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Causal Uncertainty in the Identification of Environmental Sounds

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This report is of an investigation into: (1) whether the recognition of an isolated environmental sound depends upon the number of different events that could cause the sound; (2) a method of quantifying the number of causal events; and (3) the cognitive processes that mediate the effect of multiple causation. Research in the past has focused on the acoustics of the sound in an attempt to determine which features the listener uses in recognition. However, it is well known that recognition is influenced by expectations, particularly about the number of alternatives. Three experiments on the effect of alternative causes are reported. The results of the first experiment replicated earlier results that the Hick-Hyman law applies to environmental sound identification and demonstrated the reliability of a measure of causal uncertainty. The measure is not a signal property in the usual sense. However, by reflecting the number of alternatives an individual considers in making a recognition judgment, it is a feature of a sound that is related to important aspects of recognition performance. The second experiment provided evidence toward the validity of this measure.

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The third experiment demonstrated that high probability causes quicken sound identification compared to low probability causes. This effect was found in individual listeners.

Zillions have been spent to improve long-range underwater detection, but when some stumbling crew member in a submerged submarine (lying in wait with its engines shut off) drops a wrench, only the human listener can identify the unexpected sound and draw the uncomfortable conclusion (Schroeder, 1977, p. 184)

Efforts to understand the identification or classification of signals have in recent years focused on feature-analysis models (Bisson, 1981; Getty, Swets, & Swets, 1981; Howard & Ballas, 1983). These models have as an integral component psychophysical functions which map the multiple physical features of the signal into a multidimensional perceptual space (i.e., Figure 1). Decision algorithms are employed to partition the perceptual space into the categories of interest. A probabilistic decision algorithm is often used when a category can have members which are similar to the members of other categories. This could occur in the case of sound classification under the following conditions. Assume that the categories are types of events and the sounds are examples of these events. Assume also that the sound effects of some events are similar to the effects of other, dissimilar events. To classify a sound in this case, the *conditional probability* of a particular cause given that a certain sound has occurred--$p(c|s)$--must be determined. Howard and Ballas (1983) used Bayes' rule to estimate this conditional probability from the conditional probabilities of the sound given the cause--$p(s|c)$--relative to the conditional probability of the sound given all other causes. Getty et al. (1981) estimated this conditional probability on the basis of the confusability of the stimulus with other stimuli.

From the listener's perspective, the situation is as illustrated in Figure 2 which suggests that the sound is ambiguous because it could have several causes. The listener's task is to use the information presented by the stimulus and decide upon the likely cause from a set of causes. Both Howard and Ballas (1983) and Getty et al. (1981) derive the conditional relationships in Figure 2 from probabilistic transformations of the relationships illustrated in Figure 1. This strategy requires a comparison of the stimuli to one another, a strategy available to the listener only after experiencing the complete stimulus set. This indirect derivation of the conditional probability of a cause given a sound might be unnecessary if one could directly estimate the conditional probability. A technique to directly estimate this conditional probability is presented in this report. This technique produces a measure of causal uncertainty based upon probabilities analogous to the conditional probabilities of Figure 2.

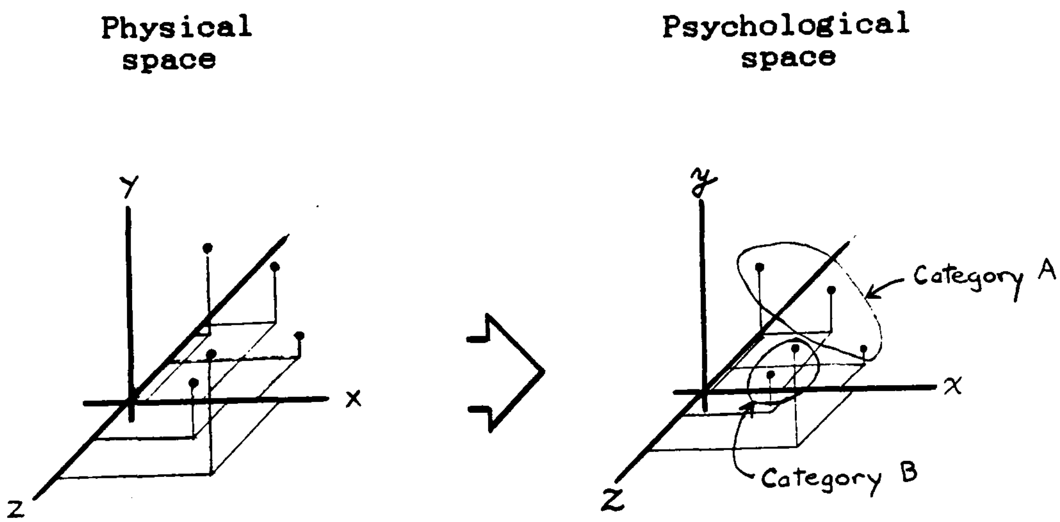


Figure 1. Representations of stimuli in feature-analysis models of classification.

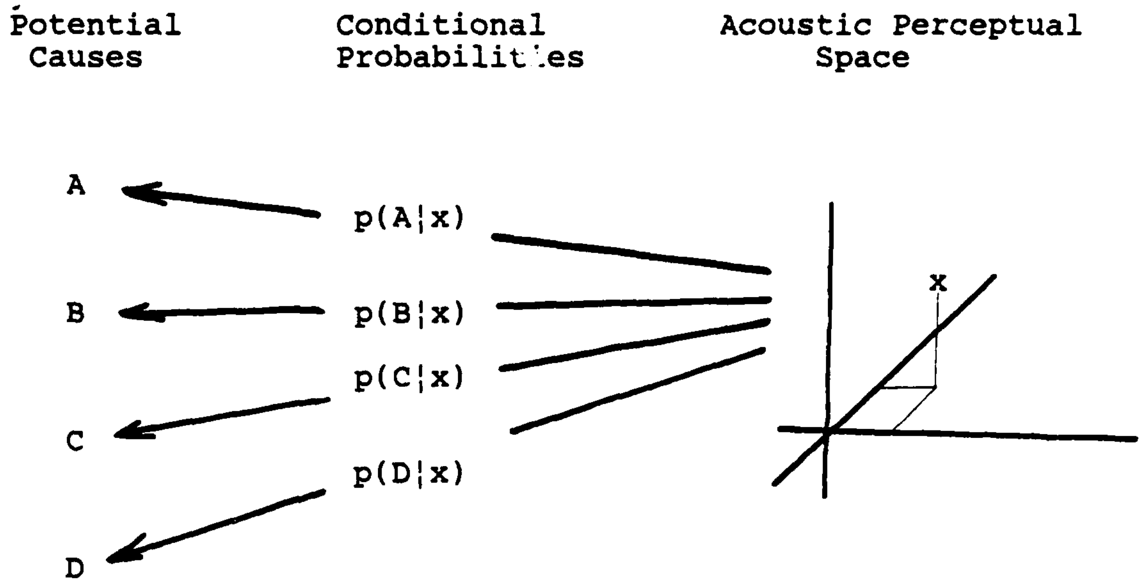


Figure 2. Sound recognition task from the listener's perspective.

Direct estimates of p(c¦s) were developed in order to investigate the hypothesis that the identification of isolated, non-speech, environmental sounds depends in part upon the number of potential causes of the sound--causal uncertainty--as illustrated in Figure 2. This hypothesis is a logical extension of the general finding that accurate identification of isolated sounds is possible if the properties of the sound--particularly the temporal properties--are specific to the mechanical activity of the source (Warren & Verbrugge, 1984). If in fact the sound properties specify several types of events, then identification is compromised. This effect is somewhat analogous to the effects of set size on choice judgments. The relationships in Figure 2 reflect differences in the number of causes and the probabilities of these causes. The effects of set size on judgments are well documented. For example, choice reaction time is a function of the size of the stimulus set, as expressed in the Hick-Hyman law (Hick, 1952; Hyman, 1953). Although the effect is well established, research on this effect has been limited to stimuli which permit a manipulation of stimulus-set size and to judgments which restrict the number of alternatives. Notably absent is research which employs meaningful, naturally occurring stimuli such as environmental sounds. The experiments in this report take up the issue of whether the Hick-Hyman law applies to the identification of environmental sounds.

Research on the identification of meaningful, non-speech sounds has focused on the importance of particular stimulus properties (Chaney & Webster, 1966; Howard, 1977; Mackie, Wylie, Ridihalgh, Shultz, & Seltzer, 1981; Talamo, 1982; Warren & Verbrugge, 1984) or on the role of verbal encoding (Bartlett, 1977). Yet identification of this type of sound requires a choice judgment in instances when the sound might have several causes, such as a loud report heard at night (gunshot?), near a highway (backfire?), around the Fourth of July (firecracker?). The ambiguity of environmental sounds is particularly pronounced when taken out of context (Ballas & Howard, in press). Some sounds presented without context appear to be similar to homonymns in speech and are uninterpretable without the context. The equivocal information in isolated sounds has received little research effort but is recognized by sound-effects professionals. Sound-effects records often contain a disclaimer that some of the sounds in the record might be interpreted differently depending upon the context (e.g., Schachner, 1982). In contrast, the equivocation of information in visual displays taken out of context is well recognized and is the subject of debate on the proper stimulus for perceptual research (Warren and Shaw, 1985).

In examining the role of causal uncertainty in sound identification, the unit of analysis for quantifying causal uncertainty has been a causal "event". The choice of this unit is based in part on the descriptions of sounds given in unconstrained identification experiments (Ballas & Howard, in press; Vanderveer, 1979). These descriptions are typically about the event that caused the sound rather than the acoustic characteristics of the sound. Furthermore, the work on auditory pattern perception (Bregman, 1978; Vicario, 1982) has demonstrated that the perception of sequences of sounds is organized into "streams" of sound which are heard to orginate from separate sources. The streams have a unity and are heard as a kind of auditory "object" projecting from a single source which has the characteristics of an event.

In order to use this unit, it must be defined. Event is taken to mean a generic spatial-temporal process which produces acoustic effects. This usage is consistent with recent ecological approaches to perception. For example, Warren and Shaw (1985) define an event as "a minimal change in an energy potential (or between energy potentials) within some intrinsically determined region of space-time" (p. 19). The generic criterion is introduced to distinguish the concept of an event from particular examples of events. The notion of process is commonly assumed in acoustics but it is important to realize that the dynamic acoustic pattern acts as a reference to the spatial-temporal event itself, and it is the event itself that is thought to be the cause.

The present research puts emphasis on the role of potential source events in the identification of sounds and in this respect is closely aligned with information theory. In this theory, the information metric H has been used to quantify the amount of information in a signal. Despite its wide range of applications and the amount of research devoted to it during the 1960-70s, information theory now receives very little notice in contemporary research. Luce (1985) has referred to information theory as a "fad" that has had little lasting impact on psychology. He argues that the measure -log p is concerned only with quantifying the amount of information, and is not at all concerned with the meaning conveyed by the information. And, as Luce notes, since the latter is of primary interest to the psychologist who is studying information processing, this particular metric is of little import to psychology.

Posner (1978) also comments on the demise of information theory in psychology. With the advent of information theory, it was thought possible to demonstrate a fixed information processing capacity in persons through the quantification of information transmission. Posner claims that when this project failed, information theory was discarded by theoretically oriented psychologists since it could no longer provide an objective, unitary basis for psychological theory. However, unlike Luce, Posner does not view information theory as being of only historical interest. The uncertainty measure makes it possible to represent the number of events and the probabilities of these events in a single metric. This makes it a useful metric in appropriate applications. These applications are suggested by Garner (1974) in a statement which summarizes the contribution of information theory: "... information theory has provided psychology with the basic concept of information itself, and it has clarified that information is a function not of what the stimulus is, but rather of what it might have been, of its alternatives" (p. 194). The existence of these alternatives is an important factor in isolated sound identification and can be quantified with the information metric.

Present Usage of H

The critiques of information theory do not question its ability to provide a rigorous and quantitative assessment of information, they only (rightly) point out its inability to assess meaning and hence expose its limited utility in the realm of cognitive psychology. The present research differs from past research in its use of the information metric in the following ways. The focus of the present research is not on the cognitive processes that mediate the transmission of information. In fact, information transmission as a measure is not directly relevant to the present research. What is of direct relevance is the amount of information contained in a given type of stimulus and whether this quantity is related to the recognizability of the stimulus. The number of possible causes for a sound signal, as quantified by the information metric, is itself being treated as a dimension or property of the stimulus in question. Thus, in analyzing sounds, no special assumptions need be made regarding the processing and the transmission of information, other than the assumptions that they do take place and that a listener's responses reflect them. On this account, the standard criticisms of information theory do not apply to the present research.

This use of the information measure does, however, present some difficulties in its calculation. In prior studies, the experimenter could specify a' priori the number of stimulus (and response) alternatives as well as the probability values of the stimuli. For example, a participant would be seated in front of a panel on which ten light bulbs were attached. The participant would be requested to respond according to which bulb was lit. Thus the number of stimuli was built into the design of the experiment and their probabilities (e.g., frequencies) were under the control of the experimenter. Uncertainty could be manipulated by varying either the number of possible stimuli or their relative frequencies. Calculation of the information statistic becomes problematic when there is only one exposure to a given stimulus because it is impossible to approximate probabilities on the basis of stimulus frequencies. This difficulty was circumvented by Bartz (1971) who demonstrated each of the alternative stimuli to the participant before taking response times. Bartz was able to do so because he could control the number and type of stimuli. In the present research it is impossible (at least at the present time) to specify on theoretical grounds the number of operative stimulus alternatives.

An alternative way of computing the information statistic (Ballas & Howard, in press; Ballas, Sliwinski & Harding, 1986) relies upon the actual identification responses given by the listeners. Participants are presented with sounds and required to identify each. The listeners' identification responses are sorted to determine how many different responses were given. The number of different responses is used to determine the number of alternatives and their relative frequencies are used to determine the probability values. Take for example a situation where ten listeners were presented with a "click-click" sound, and five responded "stapler," three responded "light switch," and two persons responded "ball point pen." In this circumstance, the number of alternatives would be 3, with probability values of 0.5, 0.3 and 0.2, respectively. The H value in this example would be 1.48.

There are three aspects of this method of computing uncertainty values that enjoy no precedent and thus require further comment. First, viewed in the context of traditional information theory, this method makes the tacit assumption that response uncertainty can be used to approximate stimulus uncertainty. The validity of this assumption, at least as a working hypothesis, is crucial to the present research since it accepts information as a property of the stimulus. For this assumption to be valid in the context of information theory, one condition must be true, namely, that there is no significant difference between stimulus uncertainty and response uncertainty. That is, information transmission must be high, for only if little information is lost between the source of a signal and its destination, can this condition be realized. This seems to be a plausible assumption since Hoge & Lanzetta (1968) demonstrated that actual response uncertainty tracked objective uncertainty that is calculable a priori (prior to any actual responses). This assumption can be supported by certain aspects of experimental design. In particular, response alternatives should not be restricted to less than the number of stimulus alternatives. In the present experiments this was assured by avioding sounds which would be unfamiliar to the listeners.

The second aspect of this method that merits further discussion is the fact that the alternative causes are not definable a' priori and could not all be presented during the experiment. For example, a presented "bang" sound might have three possible sources: a firecracker, a car backfire, or a gun. If the present research was performed analogously to traditional research, all the stimulus possibilities would be presented to each participant. In this manner, each possibility could be specified a priori. The proposed method can specify stimulus alternatives only in an ad hoc fashion, by examining the actual identification responses given by the participant. Indeed the only feasible method to determine the operative stimulus alternatives is to infer them on the basis of the responses actually given.

A third issue has to do with the possibility that the responses are not indicative of actual stimulus properties. Because the verbal reports of the listeners are used both to calculate relative probabilities and to specify the stimulus categories, there is a risk that if the participants are not accurately reporting relevant and reasonable alternatives, the acquired data are meaningless. There is reason to believe that this is not the case. When this method was used to calculate the information measure, a high correlation was obtained between information and choice reaction time. If Hick's law is assumed to cover choice reaction time in the identification of non-speech sounds, then methods of calculating H would be evaluated according to their fit with the linear relationship described by this law. Using this method of computing H, Ballas, Sliwinski, and Harding (1986) demonstrated a significant correlation ($r = .66$, $p < .001$) between H and mean choice reaction times, suggesting that an adequate measure of information had been derived. Experiment 1 was a replication of Ballas et al. with a refined procedure and a wider variety of sounds.

To test the validity of the identification responses further, these responses could be used to select stimuli in a follow-up experiment designed to test stimulus confusability in an identification task. If the alternative causes of a sound suggested by identification responses are poorly discriminated when presented for forced-choice identification, then the validity of the initial responses will be confirmed. This result would demonstrate that the alternatives provided by listeners reflect the possible stimulus alternatives. Experiment 2 tested the validity of participants' responses in this manner.

A final consideration is that the definition of the information measure requires calculations to be performed on the basis of probabilities. However, in most cases, these probabilities are estimated from frequencies and proportions. Despite the adequacy of approximating probabilities from frequencies, MacRae (1971) noted that "the mean log proportion is lower than the mean log probability" (p.270). Thus empirical measures of information consistently underestimate the quantity of information in the population. Underestimates can be corrected by a technique analogous to the way that sample variance is corrected to obtain a better estimate of population variance. Carlton (1969) has proposed a method of correcting for this underestimation using the following equation:

$$\sum_{i=1}^{n} p_i \left[\log\left(1+ \frac{q_i}{np_i}\right) - \left(\frac{\log e}{2}\right) \frac{p_i q_i (n-1)}{(np_i+q_i)^2} \right]$$

where p_i = the proportion of events of type i, $q_i = 1-p_i$, k = the number of categories, and n = the number of observations. Carlton's method is of little use because it requires knowledge of the probabilities and if these probabilities were known the information measure could be computed directly without bias. There are several techniques that can employ Carlton's equation if the general nature of the distribution of the probabilities is known. The technique most applicable to the present research is the "raw bias" method described by MacRae (1971). This method takes the distribution of sampled frequencies as representative of the population distribution. Thus, the empirically derived proportions serve as the probabilities in the above equation.

The results reported by Ballas, Sliwinski, and Harding (1986) were not based upon the calculation of unbiased measures of information. Instead of employing a correction factor in the computation of the information measures, listeners were asked to name alternative responses. This served to boost both the k and n values which would decrease bias. Unbiased information measures were recalculated from the original data but the correlations did not improve over those originally obtained and, in some instances, were substantially lower. Use of the raw bias method of correcting for bias is not as useful as simply asking listeners to provide stimulus alternatives.

In summary, the present usage of H to assess the causal uncertainty of a sound and directly estimate an analogue to the conditional probabilities in Figure 1 is supported on both logical and empirical grounds. Nonetheless, issues remain and the experiments were designed to investigate several of these issues.

Experiment 1

The first experiment replicated and refined the study reported by Ballas, Sliwinski, and Harding (1986) on the relationship between response uncertainty and identification time. In that study, a linear relationship was found between these two variables supporting the view that the Hick-Hyman law might be relevant to the identification of environmental sounds. However, two aspects of that study limited its implications. First, the stimuli included animal sounds which were recognized more quickly than the rest of the sounds, but not always more accurately. Second, the listeners received little practice in the experimental procedure and consequently, the variance in the data was large. In the present experiment, the animal sounds were used for practice and excluded from the test sounds. In addition, the sampling rate for digitizing and producing the stimuli was increased to enhance the fidelity of the sound reproduction. Furthermore, the role of prior experience with the sounds was assessed by having the listeners rate their familiarity with the events that produced the stimuli. The purpose of the experiment was identical to the previous study: to determine the relationship between response uncertainty and identification time.

Method

Participants. Thirty undergraduate students volunteered as listeners in this study and were paid for their participation. The ages of the participants ranged from 13 to 27 with most between the ages of 20 and 25. There were 14 women and 16 men. None of the listeners had hearing disorders. A majority had received musical training either instrumental or voice.

Stimuli. Forty-eight sounds (7 practice sounds and 41 test sounds, described in Table 1) were obtained from several sound-effects records, and were digitized at 20 kHz for 1.5s through a low-pass filter set at 10 kHz. A 0.5s section of the sample was selected for each stimulus, and was generated with a digital-to-analog converter (DAC) at 20 kHz, and passed through a low-pass filter set at 10 kHz. Wave forms for each of the sounds were plotted and analyzed using the ILS Software Package. For each participant, the practice session consisted of animal sounds; the test session, however, consisted of environmental sounds. The test sounds were presented in random order to control for order effects that might arise because there were several impact sounds and several explosion sounds. The sounds were selected to represent a variety of environmental sounds, to pose both easy and difficult identification problems (and accordingly, a reasonable uncertainty range), and to be completed within a 0.5s duration if the sound was noncontinuous. The sounds were presented at a comfortable listening level.

Procedure. Participants were tested individually through interaction with a microcomputer which presented both instructions and stimuli and obtained responses from a standard keyboard. The experiment consisted of two parts. In part one, the listeners were instructed to press the space bar to initiate a sound and to press it again as soon as they had a reasonable idea about the cause of the sound. On each trial, the time between the onset of the sound and the space bar press was recorded. The listeners then typed an identification of the sound, being instructed to provide both a noun and a verb. After completing the 7 practice sounds, the listeners continued with the 41 test sounds.

Table 1

Description and Source of Stimuli

Sound	Description	Source Record/Volume Side/Band
1. Telephone ringing	high-pitched ringing	SFX/5/1/6
2. Clock ticking	three clicking sounds	SE/2/B/10
3. Car horn	medium-pitched horn	SE/13/B/4
4. Doorbell	two high-pitched chimes with the first higher than the second	CBS/3/1/16
5. Automatic rifle	burst of five shots	SE/13/B/13
6. Riverboat whistle	medium-pitched whistle	SE/13/A/15
7. Water dripping	high-pitched water drip	Live recording
8. Bellbuoy	high-pitched bell	AU/4/B/18
9. Foghorn	low-pitched whistle	SE/13/A/13
10. Water bubbling	continuous soft bubbling	AU/4/A/11
11. Bugle	separate notes increasing in pitch	AU/4/B/6
12. Rifleshot indoors	single low-pitched, muffled shot	SE/2/A/21
13. Lawn mower	continuous, modulated, low-pitched motor	SFX/1/1/16
14. Church-bell tolling	two high-pitched bells	SE/2/A/8
15. Swish	oar being rowed in water; sound of water flowing smoothly	SFX/2
16. Knocking on door	three quick knocking sounds	CBS/2/2/11
17. Flush	initial phase of a toilet flush with rushing water	CBS/1/2/17

Table 1 (continued)

18.	Footsteps	woman walking quickly	SE/13/B/3
19.	Fireworks	powerful muffled explosion	SFX/8/2/11
20.	Cigarette lighter	plastic lighter being lighted with quick, grinding, high-pitched metallic sound followed by hissing sound of flame	Live recording
21.	Touch tone telephone	single high-pitched tone	SFX/5/1/10
22.	Door opening	two high-pitched metallic latching sounds, one followed immediately by the other	CBS/2/2/10
23.	Bacon sizzling	sounds of bubbling, frying oil in a frying pan	AU/4/A/8
24.	Hammering	three quick tapping sounds	SFX/3/2/13
25.	Submarine dive horn	horn of increasing and then decreasing pitch	SFX/1/2/21
26.	Person walking in clogs	two footsteps of person walking in wooden clogs, each step contains two impact sounds	SFX/3/1/25
27.	Ignition of car	three revolutions of car engine being started	SE/13/A/9
28.	Chopping of tree	single impact sound of an axe cutting into a tree	SFX/1/1/18
29.	Power saw	high pitched metallic whine	SFX/7/2/23
30.	Key in lock	two latching sounds, slightly muffled	SFX/1/2/5
31.	Cork popping	popping sound followed by soft impact of cork	SFX/5/1/13
32.	File cabinet drawer	sound of metallic wheels rolling on on a metallic track followed by the closing of metallic drawer	SFX/3/2/6
33.	Door closing	two low-pitched impact sounds, one followed immediately by the other	CBS/2/2/9
34.	Car backfire	one explosive backfire followed by an echoing clunk	SE/13/A/9
35.	Jail door closing	two echoing impact sounds, one quickly followed by the other	SFX/1/2/3

Table 1 (continued)

36.	Rifle shot outdoors	single high-pitched shot	SE/2/A/19
37.	Light switch	pull-cord light switch consisting of two high-pitched transients	Live recording
38.	Stapler	stapler being pressed, consisting of two low-pitched transients	Live recording
39.	Telephone being hung up	phone receiver being placed into its cradle producing two impacts	SFX/5/1/8
40.	Sawing of tree	a stroke of a handsaw followed by a return movement	SFX/1/1/21
41.	Electric lock	sequence of buzz and then clicking sound of lock opening	SFX/1/1/24

References for sources of recordings

SE/2: Valentino, T.J.(Producer). Sound Effects Vol.II [Album]. New York, N.Y.: Thomas J Valentino Inc.

SE/13: Valentino, T.J.(Producer). Sound Effects Vol.XIII [Album]. New York, N.Y.: Thomas J Valentino Inc.

AU/4: Holzman, J.(Producer). Authentic Sound Effects Vol.IV [Album]. New York, N.Y.: The Elektra Corporation.

CBS/1.2.3: Hoppe, E. and Dulberg,J.(Producers). The New CBS Audio-File Sound Effects Library, Vol.II [Album] (1982). New York, N.Y.: CBS Records. (CBS/1 represents the first record within the volume, CBS/2 represents the second record, and CBS/3 represents the third record).

SFX/1,2,3,5,7,8: White, V.(Producer). SFX Sound Effects [Albums]. New York, N.Y.: Folkways Records and Service Corp.

In the second part of the experiment, each of the 41 test sounds was presented again to give the listeners an opportunity to provide, if they wished, any reasonable alternatives to their original responses. Upon completion of the experiment, the participants were asked to complete a questionnaire which asked for biographical information needed to assess important characteristics of the sample (e.g., extent of formal music training). The questionnaire also included a set of rating scales that the participants completed to assess their familiarity with the events which had produced the sounds. This six-point scale was anchored by the terms "familiar" and "unfamiliar". Cohen and Cohen (1975) claim that scales of this type have interval properties for most purposes of analysis. The participants were not told that these events had been the same ones presented to them in the experiment.

Results and Discussion

As expected, the distribution of response times was skewed (Figure 3). Response times that were greater than three standard deviations from the mean for the particular sound were discarded in further analyses. With this culling of outliers, response times averaged across listeners ranged from 1253 ms for the sound of a telephone ringing to 6823 ms for the sound of an electric buzzer lock (see Table 2).

The identification responses were sorted by two research assistants on the project and a third person who was unfamiliar with the research hypothesis. This third sorter was a professional technical writer. All three individuals sorted the responses into categories of similar events using these criteria:

- Phrases using exactly the same noun and verb should be placed in the same category.

- Phrases using nouns and verbs that are synonymns should be placed in the same category.

- Phrases describing the same physical scene, as would be used to describe a scene in a movie script, should be placed in the same category.

- A phrase missing a verb such as in the response "door", should be set aside until the first pass was completed. These phrases should be placed into the most frequent category which uses the noun contained in the phrase.

- Responses which are not specific enough to be categorized,(e.g., "object hitting another object" or "item falling"), should be excluded from the sorting.

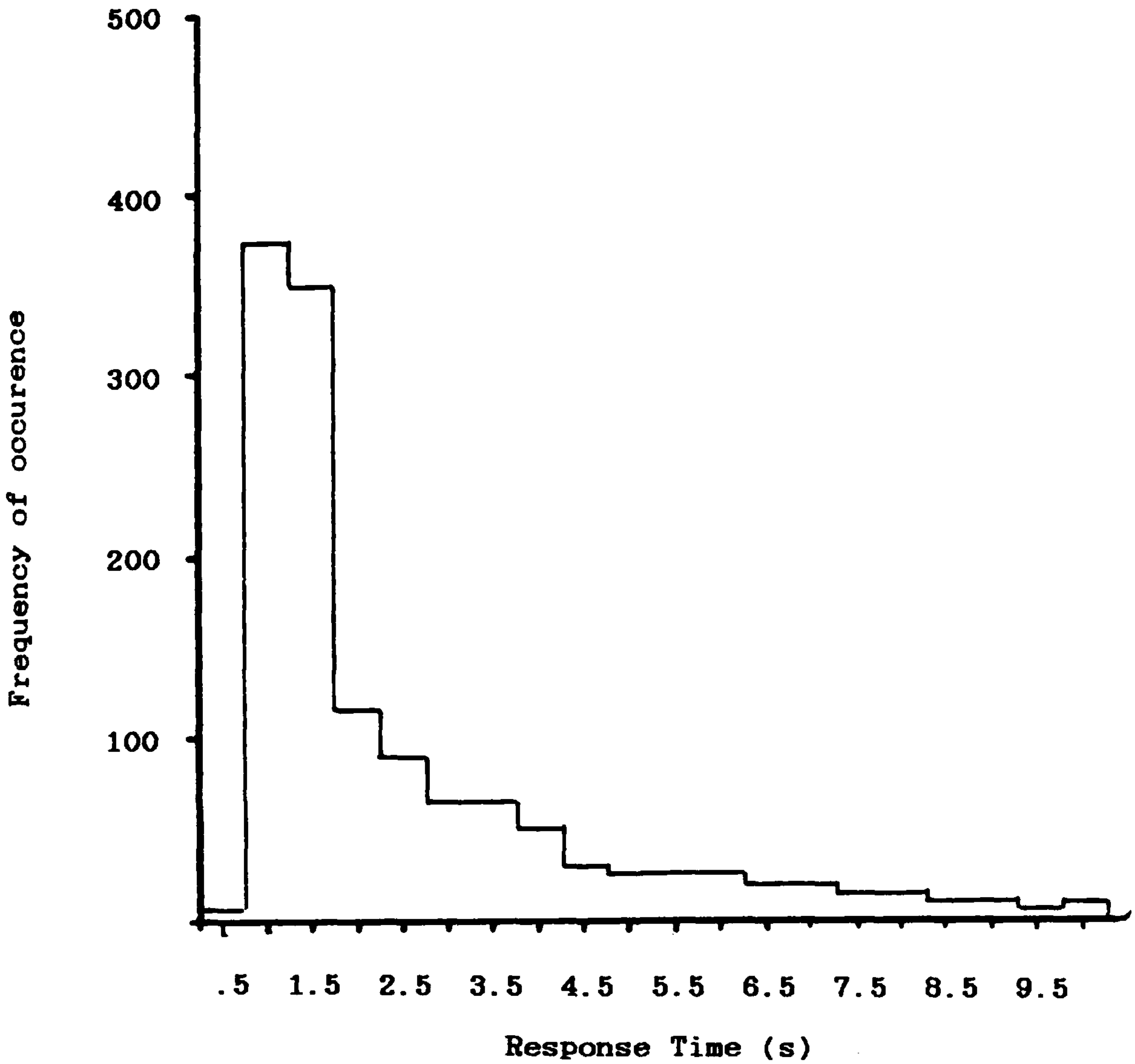


Figure 3. Response time distribution for test sounds.

Table 2

Results from Experiment 2

	SOUND	MRT	H1	H2	H3	FAM	CORR
1.	Tele Ring	1253	0.44	0.44	0.44	1.2	.09
2.	Ticking	1592	1.34	1.07	0.98	1.3	-.14
3.	Car Horn	1611	0.75	0.75	0.75	1.4	-.08
4.	Doorbell	1642	0.58	0.58	0.00	1.3	-.12
5.	Autorifle	1666	2.28	1.85	1.89	3.6	.25
6.	Riverboat	1751	1.90	1.26	0.98	3.5	.11
7.	Drip	1831	2.22	0.99	1.14	1.7	.03
8.	Buoy	1912	3.03	2.81	2.21	3.9	-.06
9.	Foghorn	2135	2.26	2.24	1.22	2.7	.39*
10.	Bubble	2325	3.72	2.68	2.75	1.6	.49*
11.	Bugle	2356	2.20	2.19	1.41	2.3	.58*
12.	Rifle In	2371	3.21	2.97	2.49	3.9	.33
13.	Mower	2596	3.77	3.65	2.73	2.6	.24
14.	Church	2614	2.88	2.89	1.68	1.9	.03
15.	Swish	2745	3.91	3.37	0.70	1.5	.19
16.	Door Knock	2779	2.16	1.98	1.44	1.3	.02
17.	Flush	2779	2.36	1.84	1.25	1.4	.50*
18.	Footstep	2823	3.48	2.53	2.04	1.2	.06
19.	Firework	2926	3.32	3.23	2.93	2.9	.33
20.	Lighter	3210	3.46	3.54	3.18	3.2	.00
21.	Touch Tone	3305	4.07	2.36	2.84	1.5	.14
22.	Open Door	3335	3.20	2.94	2.49	1.5	-.22
23.	Frying	3422	3.42	3.56	2.92	2.1	.24
24.	Hammer	3624	3.34	3.13	2.97	2.2	.32
25.	Sub Horn	3695	3.60	3.51	3.07	4.6	.18
26.	Clogs	3799	3.11	3.36	2.23	3.6	.28
27.	Ignition	3802	3.84	3.27	2.83	1.9	.26
28.	Chop	4071	4.96	4.51	3.69	3.6	.27
29.	Power Saw	4113	4.95	4.45	3.77	3.2	.02
30.	Lock Key	4240	3.44	3.67	2.96	2.0	-.16
31.	Corkpop	4296	4.10	3.60	3.44	2.5	.43
32.	Cabinet	4305	3.34	3.48	2.87	2.9	-.04
33.	Close Door	4372	3.02	2.90	2.74	1.4	-.06
34.	Backfire	4610	3.99	3.72	3.13	3.4	.29
35.	Jail Door	5197	3.96	4.13	1.50	3.8	.28
36.	Rifle Out	5240	4.46	3.88	3.11	3.2	-.06
37.	Switch	6022	4.53	4.40	3.79	2.1	-.32
38.	Stapler	6055	4.72	4.65	4.17	2.2	.04
39.	Hang Up	6660	4.97	4.78	4.44	2.1	-.23
40.	Tree Saw	6792	4.81	4.72	4.05	3.7	.25
41.	Elec Lock	6823	4.18	4.11	3.32	3.8	.16

MRT = mean reaction time(ms); H1, H2, H3 = Uncertainty values for three sorters ; FAM = average familiarity rating from biographical questionnaire; CORR = product moment correlation between FAM and MRT (* significant at the .05 level).

The initial and alternative responses were treated equivalently in the sorting. These sortings were then used to compute the uncertainty statistic using the equation:

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i$$

where H is the amount of uncertainty or causal entropy, p_i is the proportion of events of category i and n is the number of categories. As illustrated in Figures 4-6, the uncertainty values obtained from the three sorters are linearly related to the log of average response times. Produce moment correlations were .85, .89, and .82 for the two research assistants and the naive sorter. The increase in the correlation resulting from a log transformation of response time was significant for two of the sortings, $t(38) = 3.83$, 2.64 and 1.43, $p < .001$, .02, .20, for a test of differences between dependent correlations. Response times are not usually transformed by a log function in studies of the Hick-Hyman law and this result is inconsistent with the relationship reported by Ballas, Sliwinski and Harding (1986). A log transformation produced better linearity in these results in part because the response time distribution in the present experiment was truncated at the shorter times by the exclusion of the animal sounds which Ballas et al. found produced the quickest responses. Correlations between uncertainty and mean response time without the log transformation were greater than the correlation found by Ballas et al. but even the largest difference (using H2) difference was not significant, $z = 1.63$, $p = .10$ for a test of differences between independent correlations. The relationships between response time and measures of stimulus intensity (i.e., peak voltage, average power) were not significant, a finding consistent with Ballas et al. There were no significant components of higher order for the uncertainty variable.

The reliabiliies of the three sorters were significant, $r(1\&2) = .95$, $r(1\&3) = .87$, $r(2\&3) = .87$, $p < .001$. The reliability coefficients for sorter #3--the naive sorter--show that experimenter bias not is a factor in these results and indicate that the sorting procedure itself is reliable when the sorting criteria are followed. The magnitude of these reliability coefficients suggests that uncertainty values might be stable for particular sounds. If this is the case, these values could be used as a measure of the recognizability of a sound in much the same way that measures of familiarity have been developed for words and nonsense syllables. To test this possibility, it would be necessary to conduct a study similar to the present one but using different examples of the 41 sounds. The two sets of uncertainty values could be compared to determine if the values for particular sounds are consistent.

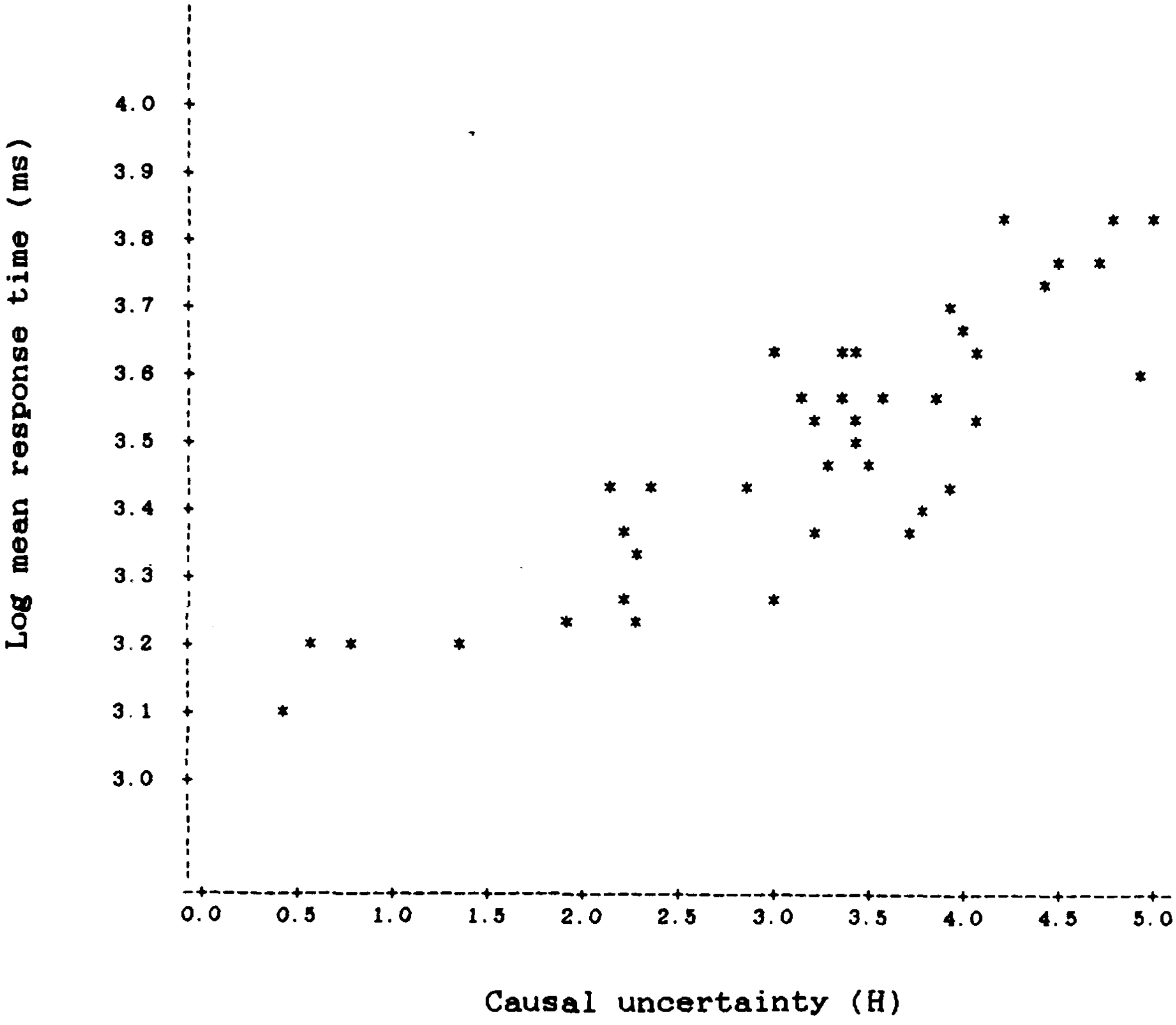


Figure 4. Relation of mean response time for test sounds to causal uncertainty calculated from sorting #1 (H1).

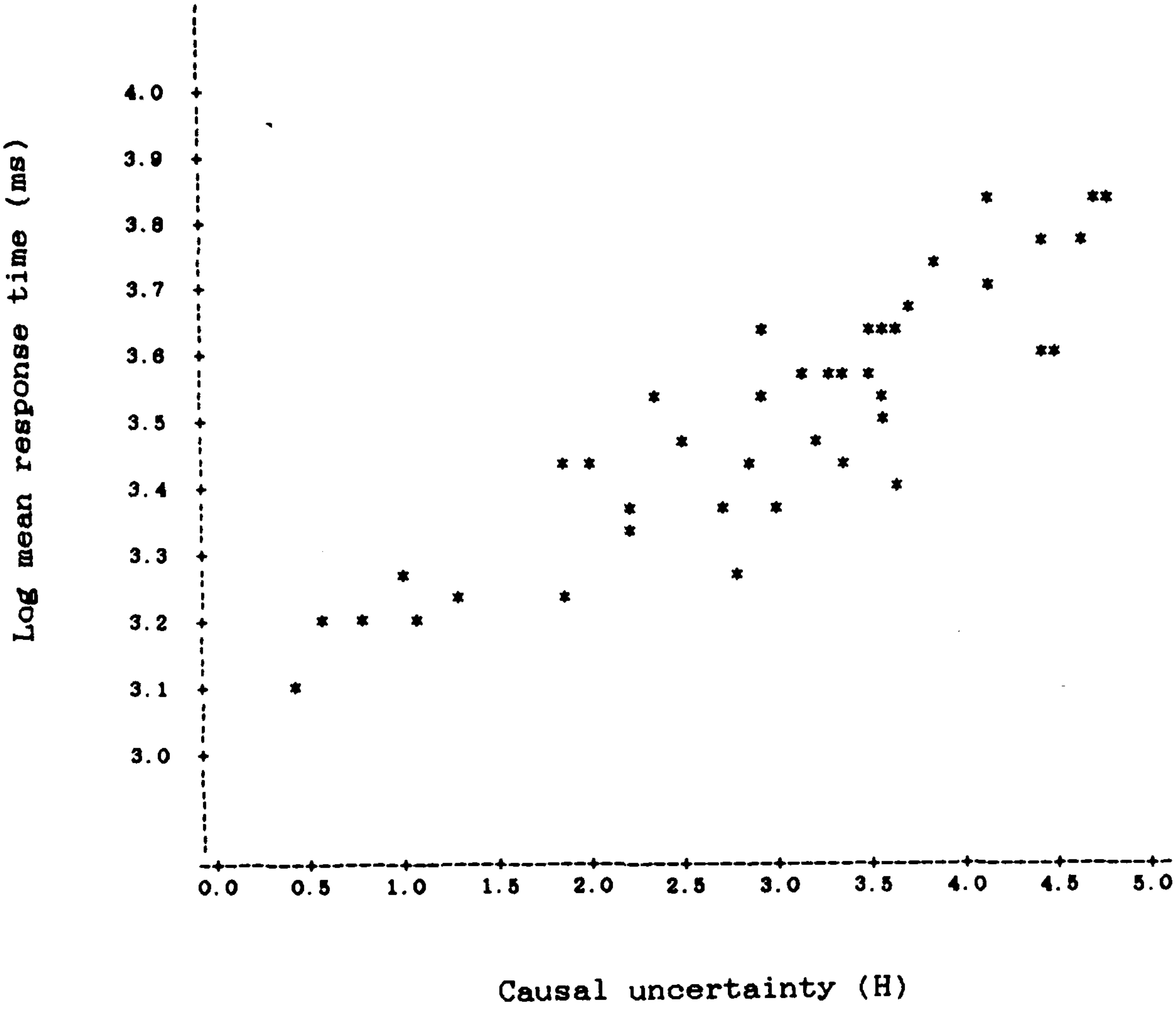


Figure 5. Relation of mean response time for test sounds to causal uncertainty calculated from sorting #2 (H2).

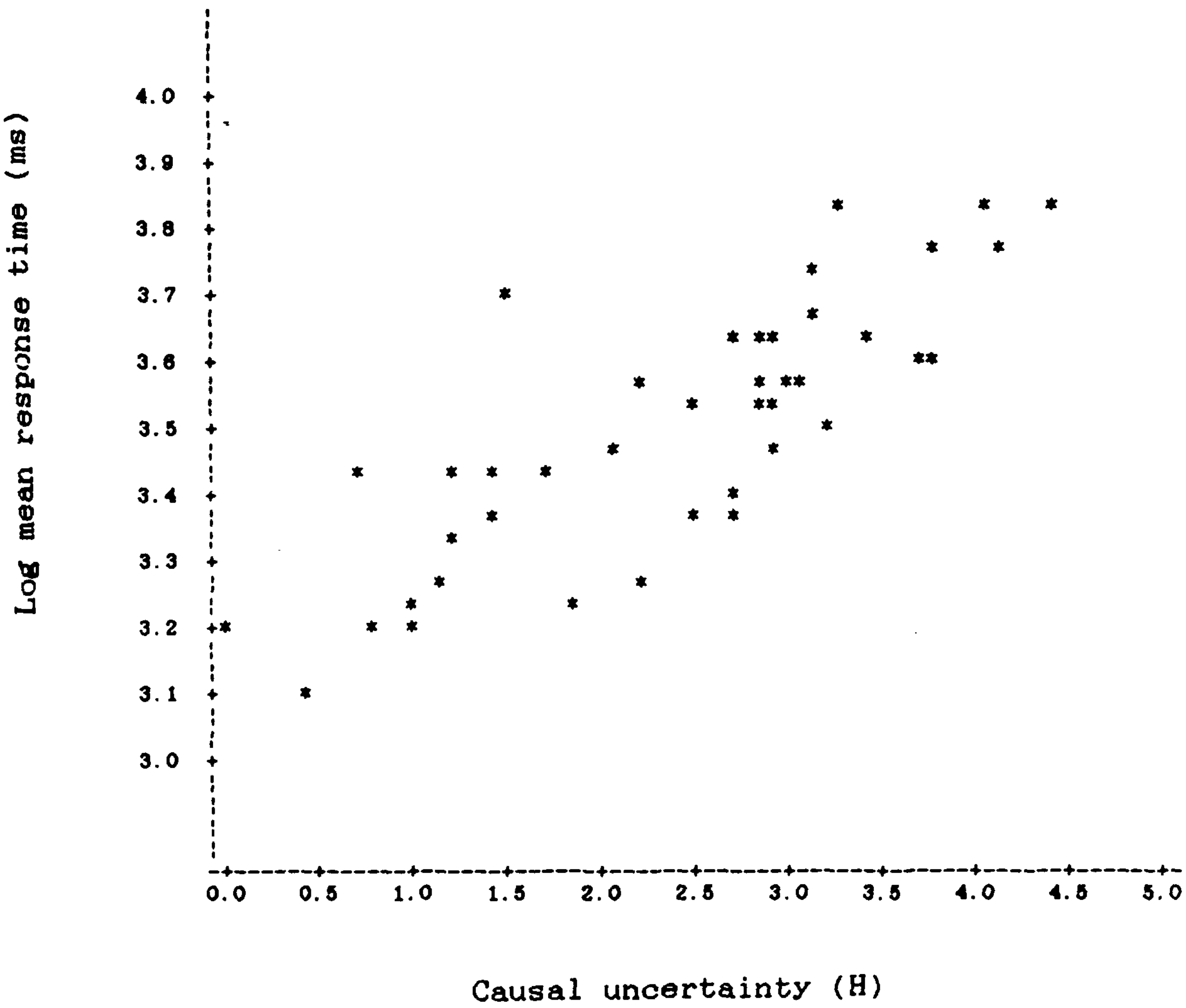


Figure 6. Relation of mean response time for test sounds to causal uncertainty calculated from sorting #3 (H3).

This strategy was pursued in this experiment by examining the uncertainty values of 15 stimuli that were common to this study and to the study by Ballas et al. (1986). It should be emphasized that the stimuli were common at the level of cause but not at an acoustic level. In other words, the two studies used different exemplars of the 15 sounds. In addition, the digitizing rate was different in the two studies. Two sortings were available for the first set of sounds and three for the second set. These five sortings were performed by five different individuals using the criteria described previously. Uncertainty values from these sortings are shown in Table 3. Reliability coefficients between the different sorters are uniformly high as shown in Table 3. The coefficients with the naive sorter are reduced markedly by the discrepant uncertainty value for the splash sound. This sorter used only two categories for the responses to this sound choosing to focus on whether or not the splash involved a human action. The other sorters discriminated between the types of human actions and the types of environmental events. With this exception, these results indicate that the uncertainty measures are consistent not only for different sorters on a specific set of sounds but also for different examples of sounds and different sorters.

Most of the uncertainty values are consistent across the sorters and studies. This consistency would be expected if the uncertainty values are considered to be a stimulus property. The basis for treating these values as a property of the stimulus and not of the observer is the inherent functional relationship between the physics of an event and its acoustic "signature". Some events produce similar acoustic signatures and are accordingly confused. The notion of confusable or indiscriminable acoustic signatures suggests that these uncertainty values can be used as a quantitative measure of the recognizability of these sounds. But first, the role of individual experience must be addressed. This is particularly important in view of the finding that particular sounds are reliably assessed at the same level of identification uncertainty. One explanation for this finding is that shared, prior experience with environmental sounds has informed us about the causes of some sounds more than others. The values could then reflect this shared variation in knowledge about sounds, rather than a variation in the breadth of possible causes for a sound.

The issue of individual experience in the identification of these sounds was assessed through the post-test questionnaire. The participants were asked to rate their familiarity with each of the events represented by the stimuli. These ratings were correlated with individual response times to determine the contribution of familiarity to identification response time. The correlations were nonsignificant except for sounds #9, #10, #11,and #17 (Table 2). Average ratings across listeners correlated

Table 3

Uncertainty Values for 30 Exemplars of 15 Sounds Common to Two Indepedent Experiments

Causal Event	Ballas et al. Sounds		Present Study Sounds		
	Sorter 1	Sorter 2	Sorter 3	Sorter 4	Sorter 5
car horn	0.0	1.9	0.8	0.8	1.3
door bell	0.8	0.3	0.6	0.6	0.0
flush	1.5	1.8	2.4	1.8	1.3
foghorn	2.3	2.1	2.3	2.2	1.2
church bell	2.6	2.7	2.9	2.9	1.7
car ignition	2.6	2.4	3.8	3.3	2.8
knock on door	2.8	2.8	2.1	2.0	1.4
door closing	2.8	2.9	3.0	2.9	2.7
backfire	2.8	3.0	4.0	3.7	3.1
bubbles	2.8	3.4	3.7	2.7	2.8
door opening	3.1	3.2	3.2	2.9	2.5
footsteps	3.4	3.7	3.5	2.6	2.0
fireworks	3.4	3.6	3.5	3.2	2.9
splash	3.6	4.2	3.9	3.4	0.7
bacon frying	3.7	3.8	3.4	3.6	2.9

Reliability Coefficients:

.86 .95
.86 .73
.87
.81 .71
.79
.56
.55

significantly with both average response time ($r = .31$, $p < .05$) and response uncertainty derived from the three sortings ($r = .39, .48, .38$ respectivly, $p < .01, .001, .01$). However, in a multiple correlation analysis with response time as the dependent variable, familiarty was a nonsignificant variable after causal uncertainty had been entered into the regression model, $F(2,38) = 0.11, 3.66, 0.11$, $p = .74, .06, .95$ for the three sortings). This means that causal uncertainty was more important than familiarity, as measured by the questionnaire, in accounting for identification response time.

Experiment 2

This experiment was designed to study the discrimination and categorization of sound "homonyms"--similar sounds caused by different events--and to assess the validity of responses given to such sounds. Identification responses in the first experiment included different causes for each sound. In some instances, these causes can be completely incongruent. For example, a squaky valve sound used in studies by Ballas and Howard (in press) was thought by some to be an elephant trumpeting. A question naturally arises about the validity of these verbal responses. To address this issue, one sound was chosen for further study to determine whether its alternative causes are reasonable. This sound is produced by a pull-cord light switch. It typically includes two "clicks" produced as the switch is engaged and released. In pilot research this sound was thought by some listeners to be caused by a paper stapler. A ball point pen was also thought to have caused this dual click. Because these reported causes are used to calculate the uncertainty measure, it is important that they not be spurious verbal responses. More to the point, is it reasonable to assume that a reported alternative cause of a sound increases identification uncertainty because it could have truly caused the sound? Furthermore, does the relative frequency of alternatives reveal the similarity between the acoustics of these alternatives and in some sense the probability of the alternatives as causes?

These questions were addressed in this experiment. Two types of events were chosen for study: light switching and paper stapling. These two events were chosen because they are relatively easy to produce, most listeners would be familiar with the events, and the events produce a pattern of complex, short duration transients--the identification of which is little understood. Multiple exemplars of each event were produced by changing the instruments and circumstances of the event. The listeners were presented with each example and asked to identify it as a switch or stapler. The paradigm was a single-interval, two-alternative forced-choice.

Method

Participants. There were twenty participants who ranged in age from 14 to 30 with most 20 years old. Eleven were women and nine were men. None of the participants reported any hearing disorders. All reported that they had heard the sounds of a stapler, pull-chain switch and push-dimmer switch. Their recent experience with these sounds had been infrequent, with five, seven, and six participants reporting that they hear the sound of a stapler, pull switch, and push switch, respectively, less than once a month. The participants were paid five dollars for participating in this study.

Stimuli. Sixty stimuli were used: thirty stapler sounds and thirty switch sounds. One of the stapler sounds was used as a practice stimulus. The sounds were obtained under the conditions listed in Tables 4 and 5. The sounds were digitized at a 20 kHz sampling rate through a low pass filter set at 10kHz. The duration of the sounds varied as shown in Tables 4 and 5. A tape was made by generating the sounds with a DAC set at a 20 kHz sampling rate through a low pass filter set at 10 kHz. The order of the stimuli was random. The tape recorder had a frequency response of 30Hz to 15 kHz.

Procedure. Participants were seated at a table where they received instructions. They were told that they would hear a series of sounds each of which would be either a stapler or a lightswitch, the latter being either of the pull-chain or push-dimmer type. At this point, the investigator placed the staplers and light switches that had been used to produce the sounds on the table in front of the participant. The participants were not allowed to handle the objects, nor were any sounds produced by these objects prior to or during the experiment. The participants were informed that half of the sounds would be staplers and half would be light switches. They were then asked to identify each sound using a 6-point scale which included a confidence rating:

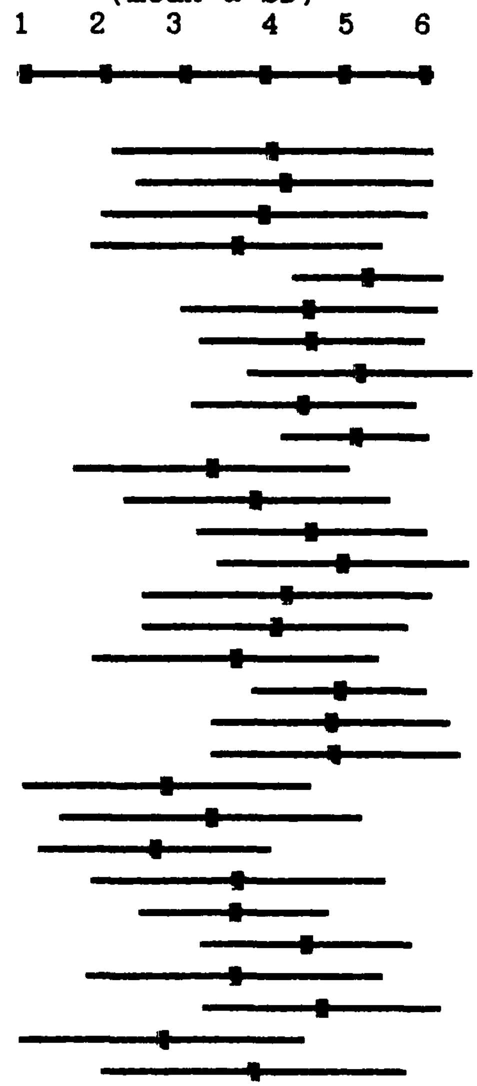
1 = Light switch, certain
2 = Light switch, probable
3 = Light switch, possible
4 = Stapler, possible
5 = Stapler, probable
6 = Stapler, certain

Thus participants were required to indicate their level of confidence in their identification of each sound. After completing one practice sound, the listeners continued with 60 test sounds.

Table 4

Production Characteristics and Response Categorization for 30 Stapler Sounds

Sound No.	Stapler Type [1]	Production Characteristics [2]	Duration (ms)	Response Categorization (mean & SD)
1	1	A	823	
2	1	A	377	
3	1	B	657	
4	1	B	296	
5	1	AC	667	
6	1	AC	303	
7	1	D	276	
8	1	D	699	
9	1	DC	642	
10	1	DC	243	
11	1	BF	507	
12	2	A	923	
13	2	A	357	
14	2	C	703	
15	2	C	567	
16	2	D	648	
17	2	D	282	
18	2	C	684	
19	2	C	349	
20	2	E	465	
21	3	A	974	
22	3	A	207	
23	3	C	706	
24	3	C	421	
25	3	D	848	
26	3	D	259	
27	3	C	779	
28	3	C	272	
29	3	BG	599	
30	3	BG	183	



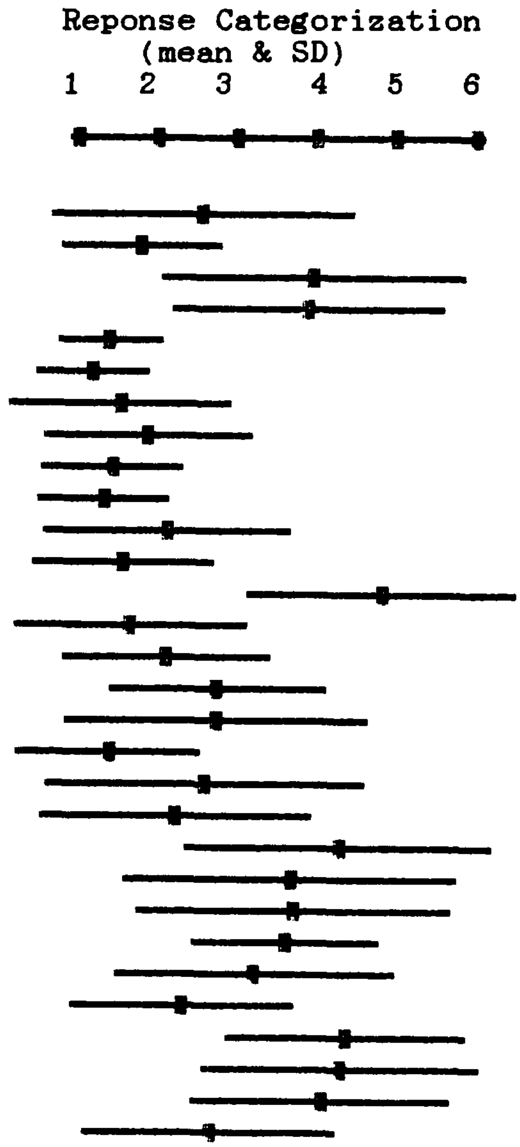
1. Stapler Type 1 was a medium sized plastic-cased stapler, (15.2cm by 5.1cm); Type 2 was a metal stapler, (20.3cm by 7.6cm); and Type 3 was a small metal stapler, (10.2cm by 5.1cm).

2. Production characteristics are as follows:
A=Press on wood desk; B=Press in hand; C=With paper; D=Press into foam; E=Press on metal wall; F=No base; G=With base;

Table 5

Production Characteristics and Response Categorization for 30 Switch Sounds

Sound No.	Switch Type[1]	Production Characteristics[2]	Duration (ms)
1	1	A	1478
2	1	A	319
3	1	B	679
4	1	B	604
5	2	A	707
6	2	A	360
7	2	C	701
8	2	C	317
9	3	A	754
10	3	A	295
11	3	C	694
12	3	C	326
13	4	A	524
14	4	A	225
15	4	C	453
16	4	C	246
17	5	A	955
18	5	A	410
19	5	C	608
20	5	C	599
21	6	D	779
22	6	D	674
23	6	DE	748
24	6	DE	572
25	6	DF	390
26	6	DF	304
27	6	DFG	775
28	6	DFG	290
29	6	DFH	870
30	6	DFH	239



1. Switch types 1-5 are chain pull switches, switch type 6 is a plastic push-dimmer switch.

2. Production characteristics are as follows:
A=Down pull; B=Straight out pull; C=Side pull; D=Handheld press; E=Side press; F=Press on wood; G=Sideways press; H=Angled press.

Results and Discussion

The average response ratings for each of the stimuli are listed in Tables 4 and 5 together with standard deviation bars. There were significant differences in the average ratings and some stimuli were rated incorrectly. Using a criterion of two standard deviations from the mean of the ratings for the type of sound, stapler stimuli #21, #23 and #29 and light switch stimuli #3, #4, #13, #21, #22, #23, #24, #25, #27, #28, and #29 were incorrectly identified. These include all but two of the push-dimmer switch stimuli. The duration of the sound was not systematically related to identification ratings. These results indicate that certain examples of a sound can be thought to have causes other than the actual cause.

Waveform and spectral analyses of the sounds using the ILS software package revealed that several features of the stimuli might be important in identification of a sound as a stapler or switch. All of the stimuli were characterized by two transients as illustrated in Figure 7. Stapler stimuli were probably identified on the basis of low-frequency components. The spectra of correctly identified stapler stimuli were characterized by low-frequency components (e.g., stapler #5 as shown in Figure 7). The push-dimmer switches shared this characteristic, and thus were thought to be stapler sounds more so than the other types of switches. Similarly, the stapler stimuli which were characterized by high-frequency components (e.g., stapler #29) were less accurately identified.

A feature of the pull-chain switches that might have been used for identification was the repeated-impulse pattern preceding the transients, especially the first transient (Figure 8). This pulse pattern was caused by the rolling chain and was evident in several of the most accurately identified switches (switches #6 and #9). A second feature that might have enabled listeners to identify the switches is the harmonic pattern that was evident in the first transient of several identified switches (Figure 9). This harmonic structure would have been caused by the reverberation of the ceramic light socket or the hanger from which the switch hung. This structure was not evident in the stapler sounds.

Two of the sounds in this study--switch #6 and stapler #17--were used in the first experiment. Data from the two experiments can be compared to determine if the free-identification of these two sounds in the first experiment reflects the ability of listeners to categorize these two sounds in the second experiment. In the first experiment, the light switch was correctly identified in 18.6% of the responses and incorrectly identified as a stapler in 4.7%. The ratio of switch to stapler responses was 3.95 : 1. The results of the second experiment were consistent in that this stimulus was rated as the most likely switch. The stapler

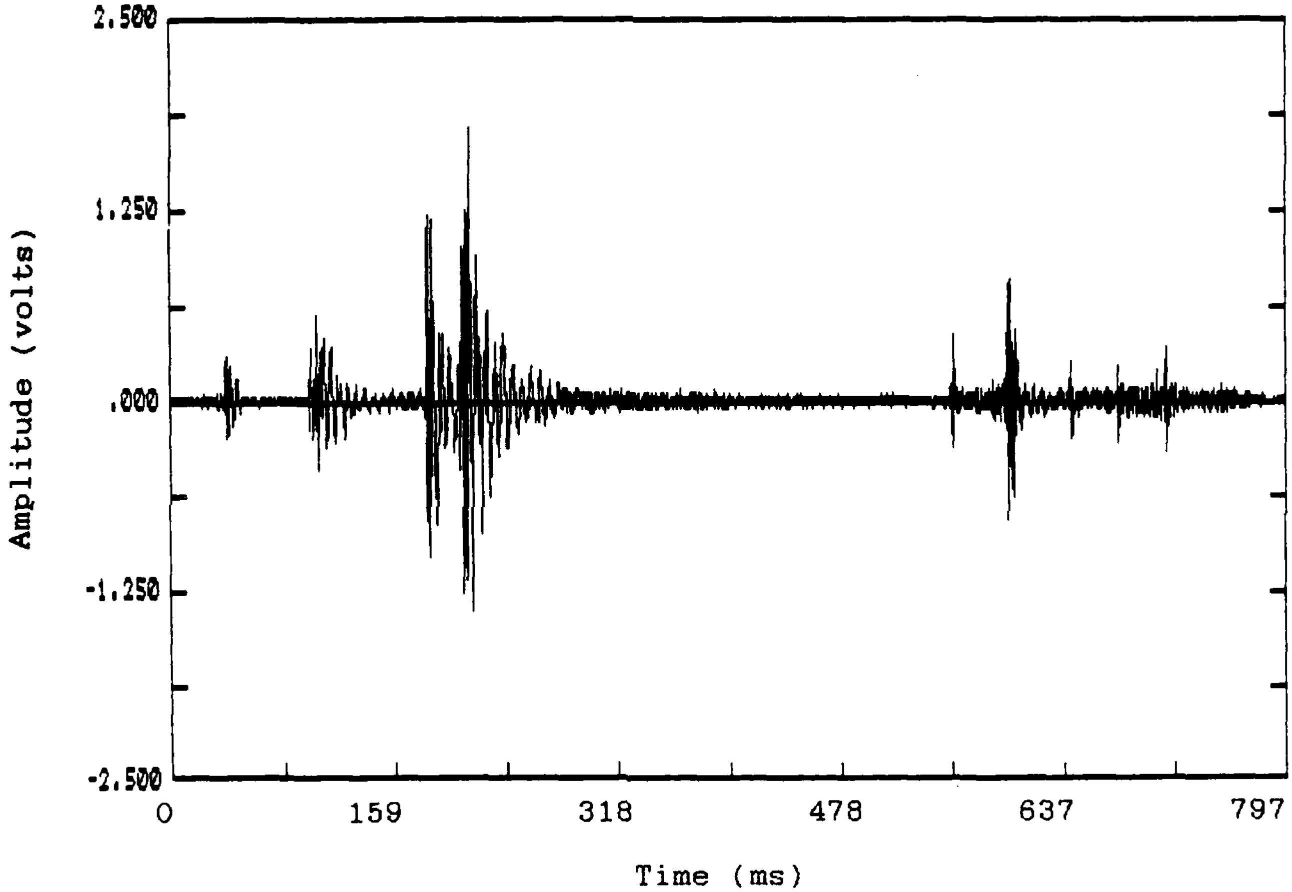


Figure 7. Waveform for stapler sound #5.

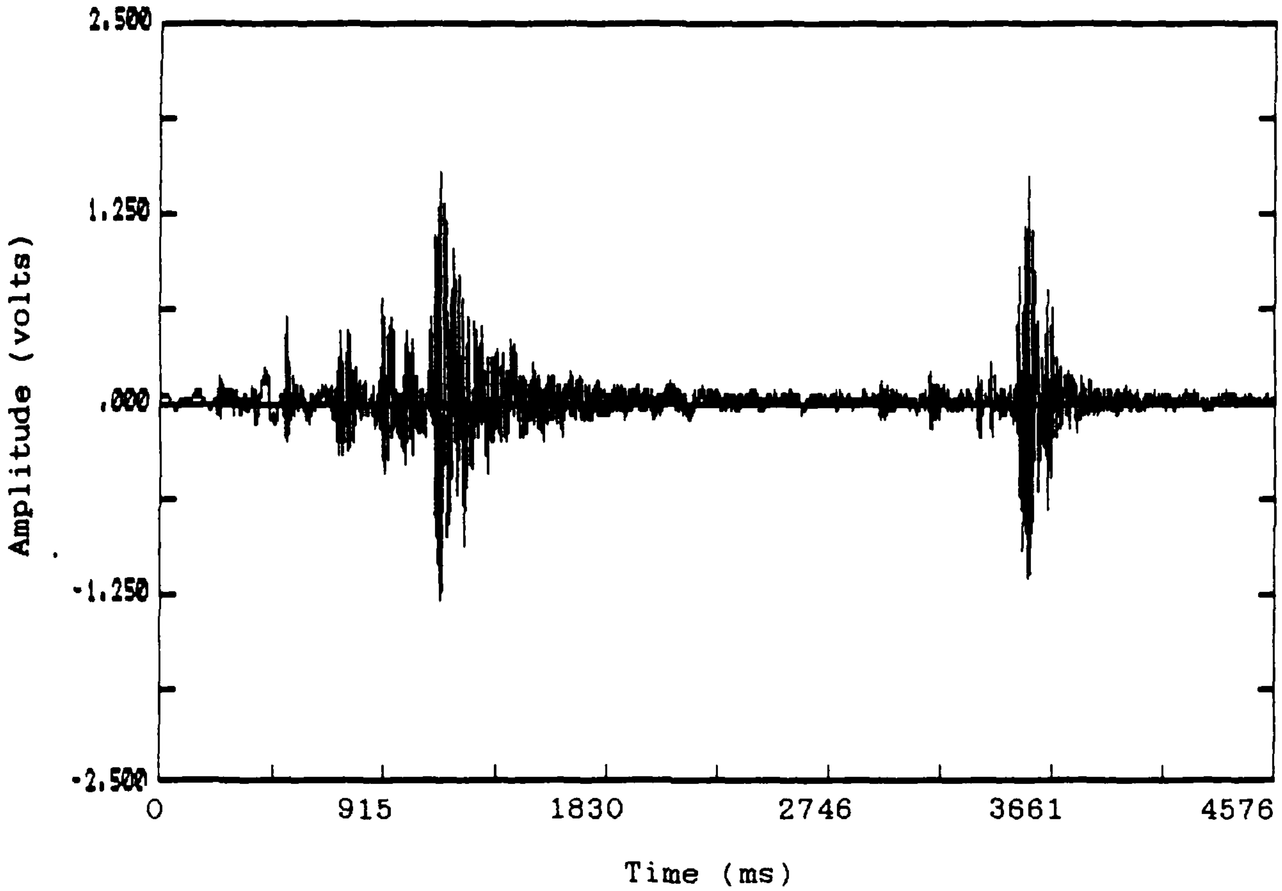


Figure 8. Waveform for switch sound #6.

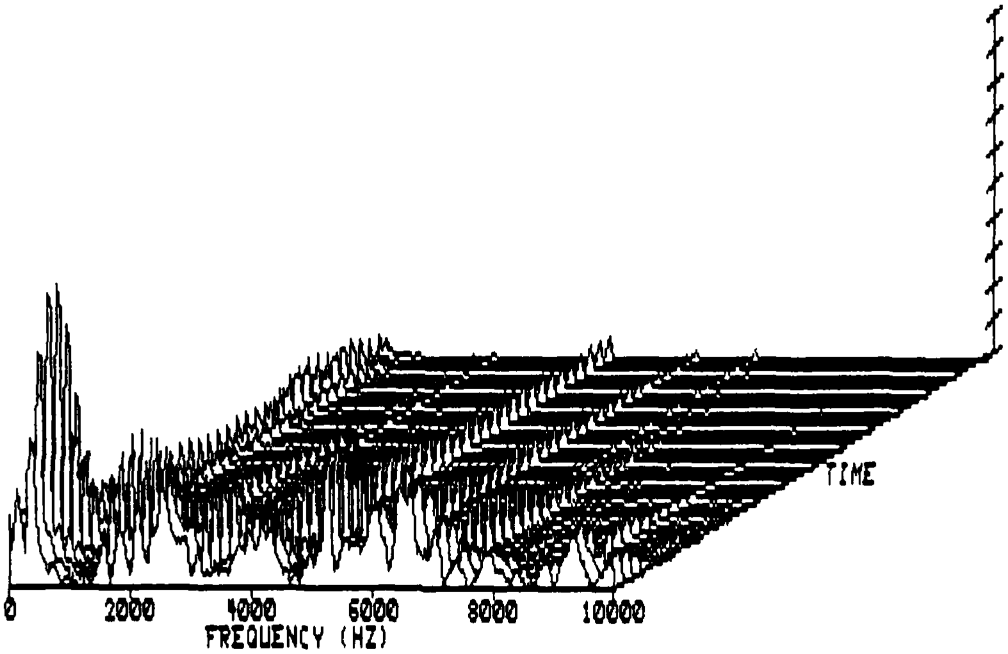


Figure 9. Spectrogram of the first transient in switch #6.

sound was correctly identified in 10.4% of the responses and incorrectly as a switch in 6.3%. The ratio of stapler to switch responses was 1.65 : 1. This was consistent with the second experiment in that this stapler was rated in the middle of the response scale. An alternative analysis of these results revealed that this consistency is approximated by a linear function. In Figure 10, the response percentages from Experiment 1 are plotted against the ratings of Experiment 2, expressed as deviations from the appropriate endpoint of the response scale. The endpoint for these deviations was the correct end of the scale for the particular sound. Four data points are possible given the two sounds and two response alternatives for each sound. The results indicate that a linear function describes the consistency of the two experiments. This function expresses the relationship between the proportion for two alternative responses given in unconstrained, unprompted identification and the rated position of the stimulus along a scale between these two alternatives. This finding means that when one group of listeners was asked to identify these two sounds, the response proportions for two alternatives reflected the ability of other listeners to categorize the sounds into these two alternatives. In other words, the response proportions found in Experiment 1 may reflect the similarity in the acoustics of these alternatives and the probability of these alternatives as causes. This finding further supports the use of the uncertainty value as a measure of the recognizability of these sounds.

Experiment 3

Although there is evidence that listeners engage in a cognitive evaluation of alternatives in identifying the environmental sounds that have been used, there is little direct evidence about the nature of this evaluation process. The evidence to date is based upon averages of reaction times across listeners and upon the sorted responses of a group of listeners. Aggregated results such as these are weak evidence that individuals engage in an evaluation of alternatives and that the number and conditional probability of these alternatives are reflected in identification response time. Furthermore, the response times could be due to response selection even though Ballas and Howard (in press) found evidence to the contrary.

In order to determine if individual listeners engage in a process that is sensitive to the conditional probability of alternative causes, a memory priming study was designed. Listeners were presented with phrases suggesting causes for a sound which they were about to hear. These phrases were taken from the results of Experiment 1 and represented two levels of causal probability for the sounds. The listeners were given adequate time to read the phrase and then

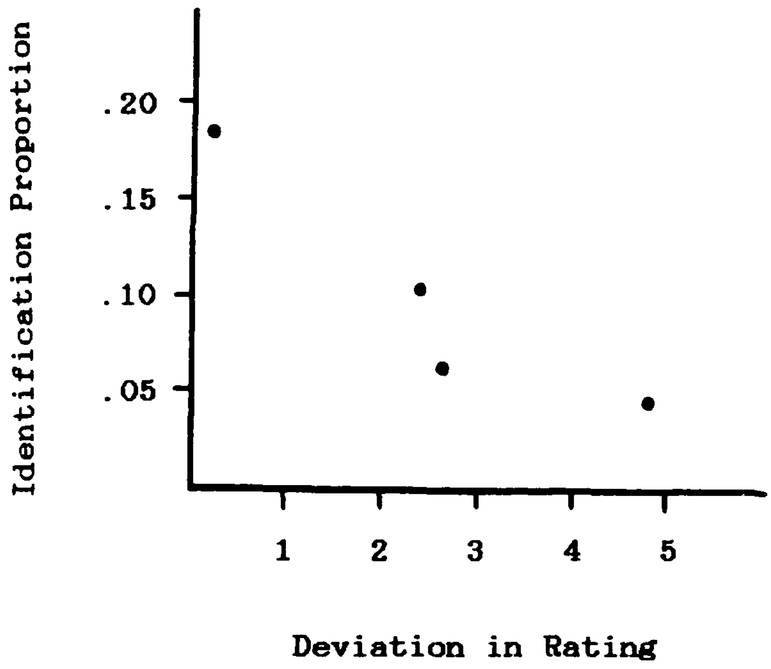


Figure 10. Linear Relationship between Identification Proportion of Experiment 1 and Rating Deviation of Experiment 2.

presented with a sound. Their task was to decide quickly and accurately if the sound could have resulted from the event described with the phrase. If individual listeners engage in a cognitive process that must link sounds to causes, and if the time course of this process is determined by the conditional probability of the cause, then response time for positive decisions should be quicker for phrases describing high probability causes. This effect should be observed in individual listeners.

Method

Participants. Ninteen students volunteered as listeners in this experiment and were paid for their participation. The ages of the participants ranged from 17 to 29. There were 10 females and 9 males. None reported any hearing disorder. Eleven had received formal training in music or voice.

Stimuli. Forty-one environmental sounds were presented, of which 29 were test stimuli and 12 were stimuli for catch trials. Sounds were sampled and digitized as described in Experiment 1. The sounds were the same as the the stimuli presented in Experiment 1. Practice sounds were the eight animal sounds also used in Experiment 1.

For each of the 41 stimuli two verbal probes were selected. One of the probes was a high-probability cause of the sound and the other probe a low-probability cause, as determined by the analyses performed in Experiment 1. For example, if in Experiment 1 a particular identification response for a sound was given 20 times and another response was given for the same sound only 3 times, these responses would be high- and low-probability causes respectively. The criteria employed in selecting causes used as probes was as follows: for a response to be used as high-probability probe, it must have been given at least twice as frequently as the response to be used as a low-probability probe; and, for a response to be used as a low-probability probe, it must have been given at least twice for a particular sound.

Procedure. Listeners were seated in front of a keyboard and computer terminal inside a sound attenuating booth. Instructions were displayed on the terminal. Each participant received a practice session consisting of two parts. In the first part, listeners were acquainted with the "yes" and "no" keys. Either the word "yes" or "no" was displayed on the screen and participants were required to press the appropriate key as quickly and as accurately as they could. Each participant received thirty of these trials. During the second part of the practice session, participants were presented with verbal probes for the eight practice sounds, just as they would during the test session.

Participants were instructed to fixate on a white dot centered on the screen prior to each trial. The participant initiated each trial by pressing the space bar, after which, the probe would appear on the screen for 1.5s. Then a sound was played over headphones to the participant. The participant's task was to decide as quickly and as accurately as possible whether the sound could have been caused by the event described by the preceding phrase. Each sound was presented twice throughout the course of the experimental session. For half of the participants the high-probability probes were presented before the low-probability probes, and for the other half the sequence was reversed. Within these two categories, sound order was randomized.

Results and Discussion

The relevant data for analysis were the response times for positive responses to valid (i.e., non-catch) stimuli. The average response time on trials with high-probability probes was 347 ms faster than the response time with low-probability probes (1261 ms and 1608 ms, respectively). Seventeen of the 19 participants responded more rapidly to the high probability probes. An analysis-of-variance verified that the effect of probe type was significant, $F(1,18) = 12.58$, $p < .005$. The responses to 24 of 27 sounds were made more rapidly if a high-probability probe was presented. Two sounds had too few responses on trials with low-probability probes for this analysis. These two sounds were the doorbell and the foghorn and the low-probability probes were "telephone" and "train hoot".

This result has two important implications. First, the determination of the cause of a sound involves a cognitive process that is related to the probability of the causes being considered. Low-probability causes take longer to confirm than do high-probability causes. Second, this effect is not due to the framing of a verbal description of the cause, as could be claimed for the results in Experiment 1. The participants in this experiment were presented with a description that had been generated by participants in the first experiment. The participants in this experiment had ample opportunity to read the description before the sound and only had to confirm or reject the suggested cause.

The issue of stereotypy is raised by the results of this experiment. A psycholinguist who reviewed the procedure suggested that slower response times could be due to a mismatch between the expected sound suggested by the phrase and the actual sound presented. The expected sound would be the stereotype held by the individual listener. Some stereotypes would be shared by most listeners. This is probably the case for a water drop sound. The acoustic "signature" of this event is limited in its permutations by the physics of the event and it is unlikely that any particular example of a water drop would be inconsistent with the stereotype held by any individual. In other instances, the stereotype held by individuals could vary. For example, one's stereotype of the sound of a typewriter could depend on experience with different typewriters or with computer terminals. An issue that arises here is the specificity of event description. If the event is specified to the level of kind-of-typewriter then the different stereotypes for typewriting actually represent different causes. If the event is characterized broadly as someone typing, then the stereotype could be very different for different individuals.

Given that stereotypes exist, it is not known whether the basis of the stereotype is linguistic or acoustic. The answer presumes an understanding of how the acoustics and verbal description of a sound are encoded in memory. Bartlett (1977) found support for a dual encoding of environmental sound and suggested that these codes are similar to the distinction between visual and verbal codes. Bartlett also found that the consistent labeling of a sound was related to better memory recognition performance. This improvement was related to several subtle aspects of identification performance in a signal detection experiment. Response bias became more conservative and the variance of the signal+noise distribution was increased with the use of labels. Thus, there are complex interactions between the verbal and acoustic dimensions of a sound.

Stereotypy is clearly a component of the verbal encoding. It is an aspect of semantic memory that is related to response time. The original work on semantic memory networks by Collins and Quillian (1969) which was based upon sentence-verification response times was later found to be confounded by the stereotypy of the verbal items employed. Recent semantic memory models have incorporated this factor into the design of the network linkages and the manner in which the network is assessed. However, there is no known work on the role of stereotypy in the encoding of the acoustic properties of a sound. Future research must pursue this issue.

General Discussion

The most important finding in this series of experiments is that the identifiability of a sound can be reliably and validly quantified with the uncertainty measure. Its validity in reflecting potential causes was supported in an initial test, although further testing would be warranted. If the reliability and validity of the measure is established, then its use as a measure of identifiability has important methodological and theoretical implications. Methodologically, a measure such as this should guide the selection of stimuli for research. In identification studies that employ real sounds the variation in the identifiability of these sounds must be considered. For example, studies assessing the effectiveness of a sound-classification aid should be designed to avoid the confounding effect of variation in sound identifiability. An uncontrolled variation could produce spurious results if more recognizable sounds were used with one decision aid and not with another. Theoretically, the reliability of this measure and its relationship to identification time and identification confidence (Ballas & Howard, in press) have implications for the design of environmental sound identification models. The findings of these experiments can be framed as requirements for such models. As such, these findings would demand that sound identification involves a cognitive consideration of alternative causes, most likely in a manner sensitive to the likelihood of these alternatives and sensitive to the similarity in acoustic signatures of alternative causes. The models of Howard and Ballas (1983) and Getty et al. (1981) are consistent with these requirements, and as noted earlier, the uncertainty measure is but a direct estimate of the conditional probabilities these models produce. Direct estimation is possible with the type of sounds used in these experiments because the listeners have a long history of experience with these sounds. Thus they have had the opportunity to develop a knowledge of the alternative causes, their perceptual effects, and the confusability of these effects. It is only because environmental sound constitutes a familiar domain of sound that estimates of these conditional probabilities can be made directly.

The response time results would present no difficulty for the probabilistic classification models because the comparison of alternatives in these models is dependent upon the number of alternatives involved. However, the models are not specific about how the number of alternatives is encoded or retrieved, which alternatives would be evaluated, and how they would be chosen. Memory network models handle these aspects of identification better. The results of these experiments would be consistent with a memory retrieval model that involves two stages, a search for causes, and an evaluation of these causes. The first stage might involve a search through a cognitive network of causes along paths that represent associative relations at an acoustic or semantic level. This type of network would be similar to the semantic networks of memory such as those suggested by Anderson and Bower (1980) and others. The structure of such a network for environmental sounds is a topic that must be addressed in future research.

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