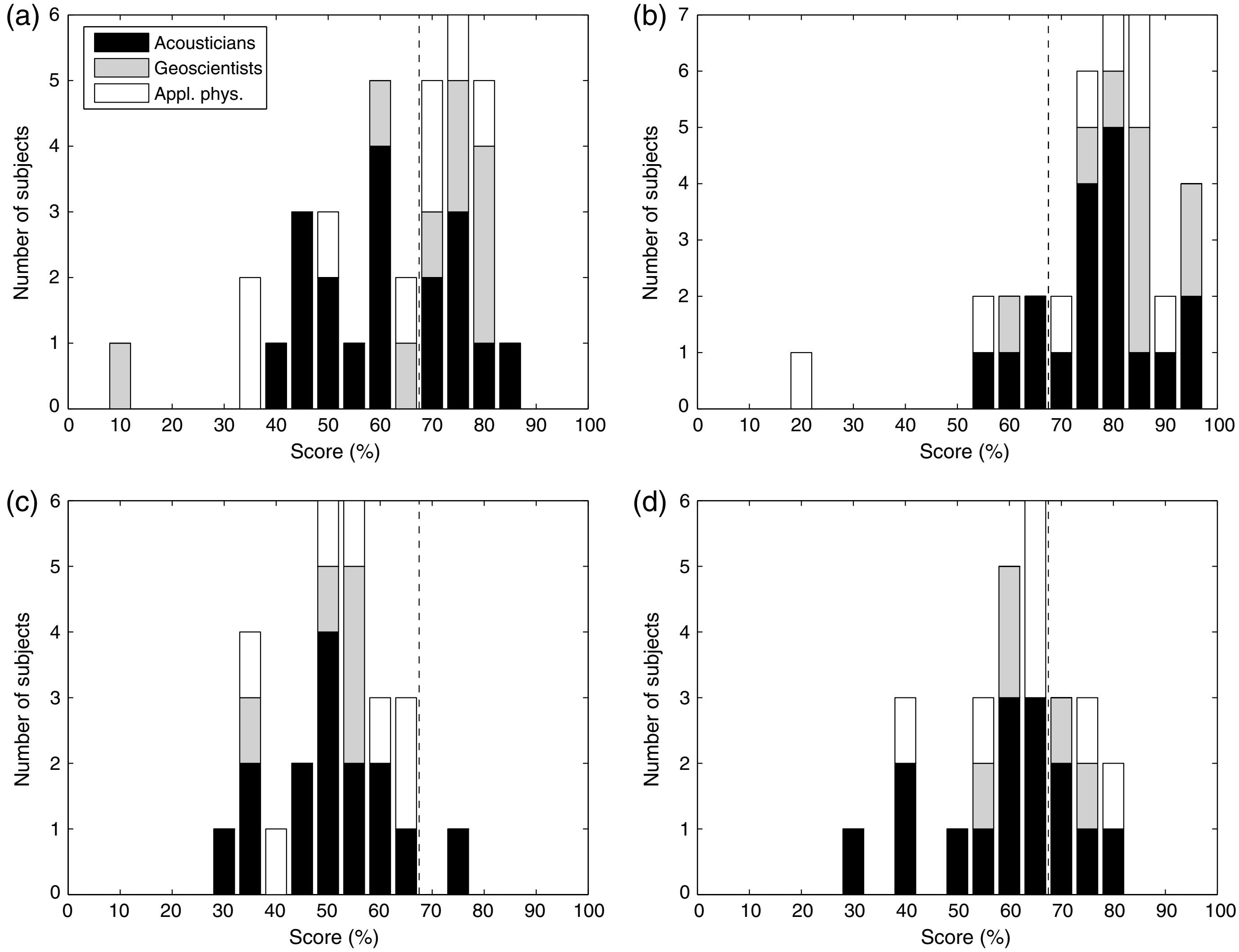
Comparison with the null hypothesis shows that the probability of achieving (at least) the average score associated with the visual test by selecting the answers randomly was relatively low ($<10\%$); we infer that at least some subjects are likely to have found visual clues in plotted seismograms. Conversely, the probability of achieving (at least) the average score obtained in the auditory test by giving random answers was about 40%, that is, too high for the average observed score to be considered significant. It might be guessed that the one subject who achieved a score of 75% might have found auditory clues in the signals, but overall the test cannot be considered a success.

Constrained Categorization with Training

About 17 subjects (10 acousticians, 4 physicists, and 3 geoscientists; 4 women and 13 men), who had already participated in both the constrained-categorization experiments accepted to undergo a training session followed by an auditory test analogous to those described above. The new exercise was conducted on data from DS2, only half of which were employed in our previous experiments. Data included in the final test had not been listened to in the course of the training session. The goal of this experiment is to determine whether performance in auditory analysis of seismic data can, in principle, be improved by training; this is determined below by comparison with performance in a similar task before training. It is therefore not strictly necessary to compare the results against those of visual analysis of the same data, and accordingly the visual test was not repeated.

Training

Subjects were trained (e.g., Thorndike, 1931; Speeth, 1961) by means of a software interface similar to that used in the actual tests. They first listened to three examples of each family, as before the previous test. They were then presented with up to 24 audified signals in the same way as previously. Half of these signals originated from thrust and the other half from strike-slip faults. Half had been listened to during the previous experiment; half were entirely new. The order in which the signals were presented was random. Upon hearing each signal, subjects were asked by our software interface to evaluate



▲ **Figure 4.** These histograms summarize the results of the constrained categorization experiments conducted before training on audified seismograms from data sets (a,b) DS1 and (c,d) DS2. Scores achieved in auditory tests are shown in (a) and (c); scores achieved in visual tests are shown in (b) and (d). The vertical dashed line marks the 99% confidence level, that is, the probability of achieving at least that score by categorizing the signal at random is less than 1%. Colors correspond to the different background of subjects, as explained in the inset.

whether it belonged to family A or B. After giving an answer, they were immediately notified whether or not it was correct (i.e., consistent with our hypothesis) by the on-screen messages "you have identified the right seismological family" (*vous avez identifié la bonne famille sismologique*) and "that is not the right seismological family" (*ce n'est pas la bonne famille sismologique*), respectively. The training session would automatically end if a subject had a perfect score after listening to the first 16 sample signals, but no subject performed so well.

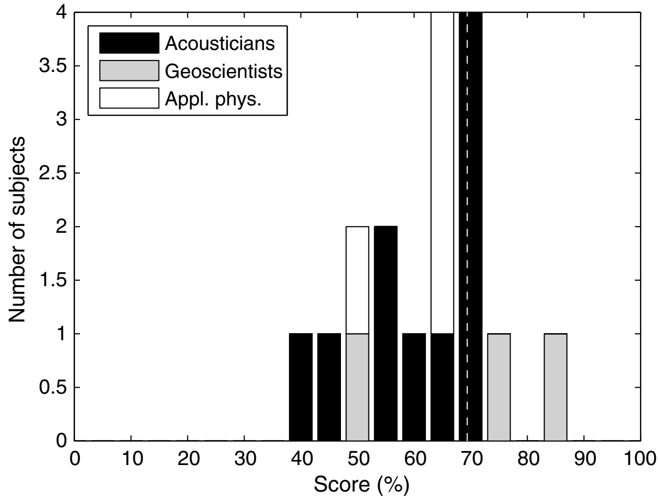
Auditory Display of DS2 after Training

After a brief pause, all subjects who undertook the training session stayed for a final test. About 36 signals were randomly picked from DS2. Half of the picked signals had to be from thrust, half from strike-slip faults. Half had to belong to the pool of signals listened to in the test of the Auditory and Visual Display of the DS2 section.

The histogram in Figure 5 shows that scores are generally higher now than when categorizing signals from DS2 before training (Fig. 4c). Only 4 out of 17 subjects did not improve their score at all. In the null hypothesis, with 36 trials, the probability of achieving a score of at least 69.4% (24 correct answers out of 36) is about 1%; 6 out of 17 subjects scored 70% or more, and we infer that at least some of those 6 learned to recognize relevant auditory clues in the data. Albeit small, these figures appear more significant if one considers that only one brief training session was undertaken.

IDENTIFYING AUDIO FEATURES RELEVANT TO CATEGORIZATION

At the end of a test, the subject was asked to briefly explain the criteria followed to categorize the signals via the on-screen message: "according to what criteria have you associated family A



▲ **Figure 5.** Histogram summarizing the results of the constrained categorization experiment conducted (on DS2) after training. The vertical dotted line, corresponding to a score of 69.4%, marks the 99% confidence level; all scores in the 67.5%–72.5% bin actually fall to its right.

and B to the signals?" (*sur quel(s) critère(s) avez vous attribué la famille A ou B aux signaux?*). The subject could answer by typing some comments through our software interface.

Given the difficulty of an exhaustive semantic study of the resulting data (Paté *et al.*, 2017), we only give here a preliminary simplistic analysis of a subset of the recorded comments. Our goal in this endeavor is to identify some of the auditory clues that lead subjects to make their choices. We focus on the subjects whose scores were the highest, because the criteria that guided them are probably related to the geophysical parameters that defined our families of signals.

Comments on DS1

We first analyze the comments made by five subjects (two acousticians, two geoscientists, and one physicist) who all achieved scores $\geq 80\%$ in discriminating audified seismograms corresponding to oceanic versus continental paths (DS1).

Table 2 shows a number of reoccurring suggested clues, namely, the presence of what the subjects identify as background noise and its timbre, the duration of what is considered by the subjects to be meaningful signal, and the identification of echos in the signal. These features can in principle be associated with quantities calculated by seismic data analysis.

First of all, it is relatively easy to identify the onset of an earthquake recording on a seismogram (i.e., the P-wave arrival), and it is then reasonable to define as background noise the signal recorded before such arrival. In all our recordings, the first 500 samples clearly precede the arrival of the main signal, and we accordingly identify them as noise. We define the beginning of the seismic signal as the first recorded sample for which amplitude is at least three times larger than the largest amplitude found within the 500 noise samples. Let n_S denote its index. Following Paté *et al.* (2017), the SNR in decibels can

Table 2
Listeners' Comments on DS1

Family A (Oceanic Paths)	Family B (Continental Paths)
Second shock very close to the first	Echo of the first impact's sound
With an echo/rebound	Small rebounds
A lot of background noise	Little background noise
High-pitched background noise	Low-pitched background noise
Background noise	Shorter and duller sound
Longer signal	Sharper and shorter
	Rising perceived frequency
	Faster arrival
	Buzz or intense reverberation after the explosion

Summary of written, verbal explanations given by five subjects (scoring $\geq$80%) concerning their auditory cateogorization of DS1. All text was originally in French and has been translated into English as literally as possible.

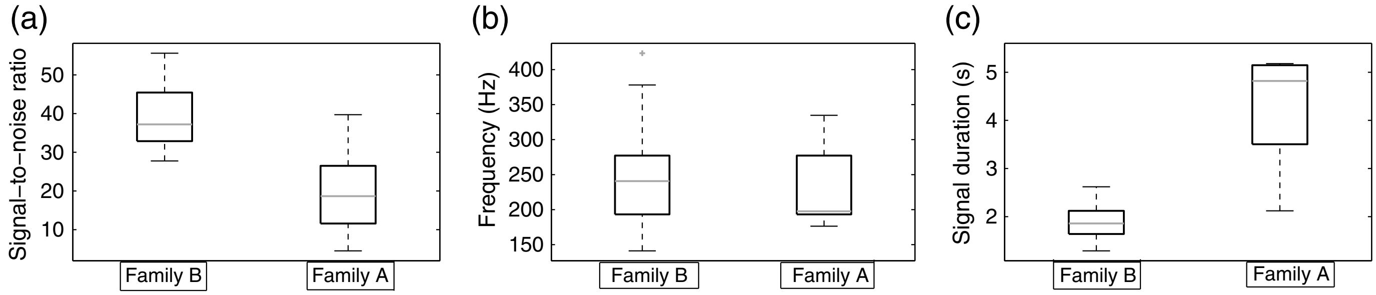
then be estimated, based on the mean amplitudes of signal and noise, by the formula

$$\mathrm{SNR} = 10 \log_{10}\left[\frac{\sum_{i=n_S}^{N} s^2[i]}{\sum_{i=1}^{500} s^2[i]}\right], \qquad (1)$$

in which $s[i]$ is the amplitude of the ith sample in a recording that consists of N samples total. We compute the SNR of all signals in DS1 and find (Fig. 6a) that continental paths tend to be associated with higher SNR values than oceanic paths. This statistical result is in qualitative agreement with the subjects' comments.

We evaluate the timbre of background noise by taking the Fourier transform of the first 500 samples only. Figure 6b shows the distribution of frequency values corresponding to the highest spectral peak in the resulting Fourier spectrum; whether the terrain traversed by the propagating seismic wave is oceanic or continental does not appear to affect significantly the frequency content of noise.

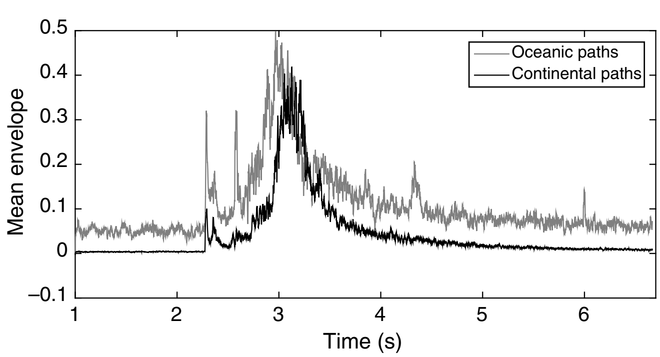
We next attempt to quantify the duration of meaningful seismic signal which the subjects believe to have recognized in their listening experiences; after the main high-amplitude interval that includes body- and surface-wave arrivals, the peak amplitude of all our signals decreases until it becomes as low as the peak amplitude of background noise. For each seismogram, we find the latest sample in which peak amplitude is as large as 10% of its maximum recorded value for that seismogram; we then measure the length of the time interval that separates it from the maximum-amplitude sample and define it as the duration of seismologically meaningful signal. Figure 6c shows how such values are distributed for signals associated with oceanic versus continental propagation paths and indi-



▲ **Figure 6.** Distributions, shown as box plots, of three physical parameters, corresponding to properties of the signal that subjects tend to describe as important: (a) signal-to-noise ratio, (b) dominant frequency of background noise, and (c) duration of meaningful signal. For each parameter, the distributions of parameter values for oceanic-path (family A) and continental-path (family B) signals are shown separately. Distributions are summarized by their median (thick gray segments), first and third quartiles (upper and lower sides of boxes), and minimum and maximum values (end points of dashed lines). Values that we neglect as outliers (their absolute value is more than 1.5 times the interquartile distance) are denoted by gray crosses.

cates that oceanic signals are, according to our definition, longer than continental ones.

Finally, echos can be identified by visual analysis of a seismogram's enevelope. We calculate the envelopes of all our audified seismograms and take the averages of all oceanic-path and all continental-path envelopes. In analogy with Paté *et al.* (2017), the envelope is defined as suggested by D'Orazio *et al.* (2011): starting with i coinciding with the index of the last sample in a signal, if sample $i-1$ exceeds sample i, then the value of sample $i-1$ is saved as the ith entry of the envelope; the procedure is iterated for the preceding sample, until the entire trace is processed (D'Orazio *et al.*, 2011, their fig. 5). The results of this exercise, illustrated in Figure 7, show that (1) the amplitude of an oceanic-path signal is generally larger than that of a continental-path signal; (2) the oceanic-path signal is characterized by a number of high-amplitude peaks that are not visible in the continental-path one; and (3) the large-amplitude portion of the signal lasts longer in oceanic-path than continental-path signal. Although the standard deviations of both envelopes are not shown in Figure 7



▲ **Figure 7.** Signal envelope averaged over all DS1 audified seismograms corresponding to continental (black line) versus oceanic (gray) paths. Each envelope is the average of 20 seismograms, used in actual tests and not as preliminary examples. Seismograms were aligned according to the *P*-wave arrival.

in the interest of readability, these inferences are confirmed even if the standard deviation is taken into account. We note that the standard deviation of the oceanic-path envelope is larger than the continental-path one. Observation (2) reflects several comments made by the subjects (Table 2).

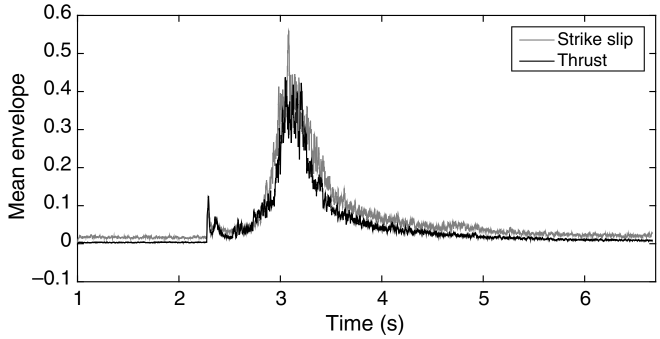
Comments on DS2

The four subjects who achieved the highest scores (>55%) without training are combined with the four who achieved the highest scores (>72%) after training, resulting in a group of eight subjects whose verbal comments are summarized in Table 3. The group includes three geoscientists, three acousticians, and two physicists. Two of the subjects in this group were also in the group discussed in the Comments on DS1 section.

Table 3 shows that, despite some contradictory comments, most subjects find strike-slip-fault signals to be characterized by a relatively weak first arrival followed by a high-energy coda, whereas, on the contrary, they associate thrust events with a strong first arrival followed by a weaker coda. This seems to be consistent with the average envelopes of Figure 8, in which (1) the initial peak is clearly identifiable for both families and is roughly twice as high in the inverse-fault case, with respect to the strike-slip-fault one, whereas (2) the later inverse-fault signal is of higher amplitude than its strike-slip-fault counterpart, with an ~20% difference in their main peaks. If the envelopes' standard deviations (not shown in Fig. 8 for clarity) are taken into account, however, this observation cannot be confirmed; more tests, with a broader data set, need to be conducted to come to a definitive conclusion.

INFLUENCE OF SUBJECTS' BACKGROUND ON THE RESULTS

Figure 9 shows that test scores are not strongly affected by the background of subjects. The average score achieved by geoscientists is always (except for the auditory categorization of DS2) slightly higher than that of the other two groups, but



▲ **Figure 8.** Same as Figure 7, but envelopes are averaged over all DS2 signals originated from thrust (black line) versus strike-slip (gray) events.

the subjects are not numerous enough for this small difference to be considered significant.

On the other hand, our analysis of the subjects' recorded descriptions of their categorization strategy shows that acousticians used about 20 more words than both other groups to qualify sounds. We interpret this result as a natural consequence of the acousticians' specific expertise in describing sounds, whereas geoscientists and physicists usually represent their data only visually. This speculation is confirmed by the study of Paté *et al.* (2017), who conducted a thorough, quantitative analysis of verbal data collected in a similar experiment (also involving audified seismic data and subjects with similar backgrounds).

CONCLUSIONS

In our experiments, listeners were exposed to two audified seismic data sets, each characterized by a single, binary control factor: the orientation of the fault (strike slip or thrust) in one case, the nature of the tectonic plate through which the recorded signal had traveled prior to recording (oceanic or continental) in the other. They were then asked to split each data set into two categories, based on examples of signals associated with different values of the control factor. Purely auditory tests were compared with similar tests, in which data were displayed visually rather than acoustically. Overall, listeners were able to categorize data based on audition alone. Their performance in visual tests was better, but performance in auditory categorization was significantly improved by a brief training session.

Asked to comment on the criteria they had chosen to categorize, listeners most often pointed to perception-based physical features that can be summarized as SNR, the duration of what they interpreted to be meaningful signal as opposed to background noise, the frequency content of background noise, and the relative amplitude of first seismic arrivals with respect to coda. At least two of these features (SNR and meaningful signal duration) do correspond to quantitative parameters that we have been able to define and calculate by simple data processing; we show in Figure 6a,c that those parameters are differently distributed, depending on the value of the relevant control parameter.

Table 3
Listeners' Comments on DS2

Family A (Strike-Slip Events)	Family B (Thrust Events)
First shock weaker than the second one	Louder low frequencies
Wave of rising frequency louder than the first heard shock	First shock louder than the second one
After the detonation, sound decays more slowly	First shock louder than the wave
Faster attack and decay	More powerful and present sound
Significant intensity even after a long time	Sound decays quickly after the detonation
Lower-frequency shock	Slower decay
Duller signal	
Higher frequencies	

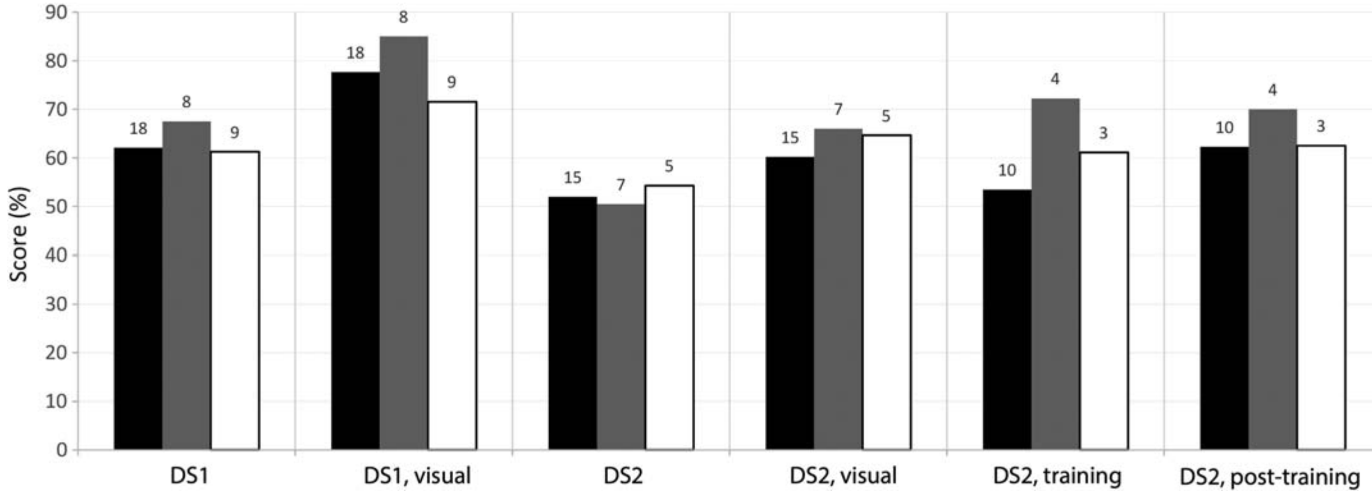
Summary of written, verbal explanations given by eight subjects (scoring $\geq 80\%$) for the auditory cateogorization of DS2 before (four subjects scoring $>55\%$) and after training (four subjects scoring $>72\%$). Again, the original French text was translated into English.

In summary, human listeners are able to identify geophysically relevant features of audified seismic data and can be trained to improve their performance at such tasks. We cannot yet predict the extent to which training can refine our skills at interpreting the data by listening, but we surmise that auditory display can be useful to a variety of endeavors in seismic data analysis.

OUTLOOK

Although the resolution and pattern recognition capabilities of the human auditory system are generally well known (e.g., Hartmann, 1999; Wang and Brown, 2006a), auditory display is not yet a routinely used tool of seismic data analysis. A case in point is the interesting work of Moni *et al.* (2012, 2013), in which an algorithm designed to mimic the human auditory system (in the words of the authors, "to solve the 'cocktail party problem,' i.e., separating individual speakers in a room with multiple speakers") was successfully applied to the problem of identifying different simultaneous microseisms. Yet, no attempt was made by those authors to simply use the human auditory system itself, listening to the audified data.

Besides the benefits derived from exploiting the natural skills of our auditory system, audification typically involves the acceleration of a seismic signal by a factor between $\sim 10^2$ and $\sim 10^3$, depending on the frequency content of the original data, which means that an entire day of seismic recording can be listened to in a few minutes with little or no loss of information. Being able to rapidly analyze large sets of data is important, because seismologists are faced today with large and rapidly growing databases. For instance, precisely locating the epicenters of



▲ **Figure 9.** Average scores by test (left to right, as indicated under each bar) and by subjects' background group. Black, gray, and white bars are associated with acousticians, geoscientists, and physicists, respectively. The number of subjects participating to a test is shown above the corresponding bar. The label "post-training" refers to the auditory test of DS2 conducted after the training session; "training" refers to answers that were given during the aforementioned training session.

seismic aftershocks requires solving an enormous number of inverse problems (e.g., Valoroso *et al.*, 2013). This cannot be entirely automated if precise results are to be obtained. All signals recorded by a seismic network can, however, be listened to simultaneously, by the principles of sound spatialization (e.g., Peters *et al.*, 2011), in an anechoic chamber equipped with a dense speaker network or, more simply, binaurally. The human auditory system is naturally equipped to locate the source of a sound (e.g., Hartmann, 1999; Wang and Brown, 2006b), and, through this setup, it is reasonable to hypothesize that one might be able to learn to roughly but quickly locate earthquake epicenters, both in the near and far field, by listening to sets of audified seismograms. This approach would involve some important approximations (neglect of dispersion and of the Earth's lateral heterogeneity, etc.), and we do not expect auditory-based localization to outperform existing algorithms, but we are convinced that it could be a useful additional tool to display three-dimensional seismological information, attractive also because of its speed and simplicity.

The auditory properties of audified seismograms have also been shown to be indicative of several specific seismic processes, including mainshock/aftershock sequences, earthquake swarms that accompany volcanic eruptions, or deep nonvolcanic tremors (Kilb *et al.*, 2012; Peng *et al.*, 2012). Audification is likely to find other potentially important applications in seismology, wherever large data sets are to be investigated and unknown/unexpected patterns recognized. Examples include the analysis of the Earth's seismic background signal (e.g., Boschi and Weemstra, 2015), with implications for monitoring of natural hazards (e.g., Wegler and Sens-Schonfelder, 2007; Brenguier *et al.*, 2008), and the problem of determining the evolution of a seismic rupture in space and time from the analysis of seismic data (e.g., Ide, 2007; Mai *et al.*, 2016). The study of large sets of audified data can further benefit from the possibilities offered by crowd-sourcing platforms; if the sounds are short and meaningful enough, if the listeners' task is simple enough, and if the data set is correctly distributed among listeners (each sound is given to at least one listener and some are given to several listeners for verification and variability assessment), then a large data set can be effectively explored by the collaborative work of a number of listeners.

DATA AND RESOURCES

The image and audio files that were presented to subjects in all the experiments described here are available at http://hestia.lgs.jussieu.fr/~boschil/downloads.html (last accessed November 2015). Some audio examples are available in the Ⓔ electronic supplement to this article. The Global Centroid Moment Tensor Project database was searched using www.globalcmt.org/CMTsearch.html (last accessed September 2016). The Incorporated Research Institutions for Seismology (IRIS) database was searched via the Wilber interface at http://ds.iris.edu/wilber3/ (last accessed September 2016). Figures 1 and 2 were made using the Generic Mapping Tools v.5.2.1 (www.soest.hawaii.edu/gmt, last accessed November 2015; Wessel and Smith, 1991). All new softwares developed for this study were written in MATLAB (www.mathworks.com/products/matlab, last accessed November 2015).

ACKNOWLEDGMENTS

We acknowledge financial support from Institut National des Sciences de l'Univers (INSU)-Conseil National de la Recherche Scientifique (CNRS), and from the European Union's Horizon 2020 Research and Innovation Programme under the Marie Sklodowska-Curie Grant Agreement Number 641943 (ITN WAVES). Danièle Dubois and Piero Poli contributed to our work through many fruitful discussions. Zhigang Peng, Debi Kilb, and one anonymous reviewer provided careful re-

views of our original article. We are grateful to the volunteers who kindly accepted to take our tests.

REFERENCES

Boschi, L., and C. Weemstra (2015). Stationary-phase integrals in the cross-correlation of ambient noise, *Rev. Geophys.* **53,** doi: 10.1002/2014RG000455.

Brenguier, F., N. M. Shapiro, M. Campillo, V. Ferrazzini, Z. Duputel, O. Coutant, and A. Nercessian (2008). Towards forecasting volcanic eruptions using seismic noise, *Nat. Geosci.* **1,** 126–130.

Cowen, R. (2015). Sound bytes, *Sci. Am.* **312,** 44–47.

Dombois, F., and G. Eckel (2011). Audification, in *The Sonification Handbook*, T. Hermann, A. Hunt, and J. G. Neuhoff (Editors), Logos Publishing House, Berlin, Germany, 301–324.

D'Orazio, D., S. De Cesaris, and M. Garai (2011). A comparison of methods to compute the effective duration of the autocorrelation function and an alternative proposal, *J. Acoust. Soc. Am.* **130,** 1954–1961.

Ekström, G., M. Nettles, and A. M. Dziewoński (2012). The global CMT project 2004–2010: Centroid-moment tensors for 13,017 earthquakes, *Phys. Earth Planet. In.* **200/201,** 1–9, doi: 10.1016/j.pepi.2012.04.002.

Frantti, G. E., and L. A. Leverault (1965). Auditory discrimination of seismic signals from earthquakes and explosions, *Bull. Seismol. Soc. Am.* **55,** 1–25.

Gaillard, P. (2009). Laissez-nous trier! TCL-LabX et les tâches de catégorisation libre de sons, in *Le Sentir et le Dire*, D. Dubois (Editor), L'harmattan, Paris, France, 189–210 (in French).

Hartmann, W. M. (1999). How we localize sound, *Phys. Today* **11,** 24–29.

Holtzman, B., J. Candler, M. Turk, and D. Peter (2014). Seismic sound lab: Sights, sounds and perception of the earth as an acoustic space, in *Sound, Music, and Motion*, M. Aramaki, O. Derrien, R. Kronland-Martinet, and S. Ystad (Editors), Springer International Publishing, Berlin, Germany, 161–174.

Ide, S. (2007). Slip inversion, in *Treatise of Geophysics*, H. Kanamori (Editor), Vol. 4, Elsevier, Amsterdam, The Netherlands, 193–223.

Kennett, B. L. N., and T. Furumura (2013). High-frequency *Po/So* guided waves in the oceanic lithosphere: I—Long distance propagation, *Geophys. J. Int.* **195,** 1862–1877, doi: 10.1093/gji/ggt344.

Kennett, B. L. N., T. Furumura, and Y. Zhao (2014). High-frequency *Po/So* guided waves in the oceanic lithosphere: II—Heterogeneity and attenuation, *Geophys. J. Int.* **199,** 614–630, doi: 10.1093/gji/ggu286.

Kilb, D., Z. Peng, D. Simpson, A. Michael, and M. Fisher (2012). Listen, watch, learn: SeisSound video products, *Seismol. Res. Lett.* **83,** 281–286, doi: 10.1785/gssrl.83.2.281.

Mai, P. M., D. Schorlemmer, M. Page, J.-P. Ampuero, K. Asano, M. Causse, S. Custodio, W. Fan, G. Festa, M. Galis, *et al.* (2016). The earthquake-source inversion validation (SIV) project, *Seismol. Res. Lett.* **87,** 690–708, doi: 10.1785/0220150231.

Moni, A., C. J. Bean, I. Lokmer, and S. Rickard (2012). Source separation on seismic data: Application in a geophysical setting, *IEEE Signal Process Mag.* **29,** 16–28, doi: 10.1109/MSP.2012.2184229.

Moni, A., D. Craig, and C. J. Bean (2013). Separation and location of microseism sources, *Geophys. Res. Lett.* **40,** 3118–3122, doi: 10.1002/grl.50566.

Paté, A., L. Boschi, J. L. le Carrou, and B. Holtzman (2016). Categorization of seismic sources by auditory display: A blind test, *Int. J. Hum. Comput. Stud.* **85,** 57–67, doi: 10.1016/j.ijhcs.2015.08.002.

Paté, A., L. Boschi, D. Dubois, B. Holtzman, and J. L. le Carrou (2017). Auditory display of seismic data: Expert categorization and verbal description as heuristics for geoscience, *J. Acoust. Soc. Am.* **141,** no. 3, 2143.

Peng, Z., C. Aiken, D. Kilb, D. Shelly, and B. Enescu (2012). Listening to the 2011 magnitude 9.0 Tohoku-Oku, Japan earthquake, *Seismol. Res. Lett.* **83,** 287–293, doi: 10.1785/gssrl.83.2.287.

Peters, N., G. Marentakis, and S. McAdams (2011). Current technologies and compositional practices for spatialization: A qualitative and quantitative analysis, *Comput. Music J.* **35,** 10–27.

Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery (1992). *Numerical Recipes in Fortran 77*, Cambridge University Press, Cambridge, United Kingdom.

Speeth, S. D. (1961). Seismometer sounds, *J. Acoust. Soc. Am.* **33,** 909–916, doi: 10.1121/1.1908843.

Tang, Y. (2014). Data sonification with the seismic signature of ocean surf, *The Leading Edge* **33,** doi: 10.1190/tle33101128.1.

Thorndike, E. L. (1931). *Human Learning*, The Century Co., New York, New York.

Valoroso, L., L. Chiaraluce, D. Piccinini, R. D. Stefano, D. Schaff, and F. Waldhauser (2013). Radiography of a normal fault system by 64,000 high-precision earthquake locations: The 2009 L'Aquila (central Italy) case study, *J. Geophys. Res.* **118,** 1156–1176, doi: 10.1002/jgrb.50130.

Volmar, A. (2013). Listening to the Cold War: The Nuclear Test Ban negotiations, seismology, and psychoacoustics, 1958–1963, *Osiris* **28,** 80–102.

Wang, D., and G. J. Brown (2006a). Fundamentals of computational auditory scene analysis, in *Computational Auditory Scene Analysis*, D. Wang and G. J. Brown (Editors), Wiley & Sons, Hoboken, New Jersey, 1–44.

Wang, D., and G. J. Brown (2006b). *Computational Auditory Scene Analysis*, Wiley & Sons, Hoboken, New Jersey.

Wegler, U., and C. Sens-Schönfelder (2007). Fault zone monitoring with passive image interferometry, *Geophys. J. Int.* **168,** 1029–1033.

Wessel, P., and W. H. F. Smith (1991). Free software helps map and display data, *Eos Trans. AGU* **72,** 445–446.

Lapo Boschi[1]
Sorbonne Universités
UPMC Univ Paris 06, CNRS
Institut des Sciences de la Terre de Paris (iSTeP)
4 place Jussieu 6
75005 Paris
France
larryboschi@gmail.com

Laurianne Delcor[2]
Jean-Loïc Le Carrou
Claudia Fritz
Sorbonne Universités
UPMC Univ Paris 06, CNRS
Institut Jean Le Rond d'Alembert, équipe LAM
4 place Jussieu
75005 Paris
France

Arthur Paté
Benjamin Holtzman
Lamont–Doherty Earth Observatory
Box 1000, 61 Route 9W
Palisades, New York 10964-1000 U.S.A.

Published Online 9 August 2017

[1] Also at Sorbonne Universités, UPMC Univ Paris 06, CNRS, Institut Jean Le Rond d'Alembert, équipe LAM, 4 place Jussieu, 75005 Paris, France.

[2] Now at Laboratory of Vibration and Acoustics, 69621 13 Villeurbanne, France; also at Airbus Helicopters, France.