Material identification of real impact sounds: Effects of size variation in steel, glass, wood, and plexiglass plates

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Identification of the material of struck objects of variable size was investigated. Previous studies on this issue assumed recognition to be based on acoustical measures of damping. This assumption was tested, comparing the power of a damping measure in explaining identification data with that of several other acoustical descriptors. Listeners' performance was perfect with respect to gross material categories (steel-glass and wood-plexiglass) comprising materials of vastly different mechanical properties. Impaired performance was observed for materials within the same gross category, identification being based on the size of the objects alone. The damping descriptor accounted for the identification of the gross categories. However other descriptors such as signal duration explained the results equally well. Materials within the same gross category were identified mainly on the basis of signal frequency. Overall poor support for the relevance of damping to material perception was found. An analysis of the acoustical support for perfect material identification was carried out. Sufficient acoustical information for perfect performance was found. Thus, procedural biases for the origin of the effects of size could be discarded, pointing toward their cognitive, rather than methodological nature. Identification performance was explained in terms of the regularities of the everyday acoustical environment. [DOI: 10.1121/1.2149839]

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I. INTRODUCTION

A growing branch of research, variously labelled *ecological acoustics* (Vanderveer, 1979), *auditive kinetics* (Guski, 2000), *psychomechanics* (McAdams, 2000), or, generally, sound source perception, investigates the perceptual correlates of the properties of sound sources. The object of study in this field can be described at three different levels: physical or mechanical (the properties of the sound source), acoustical (the properties of the sound wave emitted by the source), and perceptual (the perceived properties of the sound event). The research design in sound source recognition analyzes all the pairwise relationships among these levels (Li, Logan, and Pastore, 1991). In the present study this pairwise design was applied to one of the most investigated issues, identification of material type in impact sounds, making it possible to provide a structured framework for the understanding of everyday perception of this source property.

The vast majority of previous studies on material identification focused on the effects of acoustical measures of damping. Wildes and Richards (1988) defined a shape invariant acoustical parameter for material type, the coefficient of internal friction $\tan\phi$, which models material damping,

$$\tan\phi = \frac{\alpha}{\pi f}, \tag{1}$$

where α is the damping coefficient of the vibrational component, i.e., the inverse of the time required for vibration amplitude to decay to $1/e$ of its original amplitude, and f is its frequency. The higher $\tan\phi$ the greater the damping of the material and the faster the decay time decreases with increasing frequency. Wildes and Richards (1988) proposed material type recognition to be based on the $\tan\phi$ coefficient.

The effects of damping measures on material identification were tested in several studies using both synthetic and real sounds. Klatzky, Pai, and Krotkov (2000) investigated stimuli synthesized according to a physical model of a struck bar (van den Doel and Pai, 1998), varying a parameter related to $\tan\phi$ and the frequency of the lowest vibrational mode, later referred to as frequency, which spanned over 3.3 octaves. Four response categories were used: rubber, wood, steel, and glass. Both experimental variables affected identification: rubber and wood were chosen for higher $\tan\phi$ values than glass and steel; glass and wood were chosen for higher frequencies than steel and rubber. The same task was adopted by Avanzini and Rocchesso (2001). Stimuli were

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generated according to the physical model of a one-mode resonator, varying the $\tan\phi$ coefficient and frequency (range: 1 octave). Results were analogous to those of Klatzky *et al.* (2000), although frequency effects were less clear. Roussarie (1999) synthesized stimuli according to a physical model of a struck plate (Lambourg, Chaigne and Matignon 2001), varying damping coefficients, elastic properties, and density of the simulated plates around those characterizing glass and aluminum. The properties of the simulated hammer were also manipulated, using parameters typical of either wood or rubber. Two response categories were adopted: glass and aluminum. Identification was influenced only by the damping properties of the plates, strongly correlated with an acoustical parameter analogous to $\tan\phi$ and with the average spectral center of gravity. Variations in density and elasticity, associated with a frequency variation equivalent to a musical interval of a perfect fifth, had no effect. In summary, all these studies demonstrated material identification to be influenced by damping measures, while frequency was relevant only when ranging over at least one octave.

Other studies focused on material identification performance. Gaver (1988) studied variable-length bars made of iron or wood. High recognition performance was observed and bar length had no effect. Kunkler-Peck and Turvey (2000) investigated variously shaped plates made of steel, wood or plexiglass. Performance was almost perfect with only a secondary tendency to associate materials with shapes. Perfect performance was not confirmed, however, in a study conducted on synthetic signals (Lutfi and Oh, 1997). Stimuli were synthesized according to the wave equation of a struck clamped bar, with stimulus variability created by perturbing the density and elasticity terms. Participants were asked which of two stimuli was generated by striking a given target material (iron or glass), the alternatives being different metals, crystal or quartz. Signal frequency was given a disproportionate weight by listeners, resulting in poor performance.

Inconsistencies between results by Kunkler-Peck and Turvey (2000) and by Lutfi and Oh (1997) were explained by Carello, Wagman, and Turvey (2003) in terms of the lack of acoustical richness that might characterize synthetic signals, and thus of the absence of sufficient information for the task. However, additional studies also found impaired performance with real signals. Giordano (2003) studied rectangular steel, glass, wood, and plexiglass plates. Different stimulus sets were generated, varying also the height/width ratio of the plates and their area (both with freely vibrating and externally damped plates), as well as the material of the hammer. With freely vibrating plates identification was perfect only with respect to two gross material categories (wood-plexiglass and glass-steel), strong confusions being found within the categories. Also, externally damped glass plates were identified as made of wood or plexiglass. In any case, consistently with results of Gaver (1988) and Kunkler-Peck and Turvey (2000), identification of gross categories was not influenced by the geometrical properties of the objects. Further, the height/width ratio and hammer material variables had no significant effect. Results by Giordano (2003) were confirmed by Tucker and Brown (2003) with stimuli generated by striking variably shaped wood, plexiglass, and aluminum plates both in open air and underwater. Wood and plexiglass were strongly confused with one another and were almost perfectly discriminated from steel. A parameter related to $\tan\phi$ explained a large portion of the data variance (62–69%). In summary, Lutfi and Oh (1997), Giordano (2003), and Tucker and Brown (2003) found that recognition abilities were limited and were perfect only when involving comparisons among materials of vastly different properties (e.g., woods and metals).

Kunkler-Peck and Turvey (2000) and Tucker and Brown (2003) found the wood/plexiglass identification to be independent of the geometrical properties of the objects. In contrast, Giordano (2003) found identification within both the above-mentioned gross material categories to be based on plate area (larger plates being more frequently identified as made of steel or plexiglass) both with freely vibrating and externally damped plates. These results appeared strongly consistent across listeners, although a small percentage of participants associated wood/plexiglass with large/small plates. Given the influence of plate geometry on signal frequency, the effects of area on identification would seem to confirm results by Klatzky *et al.* (2000). The informal nature of the acoustical analyses presented in Giordano (2003), however, does not allow us to draw conclusions at this point. Indeed participants might have based their judgment on acoustical parameters other than frequency that are also affected by size variations. Furthermore, the effects of size observed by Giordano (2003) might have been caused by the absence of acoustical information which reliably discriminated between materials within the gross categories. Indeed, in the absence of such information, participants might have been forced to focus on source properties irrelevant to the task, namely size, for which a variation in the acoustical features was present. However, no test for the presence of sufficient acoustical information for perfect material identification was carried out.

Despite all the studies focusing on this topic, little is known about the acoustical criteria for material identification, because acoustical modeling of behavioral data was based on limited sets of descriptors including, at best, an acoustical measure of damping, frequency, and the average spectral center of gravity (SCG) (Roussarie, 1999). Furthermore, the ascertained association of judgments with acoustical measures of damping is not sufficient to conclude as to their relevance to material identification, where judgments might instead be based on correlated signal properties like duration, which is expected to increase with decreasing $\tan\phi$. This hypothesis is at least in part supported by the results of a recent study conducted on synthetic struck bar signals (McAdams, Chaigne, and Roussarie, 2004), based on a judgment shown in other studies (see Grey, 1977; and McAdams, 1993) to be strongly related to identification. Consistently, McAdams *et al.* (2004) found dissimilarity of impact sounds to be influenced by level-decay-rate and SCG-related descriptors, both covarying with a measure of the damping in the simulated bars.

A new study on material identification was performed, using a subset of the real signals investigated by Giordano

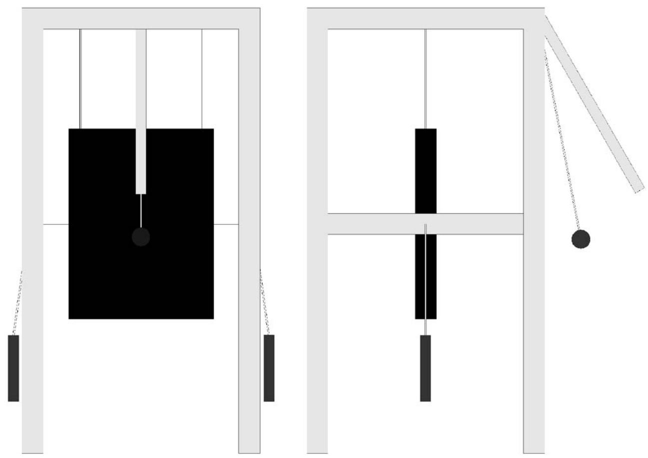

FIG. 1. Sketch of the device used to suspend and strike the plates. The pendulum and the stabilizing weights are shown in dark grey.

(2003). The complete research design in sound source recognition was adopted (Li *et al.*, 1991). A wide set of descriptors was used to characterize the information for identification available to the perceiver, extracting the vast majority of them from a simulation of the basic properties of the peripheral auditory system. For simplicity this level of characterization was termed "acoustical." Both the mechanical and acoustical determinants of experimental judgments were outlined. In particular, the power of several acoustical descriptors in explaining material identification was compared with that of a descriptor closely related to the tanϕ measure of damping. An analysis of the relationship between the acoustical and physical levels allowed us to test for the presence of sufficient acoustical information for perfect material recognition and, consequently, to test for a procedural origin of the effects of size observed by Giordano (2003). Given the interindividual differences for the wood and plexiglass recognition strategies reported by Giordano (2003), interparticipant agreement was also studied.

II. METHODS

A. Stimuli

Sounds were generated striking 2-mm-thick square plates made of four different materials: plexiglass (polymethyl methacrylate), soda-lime glass, steel, and Tanganyka walnut. Five different values were used for the length of the sides of the plates: 8.66, 12.24, 17.32, 24.49, and 34.64 cm, yielding areas from 75 to 1200 cm^2. Each plate was drilled close to the right and left top corners and close to the left and right borders, at the middle of their height (diameter, 4 mm). The upper holes were used to suspend the plates; the lower ones to stabilize them after being struck, thus avoiding amplitude modulations due to an excessive movement of the plate relative to the microphone. Plates were struck with a steel pendulum (diameter, 2 cm; weight, 35.72 g).

The apparatus used to suspend the plates was similar to that used by Kunkler-Peck and Turvey (2000) (see Fig. 1) and was made of pine wood. Both the plates and the pendulum were hung from the top shelf with nylon lines (diameter, 1 mm). The lateral holes of the plates were attached to two 150-g weights with nylon lines, passing through holes drilled in two horizontal planks attached to both sides of the structure. The pendulum was hung from the top shelf, 15 cm from the plane in which the plates lay, and was released from a fixed guide attached to the front of the top shelf, thus keeping constant the starting angle. Plates were struck in their centers. No audible multiple impacts of the pendulum on the plate were observed.

Sounds were generated in an acoustically isolated room with highly absorbing walls and were recorded using a TASCAM DA-P1 DAT recorder (48000-Hz sampling rate, 16 -bit resolution) and Beyer Dynamic digital microphone (MCD101/MPD200) positioned 45 cm from the center of the plate, opposite the struck surface. Recordings were transferred to a computer hard disk through the digital input of a Sound Blaster Live Platinum sound card. Signals longer than 1 s were reduced to this duration by applying a 5-ms linear decay. Informal listening tests showed that material identification was not influenced by this sound wave editing process. Signals were not equalized in loudness. The presentation level was the maximum level which kept the background noise, constant across the samples, inaudible. The peak levels of the signals ranged from 54 to 72 dB SPL.

B. Procedure

Stimuli where presented through AKG K240 headphones, connected to a Nikko NA-690 amplifier, which received the output of the Sound Blaster Live soundcard of the PC used to program the experiment. Participants sat inside a soundproof booth. They were told that on each trial they would be presented a single sound generated by striking an object made of one of four different materials. In order to make instructions straightforward, it was decided to use generic linguistic labels for all materials: glass for soda-lime glass, metal for steel, plastic for plexiglass, and wood for Tanganyka walnut. As the stimulus set comprised only one material type per generic category, it was assumed that this linguistic choice would not affect participants' responses. No mention was made of the geometrical properties of the objects, minimizing the non-auditory information given to participants. After presentation of the stimulus, participants were asked to identify the material of the struck object. Confidence with the response was preferred to the control of participants exposure to stimuli and of the response time, in order to provide the best possible conditions for the use of the auditory information carried by the stimuli. Thus, before giving the response, participants were allowed to replay the stimulus as many times as needed and were given no constraints on the time required to emit the response. Responses were given by pressing appropriate keyboard keys. The 20 stimuli were presented in block-randomized order for each of seven repetitions, for a total of 140 trials.

C. Participants

Twenty-five listeners took part in the experiment on a voluntary basis (age: 22–49 years; 17 males, 8 females). Given the absence of reported effects on source perception

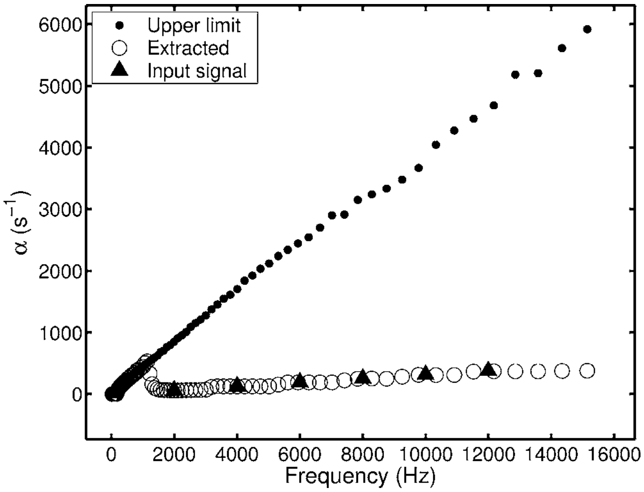

FIG. 2. Damping factors extracted from a six-component harmonic complex with fundamental frequency of 2000 Hz and unweighted $\tan\phi$ of 0.01.

performance (see McAdams, 1993, for a review of this literature), gender was not controlled. All of the participants reported having normal hearing.

III. ACOUSTICAL DESCRIPTORS

The analysis model used to extract the vast majority of acoustical descriptors was meant to simulate the output of the cochlea in response to the incoming acoustical signal. Outer and middle ear filtering were simulated with a cascade of two IIR and one FIR filters, in order to account for peak sensitivity at 2 kHz and for loss of sensitivity at lower and higher frequencies. The transfer function was derived from measures of the minimum audible field (Killion, 1978). Processing of the signal inside the cochlea was simulated with a gammatone filter bank (Patterson, Allerhand, and Giguère, 1995), with center frequencies f_c uniformly spaced on an equal-resolution scale (Moore and Glasberg, 1983) between 30 and 16000 Hz. The power in output from the cochlear filters was then added to the power delayed by $1/4f_c$ (Marozeau, de Cheveigné, McAdams, and Winsberg, 2003).

A parameter analogous to $\tan\phi$ was extracted from this representation and, given the focus of the analysis model on the properties of the peripheral auditory system, termed $\tan\phi_{\mathrm{aud}}$. Damping factors α for the signal output from each channel were computed using the regression model $\log(P)=a+bT$, where P is power, T is time, and $b=-\alpha/2$. The regression model was applied to the signal from peak power to a fixed threshold power. Figure 2 shows the analysis of a harmonic complex given by the sum of six damped sinusoids with a fundamental frequency of 2000 Hz, and with damping factors chosen to yield a $\tan\phi$ (unweighted) of 0.01 [see Eq. (1)]. Also shown is the upper limit for the damping factor of the signal in output from the cochlear channels, calculated analyzing a unitary amplitude impulse.

$\mathrm{Tan}\phi_{\mathrm{aud}}$ was computed from the damping factors weighting for the total power in output from the cochlear filters, where the higher the output power, the higher their perceptual relevance and thus weight in determining the value of this descriptor. Thus $\tan\phi_{\mathrm{aud}}$ was defined as

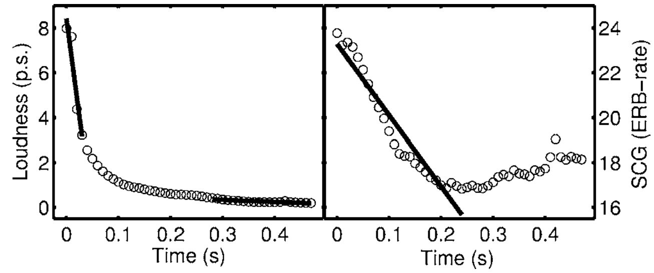

FIG. 3. Temporal functions of loudness and SCG for the signal generated by striking the 150 cm^2 glass plate. Also shown are the linear regression functions used to extract the slope measures $\mathrm{Lou}_{\mathrm{sl1}}, \mathrm{Lou}_{\mathrm{sl2}}, \mathrm{SCG}_{\mathrm{slo}}$.

$$\frac{\sum_{i=1}^{N} \dfrac{\alpha_i}{\pi f_{ci}} w_i}{\sum_{i=1}^{N} w_i}, \tag{2}$$

where f_{ci} is the center frequency in Hertz, and w_i is the sum of power from peak value to threshold. This procedure yielded, for the signal shown in Fig. 2, a $\tan\phi_{\mathrm{aud}}$ of 0.0101.

A second representation was used to extract loudness- and brightness-related descriptors. The representation used to compute the $\tan\phi_{\mathrm{aud}}$ parameter was downsampled, convolving it with a 10-ms square window, yielding a temporal resolution similar to that for loudness integration (Plack and Moore, 1990). The power in each channel was finally raised to the power of 0.25 to approximate partial loudness (Hartmann, 1997). For each temporal frame of this representation, loudness and brightness were defined, and computed, as the sum of the partial loudnesses (Zwicker and Fastl, 1999) and as the spectral center of gravity (SCG) (specific loudness weighted average of frequency), respectively. Finally, a duration (Dur) measure was extracted, offset loudness being that of the background noise (about 0.2 pseudosones).

Attack and average values were extracted from the temporal functions of loudness and SCG ($\mathrm{Lou}_{\mathrm{att}}, \mathrm{SCG}_{\mathrm{att}}$; $\mathrm{Lou}_{\mathrm{mea}}, \mathrm{SCG}_{\mathrm{mea}}$). For 17 of the sounds, the $\mathrm{SCG}_{\mathrm{att}}$ measure corresponded to the maximum SCG value, while for the remaining three signals, the peak was found in the third analysis frame (20–30 ms from onset). With loudness, the attack corresponded to maximum loudness in nine signals, while for the remaining 11 maximum loudness was found in the second analysis frame (10–20 ms from onset). Further descriptors characterized the temporal evolution of these measures and were extracted with linear regression. For loudness, $\mathrm{Lou}_{\mathrm{sl1}}$ measured the slope from the attack to the point where loudness reached half of the attack value; $\mathrm{Lou}_{\mathrm{sl2}}$ measured the slope from the point were loudness was double the final value up to the end. The SCG-over-time function was nonmonotonic for 15 signals, for which an initial decrease was followed by a final increase. Only one slope was extracted ($\mathrm{SCG}_{\mathrm{slo}}$), taking into account the portion from attack to the minimum value. Figure 3 shows the loudness and SCG functions over time for the signal generated by striking the 150-cm^2 glass plate. Also shown are the linear regression functions used to extract the slope measures.

Finally, a measure of the frequency of the lowest spectral component F was extracted, on the basis of the fast Fou-

TABLE I. Acoustical descriptors extracted from each signal. Mat.=material; S=steel; G=glass, W=wood; P=plexiglass; ρ=density; p.s.=pseudo-sones. See text for an explanation of the meaning of each acoustical descriptor.

Mat.	Area (cm^2)	ρ (kg/m^3)	$\tan\phi_{aud} \times 10^{-3}$	Dur (s)	F (Hz)	Lou_{att} (p.s.)	Lou_{mea} (p.s.)	Lou_{sl1} (p.s./s)	Lou_{sl2} (p.s./s)	SCG_{att} (ERB-rate)	SCG_{mea} (ERB-rate)	SCG_{slo} (ERB-rate/s)
S	75	7708.30	1.05	0.98	1535.15	7.24	0.95	−138.84	−0.62	25.98	21.41	−6.00
S	150	7708.30	0.86	0.98	773.44	6.89	1.45	−45.61	−0.96	24.41	19.90	−5.90
S	300	7708.30	0.90	0.98	386.72	6.17	1.81	−25.04	−1.24	23.27	20.64	−2.85
S	600	7708.30	0.37	0.98	187.50	6.80	3.15	−11.96	−2.50	24.10	21.69	−2.63
S	1200	7708.30	0.27	0.98	93.75	5.84	3.88	−4.78	−2.93	23.83	20.35	−2.97
G	75	2301.70	1.52	0.52	1406.25	8.09	1.25	−153.39	−1.17	25.38	22.48	−7.70
G	150	2301.70	4.46	0.47	750.00	7.97	1.09	−175.29	−0.93	23.76	18.59	−31.70
G	300	2301.70	2.59	0.63	386.72	8.58	1.50	−105.47	−1.12	23.07	19.33	−5.72
G	600	2301.70	1.68	0.98	187.50	7.06	1.47	−42.14	−0.69	22.96	16.86	−7.26
G	1200	2301.70	2.55	0.94	105.47	6.59	1.34	−38.41	−0.54	22.56	17.20	−5.56
W	75	718.33	19.29	0.17	527.34	5.19	0.93	−175.51	−1.40	23.51	18.18	−171.61
W	150	718.33	22.33	0.19	257.81	4.55	0.95	−131.95	−2.03	22.34	16.44	−102.38
W	300	718.33	19.03	0.30	128.91	4.56	0.83	−121.13	−1.12	21.40	15.75	−44.01
W	600	718.33	19.78	0.16	58.60	4.15	1.07	−104.69	−3.41	20.98	16.69	−52.39
W	1200	718.33	17.55	0.23	23.44	4.06	1.05	−64.57	−2.64	21.00	16.10	−36.04
P	75	1413.30	26.09	0.10	527.34	4.78	1.11	−176.74	−3.99	23.26	18.36	−153.04
P	150	1413.30	39.62	0.10	281.25	4.05	1.15	−127.72	−4.52	22.11	17.25	−148.12
P	300	1413.30	41.03	0.13	140.63	3.83	1.10	−110.59	−3.19	21.33	16.84	−114.28
P	600	1413.30	31.03	0.16	70.31	3.71	0.91	−99.08	−2.50	20.98	16.46	−123.87
P	1200	1413.30	24.50	0.17	35.16	3.79	0.91	−84.09	−2.46	20.80	15.38	−85.39

rier transform of the first 4096 samples of the signals (Hanning window). F was defined as the frequency of the first amplitude peak exceeding a fixed threshold. Amplitude threshold was defined as the maximum amplitude of the low-frequency background noise across the recorded samples. Table I shows for each signal the extracted acoustical indices. Approximate density measures for the investigated materials are also given. Notably, $\tan\phi_{aud}$ discriminated perfectly among material types, this measure increasing from steel to glass to wood to plexiglass.

IV. RESULTS

Due to the repetitions, for each sound a distribution of responses across the four categories was possible for each listener. Analyses were conducted on the individual modes of these distributions, hereafter referred to as "modal responses."

A. From physics to perception

Response profiles of small groups of participants presented macroscopic differences with respect to data pooled across all participants. Cluster analysis was used to extract groups of homogeneous response profiles. Distances among individuals were calculated using a general nominal dissimilarity measure, defined as the proportion of consistent categorizations among two participants (Gordon, 1999). An agglomerative hierarchical algorithm (average linkage) was used. The final number of clusters was chosen considering a set of statistical indices that measure the goodness-of-fit between the input data and the resulting clustering partitions (Milligan, 1996). A subset of the available indices was chosen that demonstrates superior performance in recovering the correct number of clusters (Milligan, 1981; Milligan and Cooper, 1985): the c index (Hubert and Levin, 1976), the Goodman-Kruskal γ (Baker and Hubert, 1972), and the point biserial correlation (Milligan, 1980). For the first index, lower scores indicate higher goodness-of-fit, and better partitions; for the latter two higher scores characterize better partitions. Following the suggestions by Gordon (1999), the number of clusters was chosen considering local maxima/minima of these indices across partition levels, the correct number of clusters being characterized by the highest concordance among indices. Figure 4 shows the value of the three indices as a function of the number of clusters, along with the local maxima/minima.

The final number of clusters was taken to be equal to three, this partitioning level being indicated by all three in-

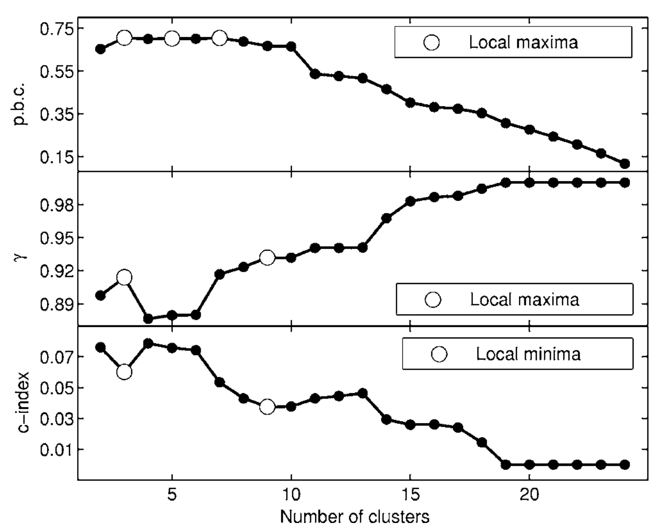

FIG. 4. Statistical indices used to evaluate the number of clusters present in the dataset across partitioning levels.

TABLE II. Contingency table for the modal response in the first cluster of participants ($N=21$). Material: S=Steel, G=Glass, W=Wood, P=plexiglass; Area: A1–A5=75–1200 cm^2. Response categories in italics.

	Metal					*Glass*				
S	1	3	17	21	21	20	18	4	0	0
G	2	2	18	21	21	19	18	3	0	0
W	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0
	Wood					*Plastic*				
S	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	0	0	0
W	19	13	10	13	2	2	8	11	8	19
P	21	21	16	6	3	0	0	5	15	18
	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5

dices. The three clusters contained 21, 3, and 1 participant(s); data for these groups are shown in Tables II, III, and IV, respectively. For the first group, performance was almost perfect with respect to the gross material categories wood-plexiglass and steel-glass, with only one wood response being given for a glass sound. Also a strong tendency to associate the glass and wood responses with smaller plates and the metal and plastic responses with larger plates was found. The same tendencies characterized the second group of participants, the only difference being the association of the wood and plastic responses with larger and smaller wood or plexiglass plates, respectively. The participant in the third cluster consistently associated metal with large wood and plexiglass plates and did not have plastic among the modal responses. Subsequent statistical modeling was performed on data from the main group of participants.

The relevance of properties of the sound source to experimental judgment was first tested. Separate logistic regression models (Agresti, 1996) were built for the perceptual categorization within each of the gross material categories (metal/glass and wood/plastic responses). The wood modal response observed for one of the glass plates was not included in the analysis. Parsimonious models were sought, following the approach suggested by Hosmer and Lemeshow (1989). Thus, before entering predictors into multivariate models, the significance of their effect was tested within univariate models. Both the material, and the area of the plates, were coded as categorical variables. The models' goodness-of-fit was evaluated with the deviance and Hosmer-Lemeshow (Hosmer and Lemeshow, 1989) statistics, nonsignificant values indicating the statistical equivalence of observed and predicted data, and thus the validity of model-based inferences. On the other hand, given the almost perfect performance level observed, data concerning identification of the gross material categories could not be modeled using logistic regression. Simple χ^2 association tests were therefore adopted.

Identification of the gross material categories was influenced by the material, but not by the area of the plates [$\chi^2(3)=416.038$, $p<0.001$, $\chi^2(4)=0.038$, $p=1.000$, respectively]. Also, steel and glass plates were identified equally often as being made of metal or glass [$\chi^2(1)=1.005$, $p=0.316$] and wood and plexiglass plates were identified equally often as being made of wood or plastic [$\chi^2(1)=0$, $p=1$]. On the contrary, plate material did not influence significantly the identification within the gross categories [Wald $\chi^2(1)=0.052$, $p=0.820$, Wald $\chi^2(1)=1.962$, $p=0.161$, for metal/glass and wood/plastic, respectively], while the effect of area was highly significant in both cases [Wald $\chi^2(4)=47.386$, $p<0.001$; Wald $\chi^2(4)=48.52$, $p<0.001$, respectively]. Finally, the effect of area alone accounted well for the within-gross category identification data [metal/glass:

TABLE III. Contingency table for the modal response in the second cluster of participants ($N=3$). Material: S=Steel, G=Glass, W=Wood, P=plexiglass; Area: A1–A5=75–1200 cm^2. Response categories in italics.

	Metal					*Glass*				
S	0	3	3	3	3	3	0	0	0	0
G	0	1	2	3	3	3	2	1	0	0
W	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0
	Wood					*Plastic*				
S	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	0	0	0
W	0	1	2	3	2	3	2	1	0	1
P	0	0	0	2	2	3	3	3	1	1
	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5

TABLE IV. Modal response for the participant in the third cluster. Material: S=Steel, G=Glass, W=Wood, P=plexiglass; Area: A1–A5=75–1200 cm^2. Response categories in italics (*M*=metal).

S	*G*	*M*	*M*	*M*	*M*
G	*G*	*W*	*M*	*M*	*M*
W	*W*	*W*	*W*	*M*	*M*
P	*W*	*W*	*W*	*M*	*M*
	A1	A2	A3	A4	A5

deviance=0, $p=1$, Hosmer-Lemeshow $\chi^2(2)=0.009$, $p=0.996$; wood/plastic: deviance=0, $p=1$, Hosmer-Lemeshow $\chi^2(3)=0$, $p=1$].

Discussion: Consistent with previous studies (Gaver, 1988; Kunkler-Peck and Turvey, 2000; Giordano, 2003; Tucker and Brown, 2003), nearly all individual listeners (88%) showed perfect identification of gross material categories (steel-glass and wood-plexiglass), independently of the geometry of the plates. From the mechanical point of view different material properties could explain this performance, steel and glass being both denser and stiffer than wood and plexiglass (see Table I and Waterman and Ashby, 1997).

Highly impaired performance was observed for the identification of materials within the gross categories: steel was perceptually equivalent to glass, wood to plexiglass. These results are consistent with those of Lutfi (2001), Giordano (2003), and Tucker and Brown (2003), but not with the perfect wood/plexiglass identification reported by Kunkler-Peck and Turvey (2000). Inconsistently with data from Kunkler-Peck and Turvey (2000) and Tucker and Brown (2003), identification within the gross categories was influenced by the geometry of the plates, glass, and wood being associated with smaller plates than metal and plastic. The possible sources for these inconsistencies are addressed in Sec. IV C.

In the Introduction, the effect of plate size on identification reported by Giordano (2003) was hypothesized to be due to the absence of acoustical differences between materials in the same gross category. It must however be pointed out that even in the absence of acoustical support for perfect recognition the observed strong concordance among listeners in associating material type with size points toward a cognitive origin for these effects, rather than to a procedural bias. Indeed, if these associations resulted from the tendency to focus on the only source property that carried significant acoustical variations (allegedly size), an equal number of participants would have associated given material types to opposite sizes. This was not the case in the current data.

B. From acoustics to perception

The acoustical basis for the perceptual categorization of materials within the same gross category was investigated, using the procedure outlined in Sec. IV A. A different approach was used for the identification of the gross categories and is presented in section IV C.

With regression models, the transform of the predictor affects its association with the predicted response. For each acoustical predictor a transform was chosen among the linear (identity transform), logarithmic and, for *F*, the ERB-rate transform, taking the absolute value of the slope-measures to evaluate the logarithmic transform. The univariate models with the different transforms of the same predictor were then compared on the basis of their log-likelihood. Thus, the chosen transform was that yielding the univariate model with the highest log-likelihood, i.e., the model closest to the unknown true probability distribution from which observations were sampled (cf. Golden, 2000). The results of this analysis are shown in Table V. The correlations among the acoustical indices transformed accordingly are shown in Table VI.

Given the presence of strong correlations among predictors, different regression models may, in principle, account for the same data. For this reason, model selection procedures that produce one single model in their output were not adopted (e.g., backward elimination, forward selection). It was thus decided to compute all possible models, starting from the univariate ones and progressively increase the number of predictors until at least one of the models was associated with a nonsignificant goodness-of-fit statistic.

For the metal/glass data set, *F* alone was sufficient to account for the observed data [deviance(8)=7.723, $p=0.259$; Hosmer-Lemeshow $\chi^2(8)=9.700$, $p=0.138$]. The probability of choosing the metal category increased with

TABLE V. Log-likelihood (LL) of the models computed to select the transform for the acoustical predictors. MG=metal/glass dataset; WP=wood/plastic dataset. The LL of the models with the selected transform is shown in boldface.

Data set	Acoustical descriptor	LL linear model	LL logarithmic model	LL ERB model
MG	$\tan\phi_{aud}$	−135.71	**−133.10**	
	Dur	−124.33	**−122.66**	
	F	−57.50	**−48.53**	−50.25
	Lou_{att}	−123.61	**−122.02**	
	Lou_{mea}	−86.70	**−85.29**	
	Lou_{sl1}	−89.08	**−88.37**	
	Lou_{sl2}	**−124.79**	−131.52	
	SCG_{att}	−87.93	**−87.84**	
	SCG_{mea}	−127.49	**−127.24**	
	SCG_{slo}	−119.08	**−108.97**	
WP	$\tan\phi_{aud}$	**−135.23**	−135.55	
	Dur	−126.59	**−121.59**	
	F	−105.30	**−101.79**	−103.34
	Lou_{att}	**−127.87**	−127.97	
	Lou_{mea}	**−130.25**	−130.85	
	Lou_{sl1}	−103.58	**−103.02**	
	Lou_{sl2}	**−134.52**	−138.72	
	SCG_{att}	−110.08	**−109.87**	
	SCG_{mea}	**−103.86**	−104.03	
	SCG_{slo}	**−118.63**	−121.96	

TABLE VI. Correlation among acoustical predictors, transformed according to the analysis summarized in Table V. The upper triangular matrix reports correlations for the wood/plastic data set, and the lower triangular matrix reports correlations for the metal/glass data set. Significant correlations ($df=8, p \leqslant 0.05$) are shown in boldface.

	WP									
MG	$\tan\phi_{aud}$	Dur	F	Lou_{att}	Lou_{mea}	Lou_{sl1}	Lou_{sl2}	SCG_{att}	SCG_{mea}	SCG_{slo}
$\tan\phi_{aud}$		**−0.692**	0.219	−0.49	0.499	0.099	−0.603	−0.047	0.178	−0.476
Dur	**−0.637**		−0.461	0.086	**−0.752**	−0.41	**0.844**	−0.377	**−0.649**	**0.718**
F	0.315	−0.471		**0.722**	0.172	**0.968**	−0.092	**0.917**	**0.802**	**−0.783**
Lou_{att}	**0.693**	**−0.783**	0.596		−0.142	**0.761**	0.345	**0.857**	0.616	−0.355
Lou_{mea}	**−0.804**	0.416	**−0.694**	−0.619		0.074	**−0.902**	0.164	0.493	−0.239
Lou_{sl1}	**0.81**	**−0.669**	**0.786**	**0.847**	**−0.929**		−0.026	**0.884**	**0.784**	**−0.732**
Lou_{sl2}	**0.8**	−0.191	0.456	0.455	**−0.934**	**0.778**		−0.021	−0.357	0.27
SCG_{att}	−0.265	−0.125	**0.749**	0.203	−0.239	0.322	−0.038		**0.852**	**−0.745**
SCG_{mea}	−0.534	−0.081	0.487	0.022	0.213	−0.036	−0.45	**0.764**		**−0.784**
SCG_{slo}	**0.792**	**−0.74**	0.455	**0.637**	**−0.685**	**0.744**	0.54	0.065	−0.354	

decreasing F. For the wood/plastic dataset, none of the acoustical predictors alone could account sufficiently well for observed responses. Five of the two-predictor models were, instead, associated with nonsignificant goodness-of-fit statistics [deviance$(8) \leqslant 13.533$, $p \geqslant 0.060$; Hosmer-Lemeshow $\chi^2(8) \leqslant 11.948$, $p \geqslant 0.154$]. For the first two models, the most important predictor, i.e., that associated with the highest standardized parameter estimate, was F, the second predictor being either Lou_{mea} or Lou_{sl2}, whereas for the other three models, the most important predictor was Lou_{sl1}, the least important predictor being Lou_{mea}, Lou_{sl2}, or Dur. The probability of choosing the wood category increased with increasing F and Lou_{mea} and with decreasing Dur, Lou_{sl1}, and Lou_{sl2} (i.e., with faster loudness decays). It is worth noting that the primary parameters F and Lou_{sl1} are highly correlated for the wood/plastic dataset. Figure 5 shows the selected regression model for the metal/glass dataset and the F-Lou_{sl2} model for the wood/plastic dataset.

Discussion: Consistent with the results of Klatzky *et al.* (2000), the metal/glass identification was based on signal frequency, glass being associated with higher frequencies than metal. As pointed out in the Introduction, the impaired performance in the identification of hard materials reported by Lutfi and Oh (1997) was due to an excessive weighting of signal frequency. A similar explanation for impaired performance might apply here. The relevance of frequency for this categorization is, however, not consistent with results of Roussarie (1999). The simplest explanation for this inconsistency that emerges from a review of previous studies is based on the range of variation of frequency within the stimulus sets; seven semitones in Roussarie (1999), 4.05 octaves in the present study.

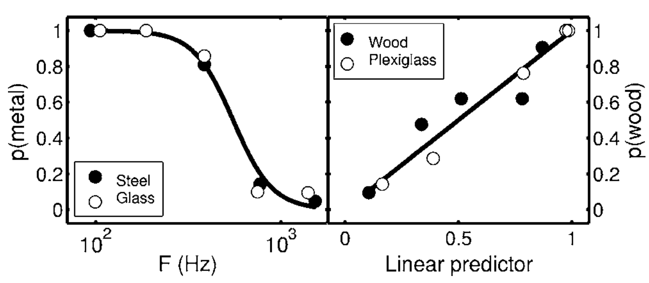

FIG. 5. Left panel: observed and predicted proportions of choosing the response *metal* as a function of the F parameter. Right panel: observed and predicted proportion of choosing the response *wood* as a function of the linear predictor in the F-Lou_{sl2} model.

Frequency was also found to explain the wood/plastic identification where, consistently with Klatzky *et al.* (2000), wood was associated with higher frequencies than plastic. However, this variable alone was not sufficient to account for the observed data, other necessary though secondary variables being either average signal loudness or Lou_{sl2}. The same data were also explained in terms of Lou_{sl1}, strongly correlated with F, and either duration, average loudness, or Lou_{sl2} as secondary variables.

Following a principle of parsimony, a common acoustical explanation for both the metal/glass and wood/plastic data was sought. It can be concluded, then, that both relied mainly on frequency, an acoustical parameter that also explains the relevance of plate size to the judgments. Frequency effects on dissimilarity rating were also reported by McAdams *et al.* (2004), although, as mentioned previously, Roussarie (1999) found material identification to be completely independent of frequency.

Finally, these analyses demonstrate that the investigated acoustical measure of damping, $\tan\phi_{aud}$, does not account for several auditory material categorizations.

C. From acoustics to physics

The presence of sufficient acoustical information for perfect material identification was ascertained. Given the almost perfect performance observed for the identification of the gross material categories, this analysis is equivalent to pointing out the possible acoustical criteria for judgment.

$\tan\phi_{aud}$ was already found to discriminate perfectly among all materials (see Sec. III). Concluding as to the presence of sufficient information on the basis of this result would be incautious if not incorrect, not the least because its perceptual relevance is questioned in the current study. Therefore this descriptor was not taken into account in the following analyses.

Logistic regression was used to find which acoustical descriptor or combination of descriptors allowed for perfect

TABLE VII. Acoustical descriptors found to categorize perfectly the contrasted materials. For each acoustical descriptor the sign of the association with the boldfaced category is also shown (e.g., the model in the bottom row shows that wood is associated with a combination of higher Lou_{att} and higher SCG_{slo} values).

Dataset	Acoustical descriptors
Steel-Glass vs Wood-Plexiglass	$Dur(+)$ $Lou_{att}(+)$ $SCG_{slo}(+)$
Steel vs Glass	$Dur(+)SCG_{att}(+)$ $Dur(+)SCG_{mea}(+)$ $Dur(+)SCG_{slo}(+)$ $F(+)Lou_{att}(-)$ $F(+)Lou_{sl1}(+)$ $F(+)SCG_{slo}(+)$ $Lou_{att}(-)SCG_{att}(+)$ $Lou_{att}(-)SCG_{mea}(+)$ $Lou_{sl1}(+)SCG_{att}(+)$ $SCG_{att}(+)SCG_{slo}(+)$ $SCG_{mea}(+)SCG_{slo}(+)$
Wood vs Plexiglass	$F(-)Lou_{att}(+)$ $Dur(+)Lou_{att}(+)$ $Dur(+)Lou_{mea}(+)$ $Dur(+)Lou_{sl1}(-)$ $Dur(+)SCG_{mea}(+)$ $Lou_{att}(+)Lou_{sl1}(+)$ $Lou_{att}(+)SCG_{att}(-)$ $Lou_{att}(+)SCG_{slo}(+)$

material identification. In analogy with the analysis of behavioral data, separate analyses were performed for the identification of the gross material categories and for identification within the same gross category. Thus, using the descriptors transformed as in Sec. IV B, regression models were sought that resulted in so-called complete separation (i.e., perfect prediction of the dependent variable, material type; Albert and Anderson, 1984). Models were selected starting from the univariate cases and the number of descriptors was progressively increased until at least one perfectly identifying model was found. For each of the considered data sets, the final models produced a threshold above and below which materials belonged to one and only one category. This threshold was defined by a value of the acoustical descriptor in the univariate case or, for models including two descriptors, by a line in the plane defined by the acoustical parameters (see Fig. 5). Table VII reports the results of this analysis.

Steel-glass sounds were thus characterized by higher values of Lou_{att}, Dur, and SCG_{slo} than those characterizing the wood-plastic sounds. It is highly likely that at least one of these acoustical parameters, eventually including $\tan\phi_{aud}$, was used by participants for identification of the gross categories. Several pairs of descriptors perfectly categorized steel and glass (11 pairs) on the one hand, and wood and plexiglass (8 pairs) on the other. Overall, two pairs of descriptors perfectly identified all material types: Dur-SCG_{mea} and Lou_{att}-F. Figure 6 shows the optimal identification criteria based on the Dur-SCG_{mea} parameters. We are thus justified in concluding on the presence of sufficient acoustical information for perfect material identification.

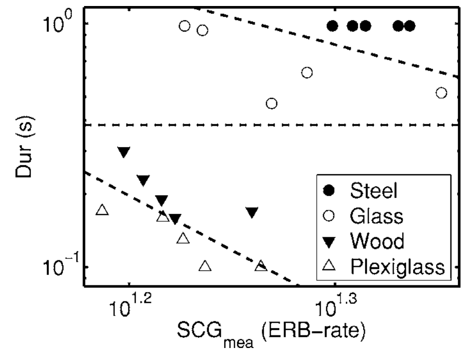

FIG. 6. Optimal criteria for material categorization. Dashed lines show the equal probability boundaries (thresholds) for the optimal criteria.

Finally, it is interesting to compare the optimal use of acoustical information with the observed behavioral criteria, focusing, in particular, on F. While optimal criteria associated steel and plexiglass with higher frequencies, participants used exactly the opposite weighting.

Discussion: Several acoustical parameters accounted for the perceptual (and optimal) identification of the gross steel-glass and wood-plexiglass material categories. Consistently with results by Klatzky *et al.* (2000) and Avanzini and Rocchesso (2001), $\tan\phi_{aud}$ had a lower value for the steel-glass signals. The same discrimination was also explained by Dur, Lou_{att}, and SCG_{slo}. Interestingly, the last of these parameters explained the perceptual relevance of damping in two of the experiments reported by McAdams *et al.* (2004). Given the presence of multiple acoustical explanations, no conclusions can be drawn on which of these parameters was actually used by listeners. In particular, it cannot be excluded that $\tan\phi_{aud}$ was attended to by listeners. Concerning within-gross category identification, the absence of perfect auditory performance is in contrast with the ability of $\tan\phi_{aud}$ to separate the different materials perfectly. It is thus evident that $\tan\phi_{aud}$ was not used by participants for these categorizations. Excluding $\tan\phi_{aud}$, several pairs of other acoustical descriptors allowed perfect within-gross category identification. Among them three were based on the main acoustical parameter used for perceptual categorizations: frequency. The optimal weighting of this parameter was, however, contrary to the observed perceptual weighting. Thus two causes for impaired performance can be hypothesized: the wrong weighting of signal frequency and the absence of focus on the other acoustical parameters necessary for perfect identification, such as attack loudness. Discriminating between these two alternatives is not possible with the available data.

The reasons for the inconsistency between the impaired wood/plastic identification reported in this study and by Giordano (2003) and Tucker and Brown (2003) and the perfect performance reported by Kunkler-Peck and Turvey (2000) still remain unclear. It should be noted however that Kunkler-Peck and Turvey (2000) did not use recorded signals, but generated them live, increasing the likelihood of making additional information for the material type available. For example, as the repetitions provided to the participants were not acoustically identical, extraction of material-specific invariant acoustical information might have been favored. Also, the manipulation of the plates necessary to hang them on the device after each trial might have generated additional acoustical signals (e.g., scraping sounds) that were potentially informative with respect to the object's material. Another inconsistency with previous studies concerns the effect of plate geometry on performance: it was secondary, at best, in Kunkler-Peck and Turvey (2000) or Tucker and Brown's (2003) data but was strong in the current data. Plausibly, the geometrical variation of the sources in these former studies came with less acoustical variation than in the present study, thus facilitating a reduced focus on this source property. Consistently, Giordano (2003) found plate area and not shape to be perceptually relevant, the former most likely causing stronger acoustical variations than the latter.

In summary, acoustical support for potentially perfect performance was highlighted. Thus, the relevance of plate area to material identification, also reported previously by Giordano (2003), is not a product of the absence of sufficient information for the task. Consequently the observed biases are likely to have a cognitive and not a methodological origin. Observed response profiles are indeed likely to reflect the regularities of the everyday acoustical environment (cf. Barlow, 2001). Concerning identification of gross material categories, available measures of the mechanical properties of engineering materials report plastics (polymers) and woods as strongly different from metals and glasses (Waterman and Ashby, 1997). Given these differences, it is highly likely that, independently of their geometry, signals originating from wood and plastic objects would always be differentiated from those originating from metal and glass objects. Consequently, the everyday perceiver would have a rather easy time learning to make robust identifications independent of object geometry, as found in this study.

The ecological explanation of the biases within gross categories is less clear. The simplest hypothesis is based on geometry. For example, the glass impact sounds experienced everyday are probably generated by smaller objects than is the case with metal objects (e.g., klinking glasses vs banging pans) and large, freely vibrating glass objects, such as the plates of the current study, would be too fragile to be of any plausible ordinary use. One might object that sounds generated by striking small metallic objects (coins or keys) are also frequently experienced. These signals, however, have a more complex nature than those investigated in the current study, comprising multiple rather than single impacts, eventually interleaved with signals generated by nonimpact interactions among objects (e.g., friction). Assuming as illegitimate the generalization of source recognition criteria from one kind of object interaction to the other, the size explanation for the metal/glass perceptual identification still seems valid. However, it does not appear convincing for the wood/plastic identification.

Given the plausible high relevance of frequency to the wood/plastic categorization, any source property that significantly affects this signal property might be a potential candidate to explain the size bias. Increasing modal frequencies come, for example, with a decrease in size and density and with an increase in thickness and Young's modulus or simply in stiffness (cf. Fletcher and Rossing, 1991). Therefore it might be hypothesized that listeners learn to associate wood with higher frequencies than plastic because the wood sounds we experience every day are generated by thicker objects than for plastic sounds. This hypothesis appears plausible, given that thin layers should be more easily manufactured with plastics than woods, but could be hardly generalized to the metal/glass case. Concerning Young's modulus, one should expect woods and glasses to be stiffer than, respectively, plastics and metals. Such differences, however, are not apparent in published measures of engineering materials (Waterman and Ashby, 1997). Concerning density, glasses and woods would then be expected to be less dense than metals and plastics, respectively. Indeed, with published measures, the average densities of these materials follow this order (Waterman and Ashby, 1997). The use of an identical explanation for both the metal/glass and wood/plastic categorizations makes this hypothesis particularly attractive.

V. CONCLUSIONS

Material identification from impact sounds was investigated. All the pairwise relationships between source, signal and recognized source properties were studied.

Analysis of the relations between source properties and recognition performance highlighted perfect identification of the gross material categories steel-glass and wood-plexiglass. However, impaired categorization of materials within the same gross category was observed, material identification relying only on the size of the objects. A strong agreement between individuals was also observed.

Acoustical criteria for material identification were investigated. Previous studies found identification to be influenced by acoustical measures of damping. Therefore, a psychoacoustically inspired measure of damping, $\tan\phi_{\mathrm{aud}}$, was contrasted with a large set of signal descriptors in its ability to explain the behavioral data. This measure was found to account only for the identification of the gross material categories, the same data being equally well accounted for by other signal properties: duration, attack loudness, and decay rate of the spectral center of gravity. Identification within the gross categories was instead found to be based mainly on signal frequency, although the wood/plastic identification was equally well accounted for by loudness decay descriptors and, as secondary variables, signal duration or average loudness. Thus, only partial support for the perceptual relevance of $\tan\phi_{\mathrm{aud}}$ was found.

Analysis of the relationship between acoustical and source properties highlighted the presence of sufficient information for perfect material identification, pointing toward the cognitive origin of the observed biases. Identification data were thus interpreted with reference to the regularities of the everyday acoustical environment.

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