Optimum Information Transfer Rates for Communication through Haptic and Other Sensory Modalities

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Abstract—This paper is concerned with investigating the factors that contribute to optimizing information transfer (IT) rate in humans. With an increasing interest in designing complex haptic signals for a wide variety of applications, there is a need for a better understanding of how information can be displayed in an optimal way. Based on the results of several early studies from the 1950s, a general "rule of thumb" has arisen in the literature which suggests that IT rate is dependent primarily on the stimulus delivery rate and is optimized for presentation rates of 2-3 items/s. Thus, the key to maximizing IT rate is to maximize the information in the stimulus set. Recent data obtained with multidimensional tactual signals, however, appear to contradict these conclusions. In particular, these current results suggest that optimal delivery rate varies with stimulus information to yield a constant peak IT rate that depends on the degree of familiarity and training with a particular stimulus set. We discuss factors that may be responsible for the discrepancies in results across studies including procedural differences, training issues, and stimulus-response compatibility. These factors should be taken into account when designing haptic signals to yield optimal IT rates for communication devices.

Index Terms—Communication, human performance, information transfer rate, mobile device.

1 Introduction

This paper is concerned with investigating the factors that contribute to optimizing information transfer (IT) rate in humans. This issue has important ramifications for the design of human-machine interfaces in a wide variety of applications, including mobile communication devices, virtual environment and teleoperator systems, as well as sensory aids for persons with impaired vision and/or hearing. The ultimate goal in the design of any display is to achieve rates of information transfer that enable the user to perform the intended task quickly and accurately (following a reasonably short training period). To date, however, few studies have assessed the information transmission capability of mobile or virtual reality systems. This is despite increasing interest in the design of haptic signals for conveying more than 1 bit of information (i.e., on and off) on mobile and wearable displays (see, for example, studies on "vibratese" [1], "haptic icons" [2], "tactile melodies" [3], "tactons" [4], and tactor arrays [5], [6], [7], [8], [9], [10], [11], [12], [13]). In most studies, performance metrics have included percent-correct scores or error rates, as well as data obtained from questionnaires. An exception is the study by Chen et al. [14] that measured information transfer for tactor localization using two 3×3 arrays placed on the dorsal and volar forearm near the wrist. Other metrics, such as task completion time [15] and detection or discrimination thresholds [16], have also been widely used when studying haptic displays. All these performance metrics can provide valuable information to designers of displays, but they also have their limitations when performance needs to be assessed in terms of communication efficiency. For example, task completion time is confounded with performance level by the participants' speed-accuracy tradeoff criteria, and therefore, the fastest user may not always be the best one. The value of error rate can be highly dependent on the context of the task. A higher localization error will result from cramming more tactors into the same area on the skin. But error rate alone cannot inform a device designer of the maximum number of tactors on a haptic display that ensures perfect localization. Discrimination thresholds carry the units of the physical parameters involved and cannot be meaningfully compared (e.g., it is not clear whether a 0.5 N force magnitude discrimination threshold is better or worse than a 23-degree force direction discrimination threshold). And the limitations of questionnaires have been addressed by Slater [17].

Information measures, however, have the potential to overcome many of the above-mentioned limitations for assessing the information transmission capabilities of visual, auditory, haptic, as well as multisensory information displays. Static information transfer (IT) quantifies the amount by which uncertainty has been reduced [18]. It is useful for characterizing performance when the task involves the correct identification of one stimulus from a set of alternatives. The IT measure is usually independent of the task context (e.g., increasing the number of stimuli in an identification task will not increase the overall information transfer once channel capability has been reached). The

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information transfer capability of different displays can be directly compared, unlike discrimination thresholds, in terms of IT in the unit of bits (e.g., a force display versus a tactor array). Furthermore, the information transmission achievable through a complex system involving many parameters (haptic force, vibration, visual color, auditory pitch, etc.) can be summarized and adequately expressed in bits [19]. Dynamic information transmission where a sequence of stimuli is presented in rapid succession and identified individually or as a group (e.g., speech, tactile ring tone, etc.) is measured by IT rate in bits/second. When signals are presented at regular temporal intervals, then the IT rate is simply the average IT per signal presentation (in bits) multiplied by the presentation rate (items/second). When interstimulus intervals vary, however, then the average IT rate can be obtained by the ratio of the overall IT over the total duration of signal presentation. This paper focuses on the factors contributing to the optimization of IT rate, which is the ultimate goal of any communication system.

The use of information concepts in psychophysical studies and in user performance assessment was introduced in the 1950s, spawning numerous publications in this area (the most famous of which are perhaps Fitt's Law [20] and Miller's classical paper [21]). There is a void in the more recent literature on applying information theory to human behavior research (although see [22], [23], [24], [25], [26]). It is perhaps time to revisit the progress that has been made in this area, and investigate what new theory and/or methodology are needed in order to apply information theory to the assessment of human performance with a haptic communication system. In this context, it is the intention of this paper to summarize past and ongoing research on the conditions for maximizing IT rate.

Although there is no well-tested and complete theory for predicting optimal IT rates for a given type of display, there are some "rules of thumb" that have arisen based on observations from some early studies concerned with this problem. One such guideline is the generally accepted view that the IT rate is dependent primarily on the stimulus delivery rate and is optimized for delivery rates in the range of 2 to 3 items/s independent of the information in the stimulus set (see [18], p. 91, citing [27]). According to this guideline, the key to maximizing IT rate is to maximize the information in the stimulus set. In this paper, we reexamine Garner's [18] "rule of thumb" in light of recent data (concerned with measuring IT rate for multidimensional tactual signals) which appear to be at odds with the general conclusions arrived at previously. In particular, these current results suggest that optimal delivery rate varies with stimulus information to yield a constant peak IT rate whose magnitude depends on the degree of familiarity and training with a particular set of stimuli.

We first review several early studies whose results form the basis of the generally accepted notions regarding IT rate (Section 2). We then describe the results of some recent studies on IT rate which appear to contradict those of the earlier studies (Section 3). We relate the results of these studies to previously reported estimates of IT rates for a variety of different highly learned methods of human communication (Section 4). Finally, we discuss the studies in terms of factors that may contribute to discrepancies in specifying guidelines for maximizing IT rate (Section 5) and present a summary of our conclusions (Section 6).

2 Review of Early Literature on IT Rate

The results of several important studies performed in the 1950s provide the experimental database from which conclusions concerning the relations among stimulus information, stimulus delivery rate, and peak rates of information transfer have been drawn. The basic measurements employed in this research are typically derived from identification experiments with the following basic characteristics: A set of K stimuli ($S_i, 1 \leq i \leq K$) is constructed for the experiment; a set of K responses ($R_j, 1 \leq j \leq K$) is constructed with a one-to-one association with each of the K stimuli; the participant is presented with stimuli selected at random from the stimulus set; on each presentation, the participant chooses a response from the response set; and the experimental results are tabulated in the form of a stimulus-response confusion matrix from which measurements of IT are computed. The quantity IT measures the increase in information about the signal transmitted resulting from knowledge of the received signal. For a particular stimulus-response pair (S_i, R_j), the quantity IT is given by $\log_2[P(S_i/R_j)/P(S_i)]$, where $P(S_i/R_j)$ is the conditional probability of S_i given R_j, and $P(S_i)$ is the a priori probability of S_i. The average IT is thus given by

$$IT = \sum_{j=1}^{K}\sum_{i=1}^{K} P(S_i, R_j)\log_2\left(\frac{P(S_i/R_j)}{P(S_i)}\right), \tag{1}$$

or, equivalently,

$$IT = \sum_{j=1}^{K}\sum_{i=1}^{K} P(S_i, R_j)\log_2\left(\frac{P(S_i, R_j)}{P(S_i)P(R_j)}\right), \tag{2}$$

where $P(S_i, R_j)$ is the joint probability of stimulus S_i and response R_j, and $P(R_j)$ is the probability of R_j.

The maximum likelihood estimate of IT, denoted IT_{est}, derived from a stimulus-response matrix is computed by approximating underlying probabilities with frequencies of occurrence:

$$IT_{est} = \sum_{j=1}^{K}\sum_{i=1}^{K} \frac{n_{ij}}{n}\log_2\left(\frac{n_{ij}\cdot n}{n_i \cdot n_j}\right), \tag{3}$$

where n is the total number of trials collected, n_{ij} is the number of times the joint event (S_i, R_j) occurs, and $n_i = \sum_{j=1}^{K} n_{ij}$ and $n_j = \sum_{i=1}^{K} n_{ij}$ are the row and column sums.

Two related measures, Information in Stimulus (IS) and Information in Response (IR), evaluate the average information in stimulus and response, respectively. They are computed as $IS = -\sum_{i=1}^{K} P(S_i)\log_2 P(S_i)$ and $IR = -\sum_{j=1}^{K} P(R_j)\log_2 P(R_j)$. The value of IS is maximized when all stimulus alternatives are equally likely, $P(S_i) = 1/K(i = 1, \ldots K)$, and $\mathrm{IS} = \log_2 K$. Likewise, the value of IR is maximized when all responses are equally likely, $P(R_j) = 1/K(j = 1, \ldots, K)$, and $\mathrm{IR} = \log_2 K$. IR can therefore be regarded as a measure of response bias; it decreases from its maximal value as response bias increases.

TABLE 1
Summary of Forced-Pace Results in [27]

N	K	IS	Stimulus Presentation Rate		Optimal Presentation Rate	Maximal IT Rate
		(bits/item)	(items/s)	(bits/s)	(items/s)	(bits/s)
1	2	1	2, 3, 4, 5	2, 3, 4, 5	3.7	2.8
2	4	2	2, 3, 4, 5	4, 6, 8, 10	2.4	4.0
3	8	3	2, 3, 4, 5	6, 9, 12, 15	2.4	5.8
4	16	4	2, 3, 4, 5	8, 12, 16, 20	2.4	8.4
5	32	5	2, 3, 4, 5	10, 15, 20, 25	2.4	10.5

N: Number of bulbs K: Number of stimulus alternatives IS: Information in stimulus

Klemmer and Muller [27] studied information transmission rate using forced pace tests as a function of the two independent variables, rate of stimulus presentation and amount of information in the stimulus set. The stimuli were flashing lights to which participants responded by pressing patterns of keys. Light patterns were displayed on $N = 1, 2, 3, 4$, or 5 bulbs, each bulb carried 1 bit of information (either on or off), and all possible patterns of lights were employed for each value of N. For each stimulus set, the number of possible stimulus alternatives is given by $K = 2^N$ and stimulus information in bits is given by $\log_2(2^N) = N$ (for the case of equal probability of presentation for each stimulus which applies to this study). For each value of N, streams of stimuli were presented at a rate of 2, 3, 4, or 5 items/s (fixed within a given run). The stimulus duration and interstimulus interval (ISI, defined as the time between the offset of one stimulus and the onset of the next stimulus) were always equal in duration, and thus, changed as a function of presentation rate such that signal duration T (and ISI) took on values of 250, 167, 125, and 100 ms at presentation rates of 2, 3, 4, and 5 items/s, respectively. For a given value of N, stimulus patterns were presented in random order at a given presentation rate. The participant's task was to identify each signal using a set of motor responses bearing a one-to-one correspondence with the signals in a given set. The output array consisted of five telegraph keys (each positioned under one finger of one hand), each of which corresponded to one of the five light bulbs. A time window was established for recording the response to a given stimulus based on an estimated distribution of reaction time (RT) derived from preliminary tests.

Additional testing was conducted using a self-paced procedure in which a new stimulus was presented 20 ms following the participant's response to the previous stimulus. The self-paced task employed 31 (rather than 32) stimulus alternatives ($\mathrm{IS} = 4.95$ bits) due to the elimination of the stimulus with no lit bulbs. Participants were instructed in this self-paced task to respond as rapidly as possible. Preliminary measurements of the mean RT in a self-paced task were used to set the signal duration for each participant such that the light-on time was roughly equal to the RT.

Stimulus-response confusion matrices were constructed and used to derive measures of IT. The IT rate in bits/second was computed as the product of the IT in bits/item and the presentation rate in items/second. The data were fit with smooth curves by the authors from which maximal IT rates were interpolated. Experimental results for the forced-pace tests are summarized in Table 1. Maximal IT rates were achieved for presentation rates between 2 and 3 items/s for stimulus sets with N in the range of 2 to 5, and at a presentation rate of 3.7 items/s for $\mathrm{N} = 1$. Maximal IT rate increased with the information of the stimulus set, going from 2.8 bits/s for $N = 1$ to 10.5 bits/s for $N = 5$. For each stimulus set, the IT rate decreased as the presentation rate increased above 2 to 3 items/s (with the exception of $N = 1$). These results imply that a reasonable approach toward maximizing IT rate lies in maintaining a presentation rate in the range of 2 to 3 items/s and maximizing the information in the stimulus set (IS).

Measurements of average RTs in the forced-pace task indicated that RT increased monotonically from roughly 260 ms for the 1-bit stimulus set to an asymptotic value of roughly 410 ms for stimulus information in the range of 2 to 5 bits. For each value of N, the reciprocal of the RT corresponded closely to the stimulus presentation rate for peak IT rate. Thus, for example, for $\mathrm{IS} = 1$ bit, the stimulus presentation rate for peak IT rate was 3.7 items/s and the mean RT was 260 ms (corresponding to $1/\mathrm{RT} = 3.8\ \mathrm{items/s}$). Similarly, for $\mathrm{IS} = 5$ bit, the peak presentation rate was 2.4 items/s and mean RT was 410 ms (corresponding to $1/\mathrm{RT} = 2.4\ \mathrm{items/s}$). In the self-paced task (with 31 stimulus alternatives and $\mathrm{IS} = 4.95$ bits), average RT was roughly 400 ms, corresponding to a presentation rate of roughly 2.5 items/s. Measurements of IT rate under the self-paced task (roughly 11 bits/s) were roughly similar to those obtained under the forced-pace task with 32 stimulus alternatives ($\mathrm{IS} = 5$ bits) and presentation rate of 2.4 items/ s. These results imply that under an ideal pacing of 2.5 items/s and an RT of 400 ms, the participant will be responding to a given stimulus as the next stimulus in the random sequence is being presented and suggest that the RT for the motor response plays a role in determining maximal IT rate. Klemmer and Muller [27] argue, however, that an inability to carry out the motor response is not a limiting factor in the maximal IT rates measured in these experiments. They base their argument on the observation of relatively high values of information in the response (IR) even at the highest rates of presentation. For example, the observed IR rate was roughly 20 bits/s out of an available 25 bits/s for $\mathrm{N} = 5$. All the maintenance of high IR rates at fast presentation rates implies, however, is that even at these high presentation rates, the participant continued to make substantial use of most of the responses, and therefore, very few (if any) of the motor actions themselves required too much time to execute. No consideration is given in this argument, however, to the correctness of the responses. Clearly, in such psychophysical tasks, the time used to respond must include not only the time used to identify the stimulus and the time used to perform the motor actions that constitute the response, but also the time required to select the motor response that corresponds to the stimulus identified. In our opinion, the argument by Klemmer and Muller (which is based on the preservation of high IR rates independent of the correctness of the responses) totally ignores this component of the RT. Further comments on this issue are included in Section 5.

Alluisi et al. [28] examined the interaction between stimulus information and rate of presentation in a visual task requiring identification of Arabic numerals. Stimuli were Arabic numerals (sets of 2, 4, and 8 numerals with 1, 2, and 3 bits of stimulus information, respectively). The stimuli were illuminated on a display screen and were presented at rates of 1, 2, or 3 items/s under a forced-pace format. (The duration of the stimuli is not available in the description of the study.) Two different methods of response were investigated: a response employing pressing of keys with fingers (each key corresponded to a different numeral using a natural placement of the fingers on the keys and assignment of numerals to the keys) and a verbal response (where the participant spoke the name of the numeral). IT was calculated from stimulus-response confusion matrices for each stimulus set and mode of response and IT rates were computed from the product of IT and presentation rate.

Different levels of performance were observed for the two different methods of response. For the verbal responses, IT rate increased with presentation rate for each of the three stimulus sets. The normalized IT (i.e., IT/IS) decreased slightly with an increase in presentation rate (going from approximately 100 to 80 percent as rate increased from 1 to 3 items/s for each of the three stimulus sets). The maximal IT rate observed using verbal responses, 7.9 bits/s, occurred with the 3-bit per item stimulus set and a presentation rate of 3 items/s. For the key-pressing responses, the maximal IT rate achieved was only 2.8 bits/s (using the 3-bit stimulus set and a presentation rate of 1 item/s). The percentage IT using these responses dropped drastically with presentation rate, going from 80 percent at the slowest rate to only 10 percent at the highest rate for each of the three stimulus sets. Alluisi et al. attribute the differences in performance between the verbal and motor response methods to a difference in stimulus-response compatibility. One might also argue, however, that the dramatic reduction in performance for the motor response method as a function of item presentation rate was due (at least in part) to insufficient time to carry out the motor response between stimulus presentations.

Three cases occurred in this study where the same information presentation rate was achieved through two different combinations of stimulus information and item presentation rate: 2 bits/s (1-bit stimulus set at 2 items/s or 2-bit set at 1 item/s); 3 bits/s (1-bit set at 3 items/s or 3-bit set at 1 item/s); and 6 bits/s (2-bit set at 3 items/s or 3-bit set at 2 items/s). In each case (and for both response methods), a higher measured IT rate was achieved with the higher-information stimulus set and the lower item presentation rate, whether for verbal or key-pressing response. The range of information presentation rates achieved in the study was limited by the fact that stimulus information never exceeded 3 bits and item presentation rate never exceeded 3 items/s. Thus, from these data, it is difficult to conclude that the optimal item presentation rate is 2-3 items/s because performance was never examined at higher rates.

We now turn our attention to the results of some recent measurements of IT rate arising from studies with the tactual reception of multidimensional signals.

3 Description of IT-Rate Studies with Tactual Signals

A somewhat different picture of factors related to the optimization of IT rate has emerged from a series of studies concerned with measuring the information transmission capacity of the tactual sensory system. These experiments employ sets of multidimensional signals created for presentation through a multifinger tactual stimulating device [29], [30], [23]. The device consists of three independent channels, each of which has a continuous frequency response from dc to 300 Hz and a dynamic range of roughly 50 dB SL at any given frequency. The stimuli were constructed using components from within each of three perceptually distinct regions of tactual sensation: slow motion (from dc to roughly 6 Hz), fluttering motion (in the region of roughly 10-70 Hz), and smooth vibration (in the region above roughly 150 Hz). One or two highly discriminable frequencies within each of these three spectral regions were selected as the building blocks of the stimulus sets. These frequency components were used to construct single-frequency waveforms, two-component waveforms (made up of one frequency from each of two different spectral regions), and three-component waveforms (made up of one frequency from each of the three different regions). Stimulus sets were created at different values of signal duration (including 500, 250, and 125 ms). At some values of frequency and duration, different values of amplitude and onset direction of movement were also employed as dimensions along which the components could vary. The resulting waveforms were combined with the attribute of location (typically three or four different values corresponding to the stimulation of three different fingers or combinations of them on the tactual display) to create a full stimulus set at a particular value of signal duration.

Initially, experiments were conducted to measure static IT for stimulus sets at each of three durations [29], [30], [23]. At 500-ms and 250-ms, stimulus sets consisted of 30 waveforms (each of which could be presented at each of four finger locations thumb, index finger, middle finger, or all three fingers stimulated simultaneously): eight single-frequency signals, 16 double-frequency signals, and six triple-frequency signals. The size of the 125-ms stimulus set was reduced to 19 waveforms: six single-frequency signals, nine double-frequency signals, and four triple-frequency signals (each of which could be presented to any of the four finger locations). These studies employed a one-interval forced-choice procedure in which one of the 30 (for 500- and 250-ms stimulus sets) or 19 (125-ms stimulus set) waveforms was presented at one of the four possible finger locations. The participant's task was to decide which of the possible alternatives had been presented on each trial using a stylus to select two icons on a tablet. One icon represented stimulus waveform (depicted graphically through displacement versus time traces) and the second icon represented finger location (depicted with text labels). The total number of alternatives was 120 (30 waveforms at each of four finger locations) for the 500- and 250-ms stimulus sets and 76 (19 waveforms at each of four finger locations) for the 125-ms set. Participants received training with each stimulus set in the form of trial-by-trial correct answer feedback until criterion performance of 95 percent correct or greater was achieved. The amount of time required to reach this level of performance varied across participants and stimulus sets and ranged from roughly 10 minutes (for the participant who was already familiar with the stimulus sets) to 6 hours. Once a criterion level of performance was achieved, participants were tested without feedback.

Estimates of static IT were derived using the empirically based observation that, for low error rates (i.e., an error rate of 5 percent or less), the quantity IT lies in the interval $\mathrm{IS}(1-2e) < \mathrm{IT} < \mathrm{IS}(1-e)$, where e is the overall error rate and IS is the information in the stimulus set.[1] Lower-bound estimates of IT were 6.5 bits at 500 ms, 6.4 bits at 250 ms, and 5.6 bits at 125 ms, corresponding to the static transmission of roughly 90-94 percent of the information available in the stimulus set.

Experiments were then carried out to estimate the IT rates that could be achieved with similarly constructed stimulus sets. In order to minimize training requirements so that IT rates could be estimated within a reasonable time frame, and yet to simulate to some degree the effects of forward and backward masking that are likely to occur when the participant is presented with a stream of stimuli, a task was employed which required the participant to identify only the middle stimulus (X) in a sequence of three consecutive stimuli (AXB). A time-line depiction of this procedure, referred to as an AXB identification paradigm, is shown in Fig. 1. The three stimuli (maskers A and B and target X) have the same signal duration (T_1) and equal intervals of silence between them (T_0). The envelope period of the stimulus is defined as $T_{onset} = T_1 + T_0$. The participant's task was to identify the target stimulus X, which was preceded and followed by maskers A and B. The maskers A and B and the target X were selected randomly from the

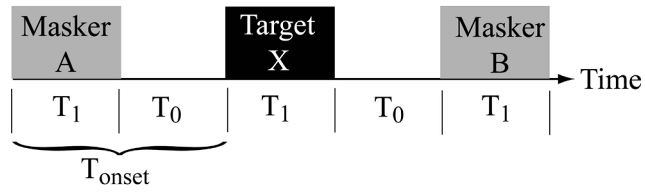

Fig. 1. Time-line depiction of stimuli in AXB paradigm.

alternatives within a given stimulus set. For each stimulus set and signal duration T_1, performance was examined as a function of T_0 (over a range of roughly 0 to 640 ms across studies). Estimates of IT rate in bits/second for each combination of T_1 and T_0 were calculated from the product of the IT per presentation in bits/item and the presentation rate in items/s (defined as the reciprocal of T_{onset}).

A summary of experimental conditions employed in several different studies with the AXB procedure is provided in Table 2 (columns 1 through 5). Seven stimulus sets are described briefly in Table 2 with regard to the number of alternatives (K) in the set, the stimulus information ($\log_2 K$), the duration of the signals (T_1), and the values of $T_{onset} = T_1 + T_0$ employed in the AXB paradigm. The experiments encompassed a range of K from 7 to 90, IS from 2.81 to 6.49 bits, signal duration T_1 from 0.125 to 0.5 s, and T_{onset} from .125 to 1.0 s.

Results obtained in these studies are shown in Fig. 2. The data shown here are results obtained with the one participant who took part in all the conditions.[2] Fig. 2a displays normalized IT (i.e., the ratio of estimated IT to IS) obtained with each stimulus set as a function of $T_{onset} = T_1 + T_0$ in the AXB paradigm. From this plot, it is clear that for a small number of stimulus alternatives (7, see open circles and squares), the participant's performance approached unity for normalized information transmission at T_{onset} values in excess of 250 ms. For a larger number of stimulus alternatives (57 or 90, see filled symbols), performance increases dramatically for T_{onset} values in the range of roughly 200 to 500 ms and then continues to improve gradually for values in the range of 500 to 1,000 ms. [The one datum point for 125-ms stimuli with 57 alternatives at $T_{onset} = 625$ ms appears to be an anomaly in that it does not follow the monotonically-increasing trend of the rest of the data plotted here.] Data for the intermediate number of stimulus alternatives (28, open triangles and diamonds) lie between those for the smaller and larger number of stimulus alternatives, demonstrating a gradual and consistent trend in the normalized IT values for all the experimental conditions tested.

In Fig. 2b, the estimated IT rate in bits/s is plotted as a function of the information presentation rate. These data indicate that the estimated IT rate in bits/s initially follows the maximum achievable IT rate (indicated by the dashed diagonal line in the figure), reaches a peak, and then decreases, as a function of information presentation rate in

1. This formulation provides a means of bounding and estimating IT from the percent-correct score when it is impractical to collect the number of trials necessary for directly calculating unbiased estimates of IT (see [22], [28], [32]). It is possible to demonstrate empirically that, for low error rates (i.e., an error rate of 5 percent or less), the quantity IT lies in the interval $\mathrm{IS}(1-2e) < \mathrm{IT} < \mathrm{IS}(1-e)$, where e is the overall error rate and IS is the information in the stimulus set. The lower bound can be shown to provide a good approximation of IT under the "worst case" assumption that all incorrect responses are distributed randomly throughout the off-diagonal cells of the stimulus-response confusion matrix, while the upper bound holds for the case in which incorrect responses are distributed such that all the errors for a given stimulus are located in the same off-diagonal cell, and a different off-diagonal cell is employed for the error responses to each stimulus.

2. Results are available on at least three or four additional participants in each of the experimental conditions (e.g., see [22], [30], [31]). The participant whose data are presented here was the only participant common to all of the conditions tested and was highly trained in the experimental tasks. His data are consistent and repeatable; thus, we use his results to provide a clear demonstration of the trends observed in our studies.

TABLE 2
Summary of Experimental Conditions Employed in AXB Testing (Depicted in Fig. 1) is Provided in Columns 1 through 5 and Experimental Results Are Summarized in Columns 6 through 8

Stimulus Set	No. of Alternatives (K)	Stimulus Information IS (bits/item)	Stimulus Duration T_1 (s)	Time between Stimulus Onsets $T_{onset} = T_1 + T_0$ (s)	Optimal T_{onset} (s)	Optimal Presentation Rate (items/s)	Peak IT Rate (bits/s)
1[a]	90	6.49	.500	.52, .60, .70, .80, .90, 1.0	.52	1.9	9.9[d]
2[a]	90	6.49	.250	.27, .35, .45, .55, .65, .75	.45	2.2	11.8
3[a]	57	5.83	.125	.145, .225, .325, .425, .525, .625	.325	3.1	12.1
4[b]	28	4.81	.250	.25, .27, .29, .33, .41, .57, .89	.250	4.0	15.7
5[b]	28	4.81	.125	.125, .145, .165, .205, .285, .445, .765	.205	4.9	18.3
6[c]	7	2.81	.250	.25, .27, .29, .33, .41, .57, .89	.250	4.0	10.9[d]
7[c]	7	2.81	.125	.125, .145, .165, .205, .285, .445, .765	.205	4.9	11.9

[a] *Tan, Durlach, Reed, and Rabinowitz (1999)* [23] [b] *Reed, Delhorne, Brughera, Durlach, Tan , and Wong (2003)* [31]

[c] *Tan, Reed, Delhorne, Durlach, and Wan (2003)* [32] [d] *Rates limited by stimulus presentation rates*

bits/s.[3] Under two of the conditions (the 90-stimulus set at 500 ms—filled diamonds, and the 7-stimulus set at 250 ms—open circles), the observed IT rate is equivalent to the information presentation rate (i.e., it follows the dashed diagonal line in these two cases). In these cases, the performance is essentially limited by the presentation rates used rather than by perceptual limits; higher IT rates might have been achieved if higher presentation rates had been tested. One trend evidenced in this plot is that performance in terms of IT rate seems to be determined primarily by the information presentation rate in bits/second. For the most part, the curves for the different conditions coincide, demonstrating peak performance at a presentation rate of roughly 15 bits/s (with the exception of the 28-stimuli set at 125 ms—open diamonds—where performance appears to peak at a presentation rate of roughly 25 bits/s).

These experimental results are summarized in Table 2 (columns 6 through 8). The maximum (peak) IT rate in bits/second obtained with each of the stimulus sets is provided along with the value of T_{onset} (and its reciprocal, item-presentation rate in items/s) corresponding to peak IT rate. For the two footnoted rates, the maximum IT rate was limited by the maximum item presentation rate used for these conditions (i.e., in these cases, the normalized IT saturated at unity; see Fig. 2a). Peak IT rates typically fell into a narrow range of roughly 10 to 13 bits/s, with the exception of the 28-stimuli set at 125 ms where peak IT rate rose to 18 bits/s. On the other hand, the optimal item presentation rate varied with the number of alternatives in the stimulus set. The optimal presentation rate in items/second typically decreased with the amount of information in the stimulus set IS (or, conversely, the optimal T_{onset} tended to increase with IS). As IS decreased from 6.49 to 2.81 bits, the optimal presentation rate increased from 1.9 to 4.9 items/s.

Summers and colleagues estimated information transfer rates associated with time-varying vibrotactile and electrotactile stimuli in several studies [33], [34], [35]. The information transfer rate for vibrotactile coding of a step change in the frequency of a pulse train was estimated to be 8.7 bits/s for practiced participants and predicted to be 10-15 bits/s for stimuli with redundant coding of frequency and amplitude changes ([33], supplemental data to Experiment 1). Another study ([34], Experiment 2) examined the trade-off between stimulation presentation rate and IS in creating an equivalent presentation rate of 19.8 bits/s using stimuli that were 480-ms long frequency- and amplitude-modulated sequences of vibrotactile stimulus elements. One set of stimuli employed six 80-ms elements with $\mathrm{IS} = 1.58$ bits and the other set employed three 160-ms elements with $\mathrm{IS} = 3.17$ bits. Using a series of three such sequences of vibrotactile stimulus elements and a 3AFC "odd-one-out" procedure, the information transfer rate was estimated to be 6 bits/s for 160-ms stimulus elements, and was substantially lower for the 80-ms stimulus elements. Thus, the trade-off between element duration and IS to create equal IT rate did not result in equivalent levels of performance, as participants experienced great difficulty with the stimuli composed of briefer-duration elements and lower IS. In another study, where participants were required to perceive differences in short sequences of time-varying tactile stimulus sequences ([35], Experiment 1), maximum information transfer was estimated to be 5 bits/s at the fingertip and 7 bits/s at the wrist.

Despite major differences in stimuli and experimental procedures (e.g., Summers et al. estimated information transfer rate from a discrimination task as opposed to an absolute identification task as we have done, and used one-site stimulation of the tactile system as opposed to our multiple-site stimulation over the kinesthetic-cutaneous range), the results from Summers et al.'s studies are roughly consistent with the results shown in Fig. 2b.

In general, our results appear to be at variance with the conclusions reached by previous investigators (e.g., Klemmer and Muller [27]; Alluisi et al. [28]) that 1) optimal stimulus presentation rate lies in the range of 2-3 items/s independent of stimulus information and 2) the peak IT rate at any given presentation rate increases monotonically with IS. Instead, the results from our current tactual research suggest that optimal stimulus presentation rate varies inversely with IS to produce a constant peak IT rate (see Table 2).

3. Note that the IT rates drop precipitously toward zero as information presentation rates increase beyond that for maximum IT rate. This is likely due to the participants' inability to keep up with incoming signals at the faster rates, and therefore, their performance quickly falls apart.

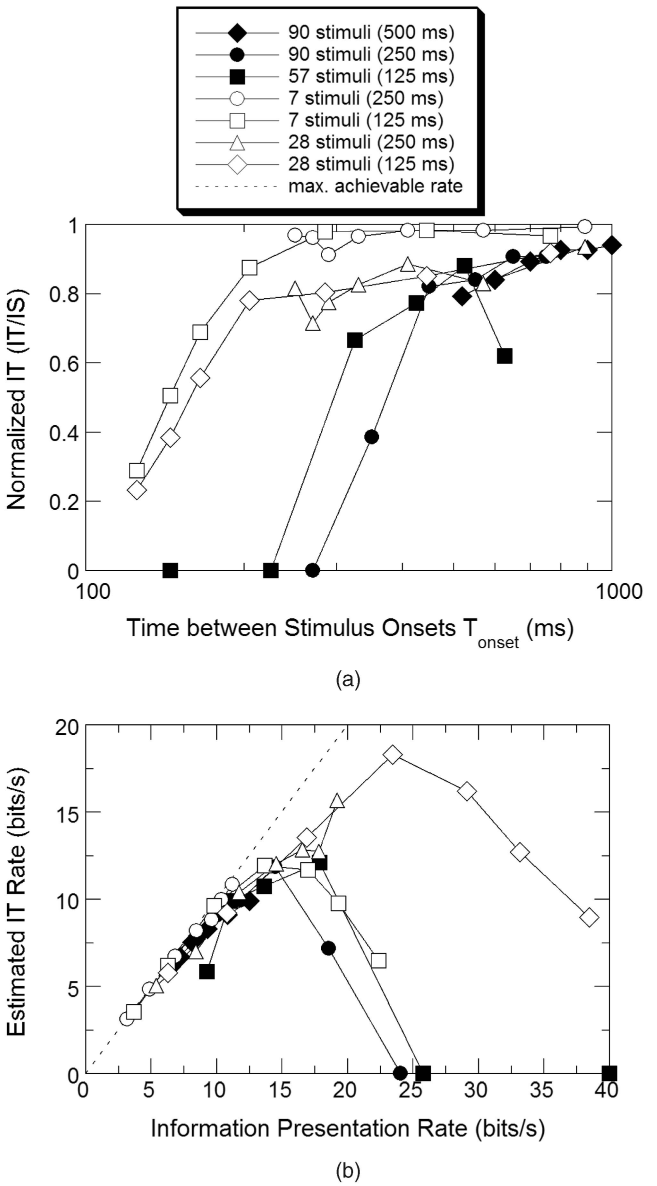

Fig. 2. Comparison of data from seven different stimulus sets for one highly trained participant. In (a), the normalized IT (i.e., the ratio of estimated IT to IS) is plotted as a function of the time between stimulus onsets ($T_{onset} = T_1 + T_0$) in millisecond for the seven different stimulus sets described in the legend attached to the panel. In (b), the estimated IT rate in bits/second is plotted as a function of the information presentation rate in bits/second for the same seven stimulus sets. The dashed line plots the maximum possible IT rate.

4 IT Rates in Studies with Highly-Learned Stimulus Sets

The experiments described in Sections 2 and 3 above are concerned with measurements of IT using artificially constructed stimulus sets. Participants are initially unfamiliar with the stimulus sets and typically receive laboratory training on the reception of these signals prior to data collection. Also of interest in considering the factors that affect IT rate are studies conducted with stimulus sets which may be regarded as "overlearned" in terms of their use as methods of communication in which participants are highly practiced. In this section of the paper, we summarize IT rates that have been estimated for highly experienced users of a variety of different methods of human communication (as estimated by Reed and Durlach [36]). It may be argued that such rates for human language currently represent a benchmark against which IT rates obtained with other types of stimulus sets may be usefully compared.

Reed and Durlach [36] estimated IT rates in bits/second (over a range of "typical" to "maximal" performance) for each of a variety of different methods and modalities of communication, including methods based on alphabetic codes (such as reading, Morse Code, and fingerspelling), phonemic codes (such as spoken English), and gestural codes (such as American Sign Language). Communication rates for typical and highly proficient users of each method were obtained from studies in the literature. These rates were converted into normalized transmission rate expressed in words/second. These normalized units were then converted into estimates of IT rate in bits/second using Shannon's [37] calculations of the information content of a single letter of the alphabet (roughly 1.5 bits/letter for sentence length strings of words). Maximal IT rates in the range of 40-60 bits/s were observed for auditory speech reception, visual reception of written text through reading, and visual reception of American Sign Language. Other than reading (which involves simultaneous availability of written letters on the page), alphabetic codes are less efficient than phonemic and gestural codes. For example, the maximal IT rates for Morse Code (auditory reception) were estimated at 4.5 bits/s and fingerspelling (visual reception) at 16 bits/s. Modality of reception also affects IT rate. For example, haptic reception of a given code typically resulted in IT rates that are roughly one-half of those obtained through the normal channel of reception (be it vision or audition).

Further insight into the effects of experience and modality on communication rate is provided by a study of the reception of Morse Code in which Tan et al. [38] examined the ability of a group of highly experienced ham radio operators and a group of naïve participants to receive Morse Code as a function of presentation rate under three different modalities. Morse Code signals for letters of the English alphabet were delivered through a motional display, through vibrotactile presentation, or through acoustic presentation. The device used for the motional display delivered sequences of up-down displacements of the fingertip and mimicked the motions used by ham radio operators when sending the Morse Code through a straight keyer. The vibrotactile or acoustic display consisted of square-wave gating of a 200-Hz sinusoidal signal applied to a minishaker vibrator or presented diotically to the two ears under headphones. The ability to receive Morse Code stimuli (single letters, three-letter random sequences, common words, and conversational sentences) was examined as a function of presentation rate in words/minute. For single letters, three-letter sequences, and common words, participants were instructed to type their responses on a computer keyboard. For sentences, the participants were instructed to repeat the sentence verbally. [Experienced participants were not tested on single letters or three-letter sequences under the auditory condition as this task was trivial for them, and the naïve participants were not tested

TABLE 3
Peak Presentation Rates in Words/Minute for Experienced and Naïve Participants in Morse Code

Participants	Stimulus Materials											
	Single Letters			3-Letter Sequence			Common Words			Sentences		
	M	*V*	*A*	*M*	*V*	*A*	*M*	*V*	*A*	*M*	*V*	*A*
Experienced	23	23	–	15	18	–	14	19	38	18	21	43
Naïve	21	20	24	9	13	22	6	9	15	–	–	–

Results are shown for each of four types of stimuli (single letters, random three-letter sequences, common words, and sentences) under each of three modes of presentation (motional—M, vibrotactile—V, and auditory—A).

on sentences as this task proved to be too difficult.] The results are summarized in Table 3, where the peak presentation rate in words/minute is shown for each condition and group of participants. An expression of the peak presentation rate in terms of peak IT rate in bits/second can be derived by assuming an average word length of four letters and a bit content of roughly 1.5 bits/letter (after Shannon [37]). This conversion factor can be expressed as IT $\text{rate (bits/second)} = 0.1 \times \text{Rate}$ (wpm).

For both groups of participants, auditory reception rates were nearly twice as high as those for vibrotactile stimulation (except for reception of single letters by naïve participants), which, in turn, were roughly 1.3 times those for motional stimulation (except for single letters). The results indicate similar peak presentation rates for single letters for both groups of participants (in the range of 20 to 24 wpm). The experienced participants outperformed the naïve participants on three-letter sequences (by a factor of roughly 1.5) and on common words (by a factor of roughly 2.3). For the experienced participants, the peak presentation rates achieved on sentences were roughly similar to those for single letters (for motional and vibrotactile presentation) and correspond to IT rates of approximately 1.8 bits/s (motional), 2.1 bits/s (vibrotactile), and 4.3 bits/s (auditory). For the naïve participants, the peak presentation rates decreased substantially as the stimuli became more complex. The ability of the experienced participants to receive Morse Code sentences made up of common words is related to their ability to chunk the "dit/dah" patterns of Morse Code into letters, which are then used to form words, which, in turn, are turned into short phrases. Thus, the grammatical and syntactical structure of the sentences provide cues which the experienced participants use in decoding the stream of incoming "dit/dah" patterns. In contrast, the naïve participants do not have the ability to process the incoming code into patterns of words and phrases necessary for sentence reception.

It is difficult to compare the Morse Code results with those of our studies on the identification of multidimensional tactual stimuli in terms of optimal presentation rates. The size of an "item" in the Morse Code studies depends on the definition of the basic unit which is used to process information, which may be "dit" and "dah" signals, letters, words, or phrases. If we assume that the basic item is a word, then the optimal item presentation rates of the experienced participants for sentence reception translate into 0.33 words/s for motional stimulation, 0.40 words/s for vibrotactile stimulation, and 0.72 words/s for auditory stimulation. These optimal item presentation rates are substantially below those observed in our studies with multidimensional tactual signals (see Table 2), as are the estimated peak IT rates. Although the inefficiency of the alphabetic code employed in Morse Code clearly imposes a limitation on the rates that can be achieved with this method, the results of this study are important in demonstrating the effects of training (as seen in comparisons of performance for experienced versus naïve participants) and modality (as seen in comparisons of the familiar auditory modality versus the motional and vibrotactile modalities) on optimal IT rates.

5 Factors Related to Outcome of IT-Rate Measurements

A number of factors probably contributed to the differences in results obtained among the sets of studies described in Sections 2, 3, and 4. One such factor is the use of a forced-pace task in the earlier studies (Section 2) as opposed to the AXB, single-trial probes in our research (Section 3). Another such factor is the amount of training and experience that participants have with the experimental stimuli (e.g., see Section 4). Additional factors that likely contribute to the outcome of IT rate measurements include such things as the inherent complexity of the stimulus set and stimulus-response compatibility. Comments on some of these factors are presented below.

5.1 Use of Forced-Pace Task

Perhaps the most crucial difference in procedure between the sets of studies described in Sections 2 and 3 lies in the use of a forced-pace task in the early studies [27], [28] as opposed to the single-trial AXB probes employed in our own research [29], [30], [23]. In the forced-pace procedure, the stimuli are presented in a continuous sequence at some given rate of presentation. The participant must respond to each stimulus as it is presented and at the same time be attentive to the next stimulus in the sequence. In this method, the participant's response to a given stimulus is looked for over some predetermined time interval based on a priori knowledge of the participant's mean RT. In the AXB procedure, on the other hand, participants are presented with three stimuli at a given rate of presentation and are asked to identify only the middle one; participants are given as much time as necessary to respond; and the next trial is initiated only after the response to the previous trial is received.

A set of advantages and disadvantages is associated with each of these methods. A major advantage of the forced-pace procedure is that it simulates more closely the demands imposed in realistic situations that require continuous processing of extended sequences of signals. The disadvantage of this method is that the time required for a motor response is interwoven into the presentation rate; the stimuli must be paced in such a way as to allow time for the participant to respond while still being able to attend to the incoming stimuli. In some ways, the forced-pace method is analogous to a speech-reception task requiring "shadowing" of the speech message. Such tasks, which require attention to "back" stimuli in a sequence, have been demonstrated to place a large demand on memory on the basis of both perceptual and neuroimaging results (e.g., see [39]).

Klemmer and Muller [27] argue that participants are not limited in the forced-pace case by their ability to make the required motor response in time but only by their perceptual ability. This argument is based on the observation that the information in the responses (i.e., IR) remains high even though IT rate drops drastically at the highest presentation rates. However, high information in the responses, IR, can be achieved merely by use of the response alternatives with relatively equal probabilities (see Section 2). As long as the participant responds to each stimulus and makes use of the response alternatives with roughly equal probabilities, it is possible to obtain high values of IR in the presence of low values of IT.

The AXB procedure has the advantage of keeping the response time separate from the presentation time. However, it has the disadvantage of probing the participant's ability to identify only the middle item in a sequence of three items. The IT rates estimated using this procedure may be considerably greater than the rates that would be achieved for longer sequences of stimuli.

Another procedural difference in the two sets of studies lies in the way in which stimulus duration and ISI are manipulated to achieve different rates of information presentation. In Klemmer and Muller's research, stimulus duration and ISI were equal and decreased with presentation rate. In our own research, the signal duration was fixed at some given value and different presentation rates were achieved by varying ISI. In one case, the stimulus duration gets shorter as presentation rate increases, but the interstimulus interval remains equal to the stimulus duration. In the other case, the stimulus duration remains constant, but the interstimulus duration is decreased in order to increase the presentation rate. The extent to which this difference in manipulating item presentation rate has an effect on measurement of IT rate is not yet clear.

5.2 Stimulus Familiarity and Stimulus-Response Compatibility

The degree to which participants are familiar with the stimuli used in experiments to measure IT rates varies across studies. Some experiments have employed stimuli that are derived from natural methods of human communication and are very familiar to the participants prior to the experimental study. Other studies have employed sets of artificially constructed stimuli on which participants receive only laboratory training. Peak IT rates for certain natural methods of communication are estimated to be as high as 40-60 bits/s (e.g., auditory reception of speech and visual reception of sign language). Peak IT rates obtained with artificially constructed sets of stimuli are typically less than 18 bits/s. For the flashing light stimuli employed by Klemmer and Muller [27], maximal IT rates ranged from roughly 2.8 to 10.5 bits/s, and for the multidimensional tactual stimuli employed by Tan et al. [23], maximal IT rates were in the range of 10 to 18 bits/s. For a given level of performance in a static identification task, the maximal achievable IT rate is likely to be higher with stimuli that are highly learned for use in natural communication as opposed to stimuli to which the participant has had a limited amount of exposure in the laboratory.

Another important factor governing performance (e.g., IT rate or RT) is stimulus-response compatibility, based on the nature of the response code assigned to the stimuli both at the level of the particular set of responses employed (Fitts and Seeger [40]) and at the level of the mapping of elements between the set of responses and the set of stimuli (Fitts and Deininger [41]). It seems unlikely, however, that this factor was a major source of the different pattern of results obtained for IT rate as none of the studies in Sections 2 or 3 appear to violate obvious rules associated with stimulus-response compatibility (see research and reviews by [42], [43], [44], [45], [46], [47], [48]). For example, the spatial correspondence employed by Klemmer and Muller [27] in mapping their visual stimuli to motor response appears to have a high degree of compatibility. Similarly, in our own studies, the mapping of the tactual stimulus sets to the visual response sets reflected the underlying dimensions employed in the construction of the stimuli, another property that is highly linked to stimulus-response compatibility.

6 Concluding Remarks

The IT rate arises from an interaction between the information in the stimulus set and the rate at which items from this set are presented to the participant. Several patterns of interactions between IS and presentation rate emerge from the studies reviewed in the present paper.

For highly learned stimuli (such as speech), IT rates are estimated to be in the range of roughly 22 to 54 bits/s. The lower end of the range corresponds to measurements of normal rates of speech production and the upper end of the range to measurements for reception of time-compressed speech. The information available in the speech signal is constant in these estimates and the range of values arises from a change in presentation rate over a range from roughly 4.2 to 10 words/s at which listeners are able to receive speech with very few errors. As the rate increases above 10 words/s (achieved through artificial manipulation of the signal), there appear to be perceptual limitations on the ability to receive the signal.

Many of the laboratory studies reviewed here were conducted with artificial sets of stimuli on which participants received some fixed amount of training prior to measurements of optimal presentation rates and peak IT rates. The interaction between IS and presentation rate in determining peak IT rates appears to depend at least in part on the experimental paradigm. For studies conducted with a forced-pace procedure, the optimal presentation rate appears to be fixed at roughly 2.5 items/s. Thus, an increase in IT can be obtained only with an increase in IS. The occurrence of an optimal fixed presentation rate likely arises from physical limitations on response time. For studies conducted with an AXB procedure, on the other hand, the peak IT rate itself appears to be fixed and comes about through a trade-off between IS and rate of presentation.

The maximum IT rates observed in studies with unfamiliar stimuli (either under the forced-pace or AXB paradigm) are in the range of roughly 10-18 bits/s, substantially lower than those observed with sets of highly learned signals. Improved maximal IT rates in such studies may be obtained through increased training on a given set of stimuli. An important consideration in training lies in the issue of stimulus-response compatibility. To some extent, increased training may lead to an improvement in the participant's ability to associate a given stimulus with a given response. There are, however, examples in the literature (e.g., [40]) that suggest that certain stimulus-response configurations set a limit on IT that cannot be overcome by training.

One final point regarding the studies considered in this review is that they are concerned solely with measuring IT rates in one-way communication segments. A more comprehensive approach would include consideration of IT rates in continuous, two-way, round-trip, communication paradigms. In one cycle of such a paradigm, it would be necessary to take into account not only the one-way presentation rate associated with the sender and the correctness of interpretation by the receiver, but also the "turnaround" time for the receiver, the presentation rate achieved by the receiver, the correctness of the interpretation of the receiver's message by the sender, and the turnaround time for the sender. Obviously, a more complex experimental protocol is required to obtain IT rates in such a two-way, round-trip paradigm compared to the experimental procedures employed in the one-way communication segments considered in the studies reviewed here.

The ultimate goal of utilizing any artificially coded haptic signals such as the tactons in mobile devices is to optmize the information throughput through such a device. This can be in the form of vibrotactile patterns that not only alert the user but convey some aspects of the nature of the alert (e.g., an incoming call, a 5-min reminder of an upcoming meeting, etc.), or a sequence of patterns on a wearable vest that spells out, say, a military hand signal. The use of information theory in characterizing IT and IT rate with these communication systems can potentially quantify user performance independent of the context of the specific task, stimulation mode, or stimulus characteristics. For example, Summers et al. (1994 and 1997) estimated IT rates achievable with vibrotactile hearing aids and compared them with those of natural speech communication methods [33], [34]. In terms of evaluating the stimulus parameters for creating communication systems, an approach has been proposed [19] for measuring ITs from each parameter of a multidimensional display using a roving-background identification paradigm. In general, the increasing severity of the "information overload" problem facing individuals in our society, and our still very restricted understanding of how to display information to alleviate this problem, strongly suggest that further research in this area is critically important.

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References

[1] F.A. Geldard, "Adventures in Tactile Literacy," *The Am. Psychologist,* vol. 12, pp. 115-124, 1957.
[2] K.E. MacLean and M. Enriquez, "Perceptual Design of Haptic Icons," *Proc. EuroHaptics 2003,* pp. 351-362, 2003.
[3] J.B.F. van Erp and M.M.A. Spape, "Distilling the Underlying Dimensions of Tactile Melodies," *Proc. EuroHaptics 2003,* pp. 111-120, 2003.
[4] L.M. Brown, S.A. Brewster, and H.C. Purchase, "Multidimensional Tactons for Non-Visual Information Presentation in Mobile Devices," *Proc. Eighth Conf. Human-Computer Interaction with Mobile Devices and Services,* pp. 231-238, 2006.
[5] A.H. Rupert, "An Instrument Solution for Reducing Spatial Disorientation Mishaps—a More "Natural" Approach to Maintaining Spatial Orientation," *IEEE Eng. Medicine and Biology Magazine,* vol. 19, no. 2, pp. 71-80, Mar./Apr. 2000.
[6] R.W. Cholewiak and A.A. Collins, "Vibrotactile Localization on the Arm: Effects of Place, Space, and Age," *Perception and Psychophysics,* vol. 65, pp. 1058-1077, 2003.
[7] H.Z. Tan, R. Gray, J.J. Young, and R. Traylor, "A Haptic Back Display for Attentional and Directional Cueing," *Haptics-e: The Electronic J. Haptics Research,* vol. 3, article no. 1, 2003.
[8] H.A.H.C. van Veen and J.B.F. van Erp, "Providing Directional Information with Tactile Torso Displays," *Proc. EuroHaptics 2003,* pp. 471-474, 2003.
[9] H. van Veen, M. Spape, and J.v. Erp, "Waypoint Navigation on Land: Different Ways of Coding Distance to the Next Waypoint," *Proc. EuroHaptics 2004,* pp. 160-165, 2004.
[10] L.A. Jones, M. Nakamura, and B. Lockyer, "Development of a Tactile Vest," *Proc. 12th Int'l. Symp. Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS '04),* pp. 82-89, 2004.
[11] L.A. Jones, B. Lockyer, and E. Piateski, "Tactile Display and Vibrotactile Recognition on the Torso," *Advanced Robotics,* vol. 20, pp. 1359-1374, 2006.
[12] I. Oakley, Y. Kim, J. Lee, and J. Ryu, "Determining the Feasibility of Forearm Mounted Vibrotactile Displays," *Proc. Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS '06),* pp. 27-34, 2006.
[13] E. Hoggan, S. Anwar, and S.A. Brewster, "Mobile Multi-Actuator Tactile Displays," *Haptic and Audio Interaction Design,* vol. 4813, pp. 22-33, 2007.
[14] H.-Y. Chen, J. Santos, M. Graves, K. Kim, and H.Z. Tan, "Tactor Localization at the Wrist," *Proc. EuroHaptics 2008,* M. Ferre, ed., pp. 209-218, 2008.
[15] A. Murray, R.L. Klatzky, and P. Khosla, "Psychophysical Characterization and Testbed Validation of a Wearable Vibrotactile Glove for Telemanipulation," *Presence: Teleoperators and Virtual Environments,* vol. 12, pp. 156-182, 2003.
[16] L.A. Jones and H.-N. Ho, "Warm or Cool, Large or Small? The Challenge of Thermal Displays," *IEEE Trans. Haptics,* vol. 1, no. 1, pp. 53-70, Jan.-June 2008.
[17] M. Slater, "How Colorful Was Your Day? Why Questionnaires Cannot Assess Presence in Virtual Environments," *Presence: Teleoperators and Virtual Environments,* vol. 13, pp. 484-493, 2004.
[18] W.R. Garner, *Uncertainty and Structure as Psychological Concepts,* Wiley, 1962.
[19] N.I. Durlach, H.Z. Tan, N.A. Macmillan, W.M. Rabinowitz, and L.D. Braida, "Resolution in One Dimension with Random Variations in Background Dimensions," *Perception and Psychophysics,* vol. 46, pp. 293-296, 1989.
[20] P.M. Fitts, "The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement," *J. Experimental Psychology,* vol. 47, pp. 381-391, 1954.
[21] G.A. Miller, "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information," *The Psychological Rev.,* vol. 63, pp. 81-97, 1956.
[22] H.Z. Tan, "Identification of Sphere Size Using the PHANToM: Towards a Set of Building Blocks for Rendering Haptic Environment," *Proc. Sixth Int'l. Symp. Haptic Interfaces for Virtual Environment and Teleoperator Systems,* vol. 61, pp. 197-203, 1997.
[23] H.Z. Tan, N.I. Durlach, C.M. Reed, and W.M. Rabinowitz, "Information Transmission with a Multifinger Tactual Display," *Perception and Psychophysics,* vol. 61, pp. 993-1008, 1999.
[24] M.K. O'Malley and M. Goldfarb, "On the Ability of Humans to Haptically Identify and Discriminate Real and Simulated Objects," *PRESENCE: Teleoperators and Virtual Environments,* vol. 14, pp. 366-376, 2005.

[25] S.J. Lederman, R.L. Klatzky, A. Abramowicz, K. Salsman, R. Kitada, and C. Hamilton, "Haptic Recognition of Static and Dynamic Expressions of Emotion in the Live Face," *Psychological Science,* vol. 18, pp. 158-164, 2007.

[26] W.M. Rabinowitz, A.J.M. Houtsma, N.I. Durlach, and L.A. Delhorne, "Multidimensional Tactile Displays: Identification of Vibratory Intensity, Frequency, and Contactor Area," *J. Acoustical Soc. of America,* vol. 82, pp. 1243-1252, 1987.

[27] E.T. Klemmer and P.F. Muller, "The Rate of Handling Information: Key-Pressing Responses to Light Patterns," Human Factors Operations Research Laboratories (HFORL) Memo Report, Air Research and Development Command, Bolling Air Force Base, Mar. 1953.

[28] E.A. Alluisi, P.F. Muller, and P.M. Fitts, "An Information Analysis of Verbal and Motor Responses in a Forced-Paced Serial Task," *J. Experimental Psychology,* vol. 53, pp. 153-158, 1957.

[29] H.Z. Tan, "Information Transmission with a Multi-Finger Tactual Display," Doctoral dissertation, Dept. of Electrical Eng. and Computer Science, Massachusetts Inst. of Technology, 1996.

[30] H.Z. Tan, N.I. Durlach, W.M. Rabinowitz, and C.M. Reed, "Information Transmission with a Multi-Finger Tactual Display," *Scandinavian Audiology,* vol. 26, pp. 24-28, 1997.

[31] C.M. Reed, L.A. Delhorne, A. Brughera, N. Durlach, H.Z. Tan, and A. Wong, "Information-Transfer Rates for Sequences of Multidimensional Tactual Signals," *Proc. Seventh Int'l Sensory Aids Conf.,* 2003.

[32] H.Z. Tan, C.M. Reed, L.A. Delhorne, N.I. Durlach, and N. Wan, "Temporal Masking of Multidimensional Tactual Stimuli," *J. Acoustical Soc. of Am.,* vol. 114, pp. 3295-3308, 2003.

[33] I.R. Summers, P.R. Dixon, P.G. Cooper, D.A. Gratton, B.H. Brown, and J.C. Stevens, "Vibrotactile and Electrotactile Perception of Time-Varying Pulse Trains," *J. Acoustical Soc. of Am.,* vol. 95, pp. 1548-1558, 1994.

[34] I.R. Summers, P.G. Cooper, P. Wright, D.A. Gratton, P. Milnes, and B.H. Brown, "Information from Time-Varying Vibrotactile Stimuli," *J. Acoustical Soc. of Am.,* vol. 102, pp. 3686-3696, 1997.

[35] I.R. Summers, J.J. Whybrow, D.A. Gratton, P. Milnes, B.H. Brown, and J.C. Stevens, "Tactile Information Transfer: A Comparison of Two Stimulation Sites," *J. Acoustical Soc. of Am.,* vol. 118, pp. 2527-2534, 2005.

[36] C.M. Reed and N.I. Durlach, "Note on Information Transfer Rates in Human Communication," *Presence: Teleoperators and Virtual Environments,* vol. 7, pp. 509-518, 1998.

[37] C.E. Shannon, "Prediction and Entropy of Printed English," *Bell System Technical J.,* vol. 30, pp. 50-64, 1951.

[38] H.Z. Tan, N.I. Durlach, W.M. Rabinowitz, C.M. Reed, and J.R. Santos, "Reception of Morse Code through Motional, Vibrotactile, and Auditory Stimulation," *Perception and Psychophysics,* vol. 59, pp. 1004-1017, 1997.

[39] J. Jonides, E.H. Schumacher, E.E. Smith, E.J. Lauber, E. Awh, S. Minoshima, and R.A. Koeppe, "Verbal Working Memory Load Affects Regional Brain Activation as Measured by PET," *J. Cognitive Neuroscience,* vol. 9, pp. 462-475, 1997.

[40] P.M. Fitts and C.M. Seeger, "S-R Compatibility: Spatial Characteristics of Stimulus and Response Codes," *J. Experimental Psychology,* vol. 46, pp. 199-210, 1953.

[41] P.M. Fitts and R.L. Deininger, "S-R Compatibility: Correspondence among Paired Elements within Stimulus and Response Codes," *J. Experimental Psychology,* vol. 48, pp. 483-492, 1954.

[42] E.A. Alluisi and J.S. Warm, "Things that Go To-Gether: A Review of Stimulus-Response Compatibility and Related Effects," *Stimulus-Response Compatibility: An Integrated Perspective,* R.W. Proctor and T.G. Reeve, eds., pp. 3-30, North-Holland, 1990.

[43] J.R. Simon, "The Effects of an Irrelevant Directional Cue on Human Information Processing," *Stimulus-Response Compatibility: An Integrated Perspective,* R.W. Proctor and T.G. Reeve, eds., pp. 31-86, North-Holland, 1990.

[44] R.W. Proctor and K.-P. L. Vu, "Roles of Task-Defined Associations and Reference Frames in Spatial Sti-Mulus-Response Compatibility," *Experimental Cognitive Psychology and Its Applications,* A.F. Healy, ed., APA Books, 2004.

[45] R.W. Proctor, H. Wang, and K.-P.L. Vu, "Influences of Conceptual, Physical, and Structural Similarity on Stimulus-Response Compatibility," *Quarterly J. Experimental Psychology,* vol. 55A, pp. 59-74, 2002.

[46] R.W. Proctor, H.Z. Tan, K.-P.L. Vu, R. Gray, and C. Spence, "Implications of Compatibility and Cuing Effects for Multimodal Interfaces," *Proc. 11th Int'l. Conf. Human-Computer Interaction,* pp. 22-27, Lawrence Erlbaum Assoc., July 2005.

[47] S. Kornblum, T. Hasbroucq, and A. Osman, "Dimensional Overlap: Cognitive Basis for Stimulus-Response Compatibility—A Model and Taxonomy," *Psychological Rev.,* vol. 97, pp. 253-270, 1990.

[48] T.G. Reeve and R.W. Proctor, "The Salient-Features Coding Principle for Spatial- and Symbolic-Compatibility Effects," *Stimulus-Response Compatibility: An Integrated Perspective,* R.W. Proctor and T.G. Reeve, eds., pp. 163-180, North-Holland, 1990.

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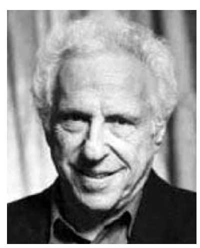

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