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Perception of audified acoustic emissions from microscopic samples

Florian Duval[1]
Aix Marseille University, UFR ALLSH
3 Place Victor Hugo, 13331 Marseille Cedex 03
France

Clément Xu[2]
ENSEA
6 avenue du Ponceau, 95 000 Cergy, France

Catherine Lavandier[3]
ETIS Lab., CY Cergy Paris University
2 rue Adolphe Chauvin,
95 302 Cergy-Pontoise Cedex, France

Arthur Paté[4]
ISEN JUNIA, IEMN UMR CNRS 8520
41 boulevard Vauban, 59800 Lille, France

Dávid Ugi[5]
Department of Materials Physics, ELTE
Eötvös Loránd University
Pázmány Péter sétány 1/A, 1117 Budapest,
Hungary

Péter Dusán Ispánovity[6]
Department of Materials Physics, ELTE
Eötvös Loránd University
Pázmány Péter sétány 1/A, 1117 Budapest,
Hungary

Szilvia Kalacska[7]
Mines Saint-Etienne, Univ Lyon, CNRS, UMR
5307 LGF, Centre SMS
158 cours Fauriel,
42023 Saint-Étienne Cedex 2, France

ABSTRACT

Recording of acoustic emission signals (elastic waves emitted by dislocation motion) during compression of microscopic samples is a novel emerging tool for the investigation of mechanical properties of materials. Yet the resulting signals can be so noisy and complex that they don't easily allow for identifying the deformation mode or the material involved. This study aims at testing if the human auditory system can pick patterns in the audified recordings (i.e. transposed from the ultrasonic to the audible range) that match the physical characteristics of the samples. In a Free Sorting Task, participants sorted sounds into groups according to perceived similarity. The sounds originated in recordings varying according to material, deformation mode, and size of the sample. During clustering and multidimensional analysis, sounds were found to be first grouped according to spectral features: Zinc and Magnesium recordings respectively produced high-pitched and low-pitched sounds. Sounds were further discriminated according to perceived sound level (soft vs. loud for slipping vs. twinning) and number of perceived sound events (no clearly associated

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[1] florian.duval@etu.univ-amu.fr

[2] clement.xu@ensea.fr

[3] catherine.lavandier@cyu.fr

[4] arthur.pate@junia.com

[5] ugidavid42@gmail.com

[6] ispanovity.peter@ttk.elte.hu

[7] szilvia.kalacska@cnrs.fr

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physical parameter). Correlations were found between subjective groupings and audio descriptors, so that audio-inspired mechanical investigations can now be envisioned.

1. INTRODUCTION

Understanding materials at the micro to nano scale is in the focus of materials science and engineering since the discovery of "size effects", a phenomenon occurring in small sample volumes as a result of reduced line defect (dislocation) content and the proximity to the surface [1]. Since then, identifying the type of deformation of materials, subjected to compressive stresses, remains a challenging task when it concerns the deformation of very small samples (typically in the scale of some tens of microns and below). It requires the use of high resolution instrumentation, including a scanning electron microscope (SEM) to visualize and fabricate the samples (by focused ion beam – FIB), and a sensitive nano-indentation system capable of operating under high vacuum conditions to apply the load on the specimen. During the compression of metallic micropillars, the surface of the prepared samples becomes inhomogeneous: as a result of collective and sudden dislocation motion and microstructure evolution, nanometric surface steps emerge on the previously smooth sides of the pillars. These steps are originating from dislocations traveling through the atomic lattice and escaping the system when they reach the surface. Capturing the images of this process by SEM has been widely used, however it only gives us partial information on the deformation activity, since dislocations which do not escape will not be visible on the surface. Furthermore, dynamical processes such as the increase of defect density [2], sudden lattice reorientation (twinning) [3] or failure of the material (fracture) [4] also need to be monitored during the external loading in order to better understand the mechanics of materials. Nowadays, it is possible to detect very faint noises (elastic waves) emitted by these processes, even in such small volumes [5]. These acoustic emission (AE) signals belong to the ultrasound domain [5] and can be recorded at a sampling frequency up to about $2.5MHz$ to track dynamical processes within the crystal structure. The objective of this experiment is to make the ultrasound dislocation recordings audible in order to test if the human ear could detect the type of deformation (dislocation motion through crystallographic slip planes, or collective lattice reorientation by twinning), without relying on the images recorded on the surface of the samples during external loading. By resampling the data at 4kHz (which means making a time dilation of the signal), it is possible to transpose the recording from the high-frequencies to the audible domain. We call this process "audification".

In this experiment, two distinct types of micropillars (small rectangular compression test samples with square-shaped cross-section and a height being three times larger than the side edges) are studied: Zinc (Zn) and Magnesium (Mg). These materials react in different ways when subjected to compression. Slipping occurs when micropillars experience lateral displacement due to applied stress. Twinning involves the formation of twin boundaries within the micropillar crystal lattice. Figure 1 shows how the atoms rearrange in different ways between both deformations.

The collection of the AE signals was performed in Hungary using a state-of-the-art nano-deformation setup, while the audification and the perceptual experiment were carried out in France. In this exploratory study, a limited number of variables has been chosen in order to answer three questions. (1) Is it possible to cluster the type of material? (2) Is it possible to cluster the type of deformation? And (3), does the size of a micropillar have an influence on the audified stimuli? Other parameters have been fixed: compression velocity was set at $10nm.s^{-1}$ for all of the micropillars. It is mentioned that in the experiments, single crystalline specimens are used, that is, the crystal orientation is identical throughout the volume (but may slightly differ from sample to sample). Whether slip or twinning takes place mainly depends on the orientation of the crystallographic planes, which we assume to be unknown for the perceptual experiment.

In the rest of this paper, section 2 presents the audification process and the audified

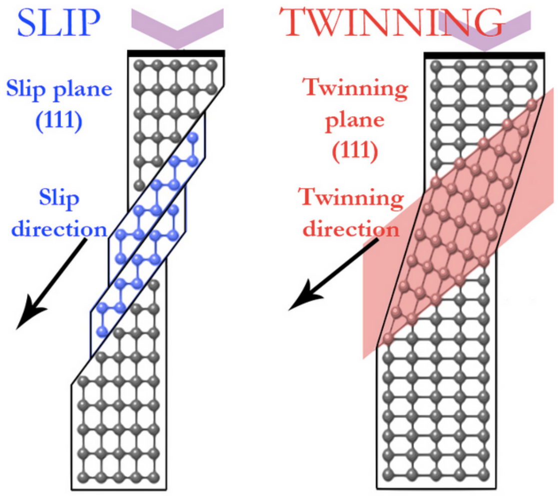

Figure 1: Representation of slipping and twinning deformations at the microscopic scale [6]. External loading is applied on the top of the micropillar (depicted with purple arrow).

stimuli. Section 3 describes the methodology of the experimental procedure. The analyses of the perceptual test are presented in sections 4 and 5 and results are discussed in section 6.

2. AUDIFICATION PROCESS

A large number of micropillars have been compressed until large deformation strains. Each compression lasted between 20 and 30 minutes and recordings had a sampling frequency of $2.5MHz$. The "dilatation" of the wave files has been chosen to make the AE signals audible, the peak values remaining distinguishable without being too short or too long. The new sampling frequency has then been fixed at $4kHz$. With this audification process, the duration of each compression would last about 10 days. Therefore, a careful selection of excerpts has been necessary to build the audio stimuli of the perceptual experiment.

2.1. Data base

In order to answer the three questions presented in the introduction, two types of materials were selected (Zn and Mg). For the zinc, three diameters were studied ($8\mu m$, $16\mu m$ and $32\mu m$) but only slip deformation was identified. For the 10 μm-samples of magnesium, three compression experiments were selected, one where only slip was identified on the SEM video, one with only twinning and one (called Mix) with both slipping and twinning taking place.

2.2. Choice of stimuli

Selecting the stimuli starts by verifying the matching between the moment of deformation and the detection of the corresponding AE signal. When a deformation occurs, a stress drop on the material is recorded. Thus, by analyzing the concordance of pressure drops and the number of AE over time, it is possible to confirm that the AE signals were emitted by a deformation process. Such a plot can be found in Figure 2. The AEs with the most energy and matching a pressure drop are then chosen to be further analysed. These AE signals contain a lot of single events that can be potential stimuli. To select the stimuli, the choice is to take the events with a high amplitude, which means the loudest events. To automate this step, a threshold at $0.01mV$ is applied for the AE signal so that only the events with high amplitudes are kept. Once these events are isolated, it is needed to keep only 4 stimuli per condition. For the experiment, stimuli of a total length of 3 seconds with a 1 second delay before the start of the event are needed. Therefore, only the events matching these conditions are finally selected. This results in a total of 24 stimuli, presented in Table 1. The visual representation of two stimuli is presented in Figure 3 as examples.

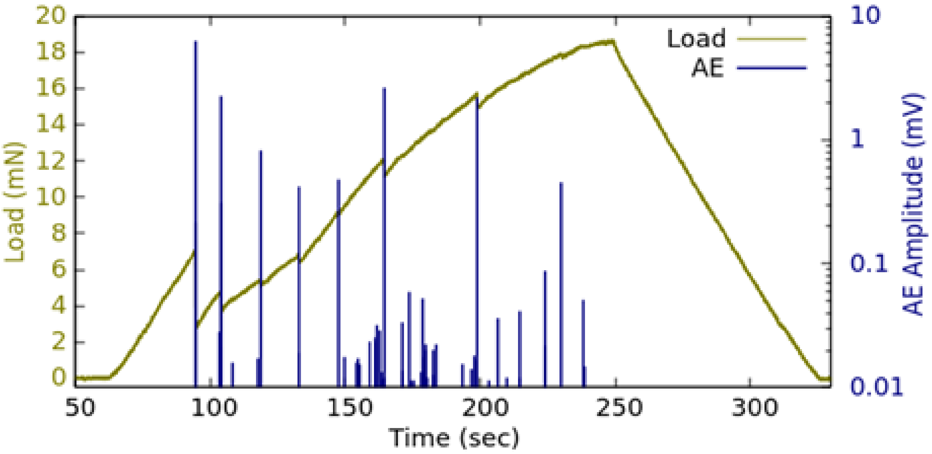

Figure 2: matching plot of the compression load (in green) acting on a pillar of magnesium single crystal oriented for twinning, and the amplitude of the recorded AE signals (in blue).

Table 1: Set of selected stimuli. All Zn stimuli are slipping samples. Zn_8_s196 means that the stimulus has been extracted from the 8μm Zn sample during the 196th second of the original 20 minutes recording. Mg_mix_s89 means that the stimulus has been extracted from the sample where both slipping and twinning dislocations have been identified in Mg, during the 89th second. In that case, visual identification may be subject to human error.

Zinc (only Slipping)			**Magnesium**		
Zn_8_s196	Zn_16_s378	Zn_32_s281	Mg_mix_s89	Mg_slip_s317	Mg_twin_s124
Zn_8_s395	Zn_16_s495	Zn_32_s326	Mg_mix_s106	Mg_slip_s323	Mg_twin_s153
Zn_8_s458	Zn_16_s495(1)	Zn_32_s327	Mg_mix_s215	Mg_slip_s338	Mg_twin_s185
Zn_8_s481	Zn_16_s634	Zn_32_s966	Mg_mix_s276	Mg_slip_s344	Mg_twin_s219

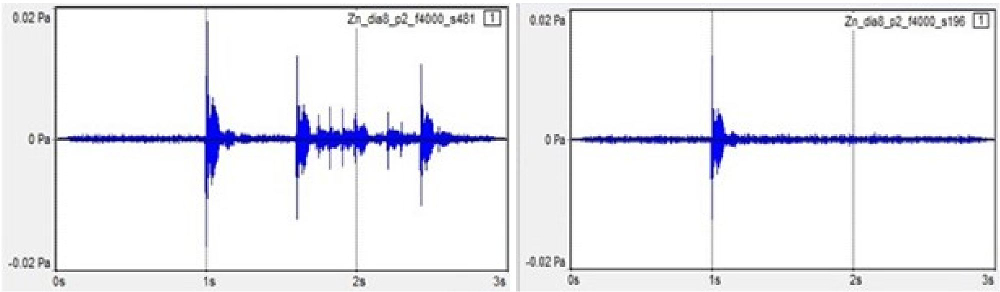

Figure 3: Temporal evolution of two audio stimuli as examples of crack-like sounds heard during the slip audio events.

2.3. Characterization of the selected stimuli

It is well known that loudness is the first dimension on which people discriminate between sounds and this dimension can mask more subtle effects when sounds are listened to during perceptual tests. In this experiment, the stimuli are composed of background noise and crack-like sounds. It was decided to equalize the background noise for all the stimuli at 42 dB(A) at the participants' ears, about 10 dB(A) above the ambient noise of the quiet room where the perceptual test was carried out.

Acoustic indicators were calculated over the whole duration of the stimuli, but also on the peak part (over a period of 400ms centered on the highest peak) and on the background noise. In total, 74 indicators were computed and a Principal Component Analysis (PCA) was applied in order to select a limited number of independent indicators which characterize the set of stimuli. Two dimensions were extracted. The first dimension was best correlated to noise level characteristics (LAeq, Loudness ISO 532B and their maximum value, Impulsive Loudness LMIS for the peak part, etc.). The second dimension characterized the spectral aspect of the sounds (Spectral Centroïd, Sharpness). This spectral effect was also noticeable on the sound level of the background noise which depended on the different sensors used for the mechanical setup (see section 5.1).

3. FREE SORTING EXPERIMENT

The aim of a free sorting experiment is to identify categories which gather similar objects. It is based on perceptual similarity or dissimilarity between a set of objects. This free sorting method has already been used in different studies [7, 8].

3.1. Participants

Thirty people were invited to participate in the free sorting experiment in a quiet room. 56% of the participants were female (50% between 18 and 30 years old) and 43% were male (37% between 18 and 30 years old). They all declared not having any audition problems.

3.2. Procedure

The procedure had been approved by the Cergy Research Ethical Committee under the number 202304 - 002. An information sheet was given explaining the origin of the sounds and the aim of the research, and a consent document was signed by both the experimenter and the participant. The instructions given to the participants for the experiment are as follows:

> *Please sort the sound samples presented to you. Group the samples which seem similar to you, and put in different groups those which seem different to you. You may form as many groups as you wish.*

Each of the 24 stimuli had to belong to only one group. The participants were free to form as many groups as they wanted and could gather any number of stimuli in a single group. At the end of the sorting, each participant was asked to write a comment for each group he/she made about its characterization.

3.3. Experimental setup

The tests were run on a laptop equipped with a RME Fireface soundcard. The stimuli were listened to through Sennheiser HD650 headphones which had been previously calibrated. Audio stimuli were monophonic, each ear being exposed to the same signal, in phase. The participants could not change the sound level of the headphones. The TCL-LabX software was used for the free sorting interface. The graphic interface displayed each stimulus as a small square icon. The 24 icons corresponding to the 24 stimuli were randomly numbered from 1 to 24. A double click on an icon launched the stimulus playback, and the icon could be moved within the entire interface area. Each stimulus can be played back as many times as wanted. An example of the software layout is presented in Figure 4.

Figure 4: Graphic interface. On the left, at the beginning of the test, on the right after the sorting session.

3.4. Dissimilarity matrix

Based on the individual experiments, an individual matrix M_k ($1 \leq k \leq 30$) is computed where $M_{k_{i,j}}$ is equal to 1 if the stimulus i is in the same group than the stimulus j and equals to 0 if stimuli i and j are placed in different groups. The individual matrices are summed over the 30 participants to build a co-occurrence matrix. This matrix is transformed into a dissimilarity matrix $D_{i,j}$ (Dissimilarity matrix = 30 – co-occurrence matrix). The elements of $D_{i,j}$ correspond to the perceptual distance between the stimuli i and j. This matrix is normalized by dividing the elements by 30 in order for the elements to vary between 0 and 1 [9].

4. RESULTS OF THE ADDITIVE TREE ANALYSIS

The distances between the 24 stimuli can be represented by a “tree” [9] where the length of the branches (connecting the stimuli) is proportional to the perceptual distance between stimuli. The aggregation of the branches at nodes may characterize categories at different levels. The orientation of the branches is arbitrary, only the distance along branches matters. The Addtree software (available from Pascal Gaillard’s Orcid Page [10]) has been used to fit the elements $D_{i,j}$ to an additive tree distance.

4.1. Categories

The resulting additive tree, represented in Figure 5 is quite easy to interpret. There are two large categories that gather magnesium pillars against zinc ones. For Mg pillars, clusters clearly separate the twinning events from the slipping deformation and the mixed modes, where AE signals originated from both twinning and slip deformations. For Zn pillars in which only slip deformation occurred, the clusters do not correspond to the initial size of the micropillar samples. The verbalizations of the participants are then very useful to characterize these three clusters (see section 4.2).

4.2. Comments

To try to get more insights into the processes of classifications, it was asked to participants to describe, with their own words, the classes they created. They were asked to explain why sounds belonged to the same class. The comments were all gathered and pooled together to perform a

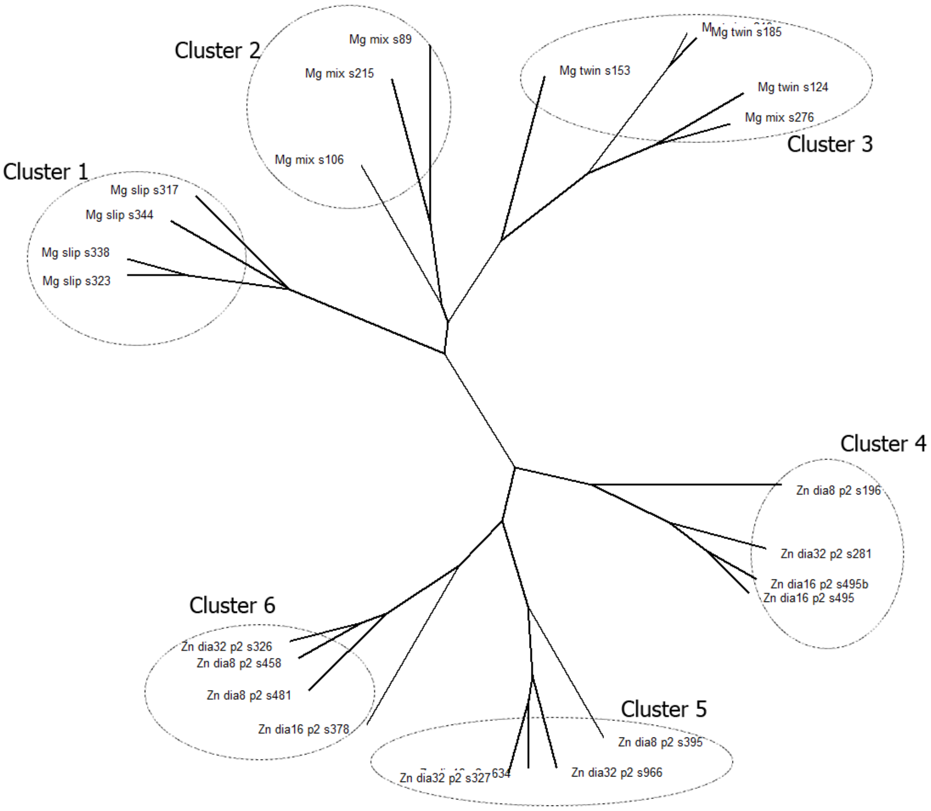

Figure 5: Additive tree of the 24 stimuli.

small verbal analysis relying on the number of occurrences of labels that describe a sound. The labels were simply proposed by the authors to characterize the words used by the participants. This count of occurrences can be found in Table 2. The labels analyzed are counted for each cluster extracted from the tree in Figure 5, and are sorted by the aspect of the stimuli that they refer to (frequencies, intensity, etc...). The methodology used to count is rather simple. When a label is used to describe a class of stimuli by one participant, it is applied to each stimulus of the class. To count the total number of labels in a cluster, it is counted from each stimulus. This is why some counts are higher than the total number of participants. It also means that the total number of occurrences depends on the number of stimuli in a cluster, so a normalization over the number of stimuli in each cluster would be a good idea to avoid biases in the data. Since in this experiment, only clusters 2 and 3 have different numbers of stimuli, respectively 3 and 5, than the other clusters who have 4, the raw data is already good and can give some clues about the differences between clusters. Consequently, statistical analysis on these data has not been conducted, so only a mere description of the counts is presented to extract insights for further studies.

From Table 2, it is the difference in frequency (“low-pitch” vs “high-pitch”) that differentiates Mg (clusters 1, 2 and 3) from Zn (clusters 4, 5 and 6). The difference between Mg slipping (cluster 1) and Mg twinning (cluster 3) is the perceived intensity of the sounds (“hard to hear” vs “loud, violent”), while cluster 2 seems to fall in between (weak and medium intensity). Concerning the Zn clusters, the difference with the intensity is not so clear, but the difference between the number of impacts and the perceived rolls or rebounds seems to be important. Indeed, the difference between cluster 4 and 6 seems to rely on “one impact” vs “several impacts”, while the very high number of rolls and rebounds seems to differentiate cluster 5 from the rest.

Table 2: A summary of the labels most used to describe the sounds in each cluster. Different sets of labels, separated by commas, describe the sounds. The number in brackets corresponds to the number of occurrences of this same idea. For example, “Low, Hard to hear, Weak intensity (52)” means that “Low”, “Hard to hear” and “Weak intensity” are all labels that describe a sound with low intensity, and this meaning has been counted for a total number of 52 times.

	Frequency	**Intensity**	**Distance and Duration**	**Impact**	**Roll/Dry**
Cluster 1	High-pitched (39)	Low, Hard to hear, weak intensity (52)	Far (15) / Long (9)	Several impacts, cracks (28) / One impact (11)	Roll, Rebound, Echos (25) / Dry (4)
Cluster 2	High-pitched (39)	Low, weak intensity (17) / Medium intensity (12)	Far (6)	Several impacts, cracks (28) / One impact (8)	Roll, Rebound, Repetition (24) / Dry (4)
Cluster 3	High-pitched (68)	High intensity, loud, violent (60) / Weak intensity (6) / Medium intensity (3)	Near (9)	Several impacts, cracks (19) / One impact, hit (28)	Roll, Rebound (16) / Dry, Clear (28) / Percussive, Drum (22)
Cluster 4	Low-pitched (49)	High intensity (9) / Medium intensity (16) / Low intensity (7)	Far (11)	Several impacts, cracks (8) / One impact (48)	Roll, Rebounds (16) / Continuous (10)
Cluster 5	Low-pitched (38)	High intensity, loud (12) / Low intensity (5)	Long, Go on, Stretch out (14)	Several impacts (21) / One impact (9)	Rolls, Rebounds, Repetitions (54) / Echo (9) / Dry (3) / Continuous (13)
Cluster 6	Low-pitched (47)	Medium intensity (12) / Low intensity (6)	Long (10)	Several impacts, cracks (44) / One impact (13)	Rolls, Rebounds, Repetitions (36) / Dry (4)

5. RESULTS OF THE MDS ANALYSIS

From the same dissimilarity Matrix used for the tree analysis, a classical multidimensional analysis has been carried out. The rationale behind this analysis is that the dissimilarities are based on continuous dimensions, which can be obvious for certain sensations (loudness for example), but more debatable for the timber effect in this experiment, where two groups are clearly identified (Zn and Mg).

5.1. MDS analysis

From the study of the variance, the number of dimensions should be fixed at 5, but only 4 dimensions were explainable with the comments of participants, so the first 4 dimensions were kept (variances are respectively 28%, 17,4%, 13,3% and 10%).

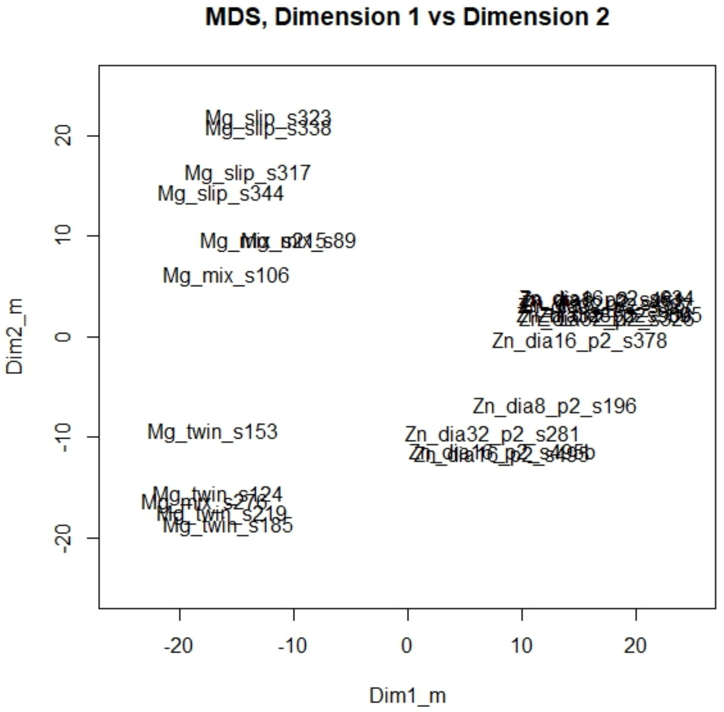

Figure 6: Perceptual plan built on the two first dimensions.

Figure 6 represents the stimuli in the first two dimensions of the MDS. The first dimension is characterized by a higher pitch for Mg samples than for Zn ones. Unfortunately, the AE sensor that was used for the Zn compressions differed from the Mg experiments. To the contrary, the importance of standardized AE sensor application is proven by the current audification perceptual tests, and also visualized by the spectrograms in Figure 7, highlighting the differences in background noise.

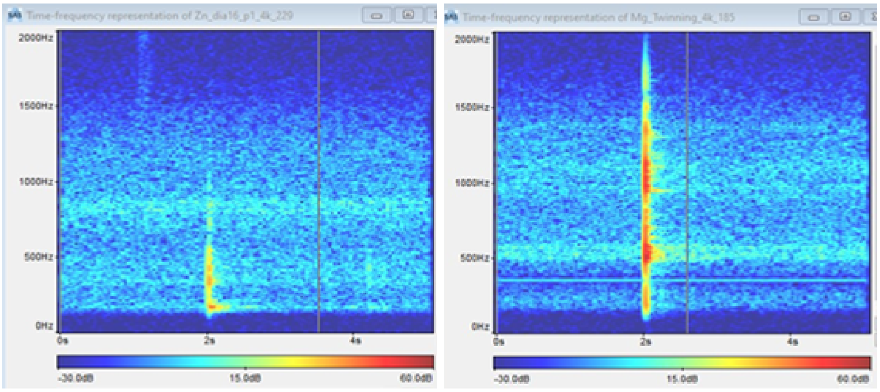

Figure 7: Spectrograms of two different audified excerpts (left) from Zn compression with a loud bandwidth at 800 Hz and (right) from Mg compression with louder bandwidths around 500 Hz, and between 1000Hz and 1400 Hz.

The second dimension corresponds to the feeling of loudness. Participants characterized the Mg twinning samples as “strong, percussive or violent cracks” and Mg slipping samples as “distant, discreet or light” sounds. It is also interesting to note that in that plane, the size of the Zn pillars has no impact on the sound perception.

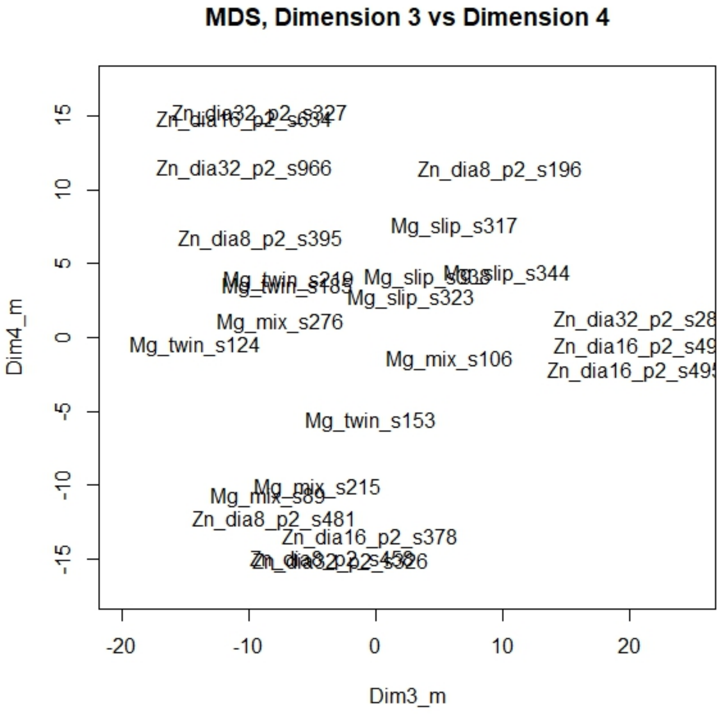

Figure 8: Perceptual plan built on the third and fourth dimensions.

Figure 8 represents the stimuli in the third and fourth dimensions of the MDS. This perceptual space puts the “single cracks” on the right side, and among the “multiple cracks” on the left side, people discriminate stimuli where they hear “repeated but separate peaks” (on the bottom of the dimension 4) from stimuli where they hear “long and rumbling” sounds (on the top of the dimension 4). It is interesting to note that the dispersion of the Mg stimuli is limited compared to the Zn stimuli that cover all the surface. The difference between slipping and twinning dislocations is better characterized by the loudness effect than by the number of the peaks.

5.2. Correlations

To characterize the perceptual dimensions with acoustic indicators, the correlations between the 74 indicators and the four dimensions of the MDS have been calculated. They are presented in Table 3. Again, the first dimension, highly correlated to pitch descriptors, discriminates the low pitch stimuli versus the high pitch ones, that corresponds to the Zn samples versus Mg samples. This is not due to the crystal difference but to the sensors that have been differently used during the mechanical process. The second dimension is correlated with sound level indicators. The third dimension also seems correlated with sound level indicators but much less than the second dimension. Finally, the fourth dimension is not correlated to the usual descriptors that were used. It appears that only the first and second dimensions can be explained with conventional descriptors (Loudness, Sharpness and Roughness), as the third dimension is poorly correlated with low significance. A lack of descriptors for impulsive sounds as well as for things such as “rolls, rebounds, rumblings”, described in the verbal analysis, can be an explanation to such results.

Table 3: Correlations between acoustic indicators and MDS dimensions. The statistic used is the t of Pearson. Significances, *: p-value<0.05, **: p-value<0.01, ***: p-value<0.001.

Acoustic Indicators	**Dim 1**	**Dim 2**	**Dim 3**	**Dim 4**
Leq, total (dB(A))	-0.40	-0.71***	-0.48*	-0.09
ISO Loudness, total (sone)	-0.33	-0.72***	-0.45*	0.12
Max Leq, total (dB(A))	-0.40	-0.75***	-0.41*	0.05
Max ISO Loudness, total (sone)	-0.37	-0.74***	-0.42*	0.10
Impulsive Loudness LMIS, peak part (sone) [11]	-0.39	-0.72***	-0.44*	0.08
Sharpness, total (tone)	-0.94***	0.17	-0.07	0.04
Spectral Centroïd, total (Hz)	-0.95***	0.03	-0.13	0.06
Sharpness, background (tone)	-0.94***	0.23	-0.16	-0.05
Spectral Centroïd, background (Hz)	-0.86***	0.27	-0.20	-0.07
Roughness, total (asper)	0.57**	0.09	-0.34	0.33
Fluctuation Strength, total (vacil)	-0.30	-0.76***	-0.34	-0.14

6. DISCUSSION AND CONCLUSION

This perceptual experiment was built to answer three questions (see section 1).

- It is possible to say without any doubt that the size of the crystal pillar has no influence on the dislocation sound perception.
- For the first question about the discrimination of the materials, it is not possible to answer because of the bias due to the change of sensors. As it has been said in section 5.1, the acoustic emissions had been proposed originally to illustrate the mechanical process of dislocation, and not for perceptual tests. This perceptual study was a kind of proof of concept, but it is clear that, for future research, it is important to keep the same acoustic sensor for collecting dislocation emissions.
- For the discrimination of the type of deformation, it seems that a high sound level characterizes twinning and medium or low levels characterize the slipping mechanism of dislocation.

For this last point, a deeper look was made at the Mg signals collected during the experiment where slip and twinning deformations were identified. When looking at the video recording at the 89^{th} and 106^{th} second, the deformation seems to be by twinning, and when looking on the additive tree or on the MDS perceptual space, stimuli are situated in the middle, a little bit closer to a slip activity. When looking at the video recording at the 215^{th} and 276^{th} second, the deformation seems to be by slipping, and when studying the additive tree or the MDS perceptual space, Mg_mix_s215 is situated in the middle, but Mg_mix_s276 is definitely clustered in the twinning group. Based on the provided information, it seems possible that both mechanical processes happened within the same second. Furthermore, the perceptual tests also confirmed that the "strength" of the two distinct deformation signals differ considerably. Based on the response of the individuals, twinning exhibited stronger, more prominent crackling-like noise, while slip deformation by dislocation motion produced less violent, distant noises. The underlying physics behind these observations is that twinning usually happens very rapidly, and it involves a larger number of atoms to be re-oriented in a short period of time. On the other hand, slip mechanisms are associated to the collective motion of dislocations: line defects move in an intermittent way that involve fewer atom rearrangement in a shorter range.

This study showed that perceptual experiments could give some interesting information about the dislocation process. More materials should now be studied, with a careful attention on the mechanical experimental setup for the choice of acoustic sensors. A specific system should be also proposed to better synchronize the audio file with the video. As the sampling frequency of both modalities are very different, errors of synchronization could easily arrive and could lead to misinterpretation.

7. ACKNOWLEDGEMENTS

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