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The remarkable inefficiency of word recognition

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Do we recognize common objects by parts, or as wholes? Holistic recognition would be efficient, yet people detect a grating of light and dark stripes by parts. Thus efficiency falls as the number of stripes increases, in inverse proportion, as explained by probability summation among independent feature detectors¹. It is inefficient to detect correlated components independently. But gratings are uncommon artificial stimuli that may fail to tap the full power of visual object recognition. Familiar objects become special as people become expert at judging them^{2,3}, possibly because the processing becomes more holistic. Letters and words were designed to be easily recognized, and, through a lifetime of reading, our visual system presumably has adapted to do this as well as it possibly can. Here we show that in identifying familiar English words, even the five most common three-letter words, observers have the handicap predicted by recognition by parts: a word is unreadable unless its letters are separately identifiable. Efficiency is inversely proportional to word length, independent of how many possible words (5, 26 or thousands) the test word is drawn from. Human performance never exceeds that attainable by strictly letter- or feature-based models. Thus, everything seen is a pattern of features. Despite our virtuosity at recognizing patterns and our expertise from reading a billion letters, we never learn to see a word as a feature; our efficiency is limited by the bottleneck of having to rigorously and independently detect simple features.

The role of components in object recognition is still mysterious⁴⁻⁷. For most objects we don't even know what the components are, but we do know that words are made of letters. Is a familiar word recognized as an image, or as a combination of individually recognized letters? Despite a century of careful study⁸⁻¹⁶, it has never been noted that these two alternatives predict very different thresholds for identifying words. Once we have defined a few terms, you can test the predictions with your own eyes.

The strength of visual signals is traditionally specified by 'contrast', which here is the ratio of the luminance increment of the letter or word to the background luminance. However, for ideal-observer analysis it is helpful to specify 'contrast energy', which for a letter or a word is the product of squared contrast and 'ink' area. In general, contrast energy is the integral of the squared signal contrast over the extent of the stimulus. Energy matters: mathematical work on radar in the 1950s proved that the energy of a known signal completely determines its detectability in white noise¹⁷. 'Threshold', the border between seeing and not seeing, is defined here as the contrast or energy required by the observer to correctly identify the letter or word 64% of the time.

In Fig. 1a, the two lines of faint text have the same overall contrast energy, but differ in the way that the energy is distributed. To optimize recognition by parts, the first line gives each letter the same energy. To optimize recognition as wholes, the second line gives each word the same energy. Recognition by parts predicts that the longer words in the second line will be illegible, as you see, because there isn't enough energy per letter. Recognition as wholes predicts that all words in the second line will be equally legible, contrary to what you see. Figure 1b shows the predictions for your word threshold on blank and noisy backgrounds. The same analysis applies to both backgrounds because the observer effectively adds his or her intrinsic visual noise to the display¹⁸.

Our recognition-as-wholes predictions are based on the ideal observer, which, given the stimulus and its statistics, achieves the best possible expected performance by choosing the most probable letter or word^{17,18}. We can assess human performance on an absolute scale by defining 'efficiency' as the ratio of the ideal's threshold energy to the human observer's: the fraction of the energy used by

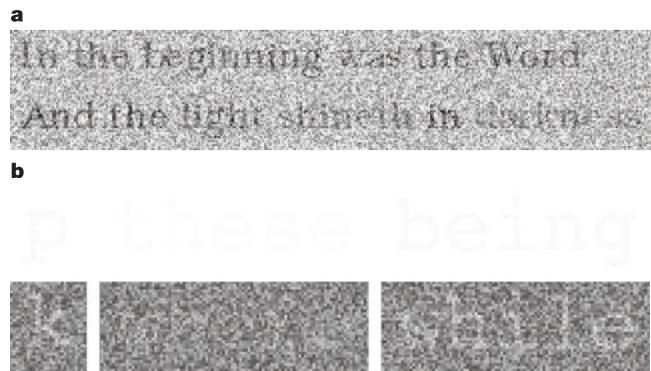


Figure 1 By letter or by word? **a**, Both lines of the quotation have the same total contrast energy. In the first, the energy is divided equally among the letters. In the second, the energy is divided equally among the words, regardless of length. In principle, at a given noise level a pattern's detectability depends only on its energy, but in the second quotation the short words pop out and the long words disappear. This word-length effect shows that human readers cannot efficiently integrate the energy across a whole word. (The quotation reads 'In the beginning was the Word ... And the light shineth in darkness'.) **b**, Two predictions for the word threshold. The left column shows a letter at threshold on a uniform white background (top row) and on a noisy background (bottom row). They may take a minute to appear. The middle column shows a 5-letter word at the same energy ($1/\sqrt{5}$ the contrast), which is the threshold predicted by recognition as wholes, and the right column shows a word at 5 times the energy (the same contrast), which is the threshold predicted by recognition by parts. The words in the middle column would be identifiable if you could see words as efficiently as you see letters. (The first line reads 'p', 'these', 'being', and the second reads 'k', '?????', 'while', where the identity of the middle word remains undisclosed.) Note: The faint lettering on a white background is at the limits of what can be rendered on the printed page. The PDF of this letter prints the figure successfully on most modern printers, especially colour printers. If in doubt, readers are urged to refer to a more robust version of Fig. 1b available as Supplementary Information, which accommodates variations in printers' rendering and readers' sensitivity.

the observer that is ideally required to account for the observer's measured performance^{18,19}. This strips away the intrinsic difficulty of the task, exposing a pure measure of human ability.

Our argument begins with our finding that human efficiency for word identification is inversely proportional to word length, independent of the number of possible words, as predicted by recognition by parts with suppression of weak signals, 'squelching'. Then we show that, notwithstanding the well known 'word superiority effect', human word identification never exceeds the accuracy attainable by strictly letter-based models. Related work indicates that letters are made of features. Finally, we conclude that visual recognition of even the most familiar objects is severely restricted by a first stage of independent feature detectors that squelch and each integrate no more than a letter, and probably much less.

The word-length effect, for words 2–16 letters long, is shown in Fig. 2 for two observers. Figure 2a shows that their threshold energy is proportional to word length, whereas the ideal observer's

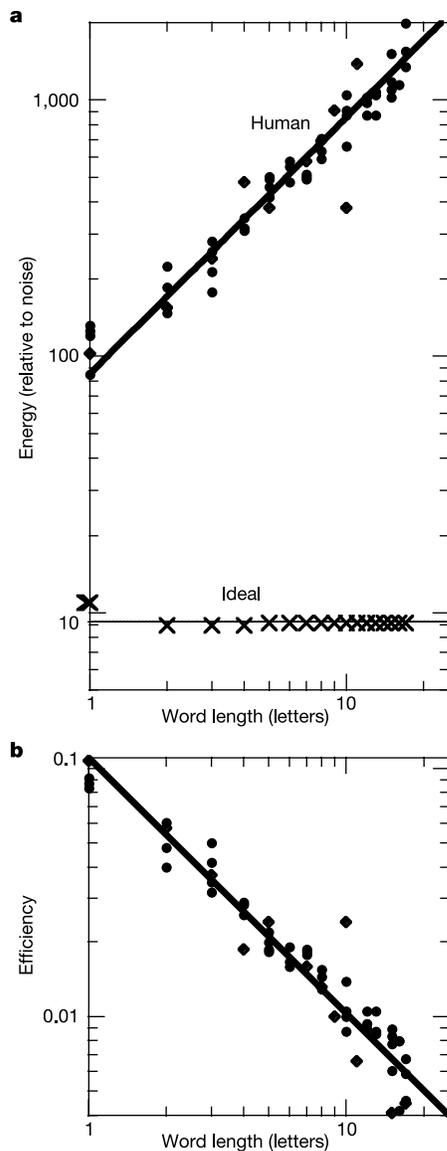


Figure 2 The effect of word length. **a**, Threshold energy for identifying one of 26 words, as a function of word length. The data at length 1 are for single letters. The ideal observer's thresholds (crosses) lie near the zero-slope line. The human observers' thresholds (JP, circles; JG, diamonds) lie near the unit-slope line. **b**, Efficiency (the ratio of ideal and human thresholds) derived from **a** as a function of word length. The points are close to the line with -1 slope: efficiency is inversely proportional to word length.

threshold is practically independent of word length. Figure 2b shows that efficiency, the ratio of ideal and human thresholds, is inversely proportional to word length. Efficiency for n -letter words is $1/n$ that for single letters. This result is not surprising for longer words, as observers take in only a modest number of letters in a glimpse, perhaps 4.5 (ref. 20), which predicts the reciprocal drop in efficiency for longer words, as the ideal observer uses all the letters. What is surprising and important about Fig. 2 is that the same slope extends left to the shortest words, and even single letters. Thus, the required energy per letter is independent of word length.

This is not merely a consequence of just size or contrast. Although a word is bigger than a letter, and words and letters have the same threshold contrast, the human limitation demonstrated in Figs 1 and 2 is neither an inefficiency for all large objects nor a fixed threshold contrast that all objects must exceed to be seen. Increasing letter size fivefold, to match the width of a word, reduces the letter's threshold contrast, in noise, fourfold²¹. Because seeing the large letter requires only a fraction of the contrast required to see a similar-width word, any explanation of the poor visibility of words must penetrate past their size to consider their internal structure. Our results indicate that, rather than directly recognizing complex familiar objects, such as words, our visual system detects smaller components—letters or perhaps features of letters—and only then recognizes the object specified by these components. Nothing is seen unless its components are detected^{22,23}.

One might ask whether the human observer could reasonably be expected to confine his or her word search to the 26 words used in the test, as the ideal does. Our design minimized this concern by using the 26 most common n -letter words, and displaying them as the response alternatives in every trial. Identifying letters independently (recognition by parts) is inefficient because the letters in a word are correlated. That's because the number of n -letter words, 26 in our experiment or thousands in real life, is a tiny fraction of the number of possible strings, 26^n . Still, one might worry that this human inefficiency is an artefact of using only 26 words. We addressed these concerns by measuring human and ideal thresholds for identification of one of 2,213 five-letter words (the most common 2,213), presenting each word at the same relative frequency as it appears in print²⁴, and found the same efficiency (approximately 4%) as for the 26 most common. (These efficiencies, for experienced observers with Courier font, are slightly higher than in Fig. 2, which is for new observers with Bookman font. The 100,000-trial experience, in various conditions, and the Courier font both contribute to the $\times 1.5$ higher efficiency²¹.) Finding the same efficiency means that human and ideal thresholds are affected equally by word frequency. Thinking that perhaps only extremely common words enjoy recognition as elementary visual patterns²⁵, we measured human and ideal thresholds for identifying the five most common 3-letter words (the, and, was, for, his). The least frequent of these words (his) is encountered 100 times in an hour of reading, nearly 400,000 times in a decade of reading an hour a day. Even so, the five most common 3-letter words yield practically the same efficiency as the 26 most common (4.8% compared to 4.5%) and reciprocity holds: the efficiency for identifying the five most common 3-letter words is $1/3$ that for single letters: 4.8%/15%. Changes in intrinsic task difficulty—5, 26 or 2,213 alternatives—invalidate comparison of raw thresholds unless modelling assumptions are made, but efficiencies are always directly comparable.

The ideal observer chooses the best-matching template, using one template for each possible word. The root mean square (r.m.s.) difference between the stimulus and the template is a measure of the likelihood that the stimulus is the template plus noise. To choose the most probable word the ideal observer weighs each word's likelihood by its frequency. Template matching integrates energy efficiently over the extent of the template. If humans did template matching, with accurate templates for words of every length, then the slope in Fig. 2b would be zero, not -1 . Figure 2 indicates the

letters to nature

absence of templates of more than one letter, as the energy beyond one letter doesn't reduce the required energy for the first letter.

The brain is well equipped to do template matching. A typical neuron sums over 10,000 synapses, each with a different gain. Any neuron that integrates over part of the visual field computes the likelihood of the presence of a signal matching the neuron's sensitivity profile. Thus, neurons with very simple receptive fields have been called "fly detectors"²⁶. One can speculate that there might be neurons (perhaps in brain area IT) that linearly integrate over more complex receptive fields that match a face, letter or word, but such neurons would allow the observer to attain much higher efficiencies than found here, placing their existence in doubt.

In principle, identifying a letter independently requires the same energy for that letter as would be required to identify the whole word (if there are, as in Fig. 2, the same number of possible letters and words). The fact that a word is unreadable by our observers unless its letters are separately identifiable is evidence for recognition by components; that is, identification of the word is mediated by independent detection of components that are a letter or less. We define 'features' as image components that are detected independently, unaffected by the presence of other features. Independent feature detection is a bottleneck, especially when feature thresholds are high; complex objects will be visible only when the energy per feature reaches threshold.

Our data indicate that there are no multi-letter features. Efficiency for letters is independent of age after ten, only weakly dependent on size and alphabet (English, Armenian, Devanagari and Hebrew), and inversely proportional to complexity²¹. 'Complexity' is a scale-invariant physical measure: perimeter squared over 'ink' area²¹. The number of features in a letter may be proportional to its complexity. It seems that in identifying letters, observers use no feature more complex than the average letter in the simplest alphabet tested²¹, about one-third the complexity of the Bookman and Courier fonts used here. As letters and words are designed to be legible, and the reader's visual system presumably has adapted itself to them as much as it can, we conclude that the feature bottleneck is unavoidable. Objects are recognized by means of independent detection of their component features, which are much simpler (less complex) than a single Bookman letter.

The efficiency result—the reciprocal relation between efficiency and number of components—is secure and assumption-free, but how general is it? We extended it from obscure gratings¹ to common words. It also applies to letters if we suppose that complexity is proportional to the number of features. But these stimuli were all at threshold. Threshold stimuli are directly relevant to real-life reading of highway signs, which are usually read at great distance as soon as they become readable. Might ordinary reading, at high contrast, be mediated by different mechanisms? That seems unlikely. Critical-band masking studies have characterized the channels (feature detectors) that mediate letter identification at threshold²⁷. Experiments at high supra-threshold contrasts, measuring the effect of noise on reading rate, reveal the same channel tuning²⁸.

We usually see things quite reliably or not at all, with a fairly abrupt transition between the two. Indeed, the 'psychometric function', the probability of seeing, rises much more steeply as a function of contrast than predicted by theory of signal detectability for an exactly known signal¹⁷. The steep psychometric function means that weak signals are suppressed. Engineers call this 'squenching': in better walkie talkies, a nonlinear analog circuit turns down the volume when the signal is weak relative to the background noise, to cut out the hiss when no one is speaking. In the same way, human vision squelches features, allowing them to pass only if they are well above the noise. We call this 'detecting rigorously'. It achieves reliability at the expense of efficiency. The human visual system has a vast number of feature detectors, each of which can raise a false alarm, mistaking noise for signal. Squelching blocks the intrusion of countless false features that would besiege us if weak features were

not suppressed. However, it impairs our ability to see more complex objects, like words. In the limiting case, squelchers pass all signals above a certain threshold contrast, and none below. Whether the squelch is gradual or abrupt, it is, in effect, deciding whether or not a signal is present and acting on that decision.

Discussions of letter and word recognition typically suppose various stages in the recognition process: identification of features, then letters, then the word^{14,29}. One approach to modelling how an observer performs a task is to specify just the first stage of processing, leaving subsequent stages unspecified. However, such models must avoid the common mistake of specifying a transformation that preserves all task-relevant information. Such a transformation can always be undone by the subsequent unspecified stages, so it does not constrain performance, making the model psychophysically inconsequential and untestable. Proposing a first stage constrains performance only to the extent that the stage discards task-relevant information. In that spirit, when we assert that a part of a model, or the brain, 'makes a decision', we mean not only that it passes that decision on, but also that it discards (fails to pass on) the information the decision is based on. Thus, we consider the idea that all word and letter identifications are strictly letter-based; that is, they depend on the visual stimulus solely through a stage that identifies each letter independently and passes on only that identification, discarding the rest of the stimulus information. We leave the later stages, after letter identification, unspecified. Each decision is a bottleneck.

Selfridge's Pandemonium Model²⁹ cascades row after row of 'demons' that compute the likelihood of features, then letters, and then words, achieving perfect efficiency by not discarding any choice-relevant information until the final shouting match. It is an ideal observer. Similarly, the Interactive Activation Model¹⁴ computes each possible letter's likelihood at each letter position, and postpones the information-discarding shouting match until the final response-selection stage. Presumably, given optimal weights and extended to report whole words, it would be nearly ideal, so it too would have similar energy thresholds for words and letters, unlike what we report here for human observers.

It is a simple matter to calculate how accurately a word can be identified by a strictly letter-based observer. The observer's first stage identifies the letters independently. These identifications are tentative. To perform optimally, the observer, having the string of tentatively identified letters, uses a historical table of his or her single-letter confusion probabilities (identifying one letter as

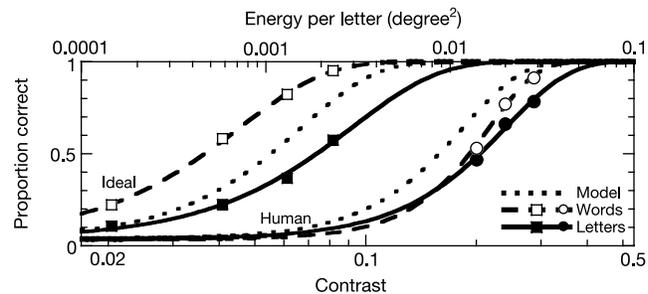


Figure 3 Proportion correct in identifying a letter (filled symbols) or a 5-letter word (open symbols) in noise as a function of contrast. Average energy per letter is indicated on the upper x axis. This is for one human, WT (3,000 trials per point), and the ideal observer (100,000 trials per point). Note that the human's contrast thresholds (64% correct) for letters and words are similar, whereas the ideal observer's are very different. For each observer, the dotted line is the best possible strictly letter-based word identification performance, given the observer's measured single-letter confusion probabilities (of identifying each letter as another) at that contrast. (A second human observer, DM, gave very similar results, not shown.) All curves are maximum-likelihood Weibull fits ($\gamma = 1/26$)²¹.

another) at that contrast to choose the most probable word from the list of alternatives. (The ideal, described earlier, computes each possible word's likelihood based on the stimulus. Our letter-based two-stage observer is not ideal, and must settle for likelihood based on the independent letter identifications, rather than the stimulus itself.)

The performance of this best-possible letter-based observer is plotted as the dotted curves in Fig. 3. The left curve is based on the ideal's single-letter confusion probabilities at each contrast, and the right curve is based on the human's. Each dotted curve is the best possible accuracy for strictly letter-based word identification by that observer, given the observer's measured letter performance. Note that the human's word performance (right dashed line) never exceeds this letter-based bound, whereas the ideal's word performance (left dashed line) far exceeds it. Thus, despite reading for decades, a hundred million words²¹, our observers identify even the most common words with an accuracy attainable through strictly letter-based identification.

Humans squelch features. The ideal observer does not. Nor does the two-stage model based on the ideal letter identifier. It is inefficient to detect correlated components independently, and this is exacerbated by squelching. We can calculate efficiency from the threshold contrasts of the curves in Fig. 3 for lengths 1 (letter) and 5 (word). Efficiency of the model, which doesn't squelch, drops as words grow longer. Efficiency of the human, who does squelch, drops more, as the reciprocal of word length.

At first sight, our conclusion may seem incompatible with the hundred-year-old 'word superiority effect', whereby a letter within a word is recognized better than a letter presented in isolation or in a scrambled word⁸⁻¹⁶. The word context improves letter identification even when it provides no information that can distinguish between the response alternatives. For example, coin versus join is easier than c versus j. Thus, in Fig. 4, the proportion correct for words (dashed line) is higher than that for letters (solid line). But is the observed context effect big enough to prove that the internal letter identifications are not independent of each other? No, it's too small. The human performance plotted in Fig. 4 is consistent with strictly letter-based word identification. The dotted line shows how well the observer would perform by first identifying the test letter as a ... z, and then choosing the more likely of the two response alternatives (for example, 'c' or 'j') based on her own single-letter confusion probabilities. This is the best possible strategy for an observer who is strictly letter-based. This letter-based upper bound applies to both letter and word conditions, and in fact is above both. The worse human performance shows that the observer is not using the optimal strategy, quite possibly because she doesn't know her own

single-letter confusion probabilities and thus fails to choose the most probable letter or word (c or j) given her tentative internal letter identification (a ... z). The strictly letter-based upper bound is also above the word advantage found in other studies, which find the proportion correct for letter identification to be 0.05-0.15 greater in a word context¹⁰⁻¹⁶. The word context (dashed line) improves performance, bringing it closer although still not exceeding the (dotted) upper bound. The slightly higher human performance in a word context (the word superiority effect) suggests that observers more accurately incorporate their historical confusion probabilities when reading words than when identifying letters, which is consistent with the observation that observers perform better if they attend to the entire word rather than just to the target letter¹². Perhaps years of fast reading have trained the second-stage word-recognition process to learn the observer's letter-confusion probabilities, to more efficiently map strings of tentatively identified letters to real words. Figure 4 shows that the 0.10 upward increase in accuracy corresponds to a factor of $\times 1.15$ leftward reduction in threshold contrast ($\times 1.3$ in energy). Thus, there are not one but two effects, one small and one large. The word superiority effect increases efficiency by a mere factor of $\times 1.3$. The word-length effect, described here, is big, reducing efficiency by the word length, $\div 5$ for a 5-letter word. Both effects are consistent with strictly letter-based word identification.

In evaluating whether recognition is by parts or as wholes, we took a 'best of breed' approach, considering the best possible performance of models that conform to simple assumptions about the observer's internal processes. Our analysis has focused on letters because they are obvious components of words. More generally, the same approach may be applied to critically test any conjecture that object recognition is mediated by independent decisions about a specified set of features or components. The components in objects are usually correlated, so object recognition based on independent decisions about components is inefficient, especially with squelching. Having to independently and rigorously detect the components makes efficiency inversely proportional to their number. □

Methods

Testing

In each trial the signal was one of 26 possible letters (a ... z), or 26 possible words. The word list for each length (2-16 letters), for example 'of, to, in, ... , pa' for 2-letter words or 'responsibilities, misunderstandings, characterization, ... , aristocratically' for 16-letter words, consisted of the 26 most common words of that length, excluding words that are normally capitalized (such as 'American'), words containing punctuation, and nearly identical words²⁴. The signal—a letter or word—was briefly presented (200 ms) either on a blank 50 cd m⁻² gamma-corrected screen (for human observers) or in gaussian noise (for both human and ideal observers). The blank screen and the noise had the same mean luminance (unlike the two rows of Fig. 1b). The task was to identify the signal by choosing one of the 26 signals, which were displayed for the human observer on an immediately-following response screen. (Increasing the viewing time, as in the printed demonstrations in Fig. 1, does not affect identification on the static noise background, but does aid identification on a blank background, because detection is then limited by the observer's intrinsic visual noise¹⁸, which is dynamic. See also ref. 15.) The text was rendered at 29 point in an off-screen image using the uniformly spaced TrueType Courier font (Fig. 1b), except for Figs 1a and 2, for which we used the proportionally spaced PostScript Adobe Bookman font. Efficiency of letter identification is slightly higher using Courier than using Bookman²¹. In the noise conditions, independent zero-mean gaussian samples, with standard deviation equal to 25% of the mean luminance, were added to the pixels of the off-screen image. The off-screen image was then doubled in size horizontally and vertically by pixel replication, and copied to the screen. The screen displayed 31.3 pixels per degree at the 0.6 m viewing distance. The power spectral density of the noise was $N = 10^{-3.59} \text{ deg}^{-2}$. The typographic x-height of the displayed text was 0.83 deg (Courier) or 0.89 deg (Bookman).

Modelling

The results of the simulations at three contrasts were fit with a Weibull psychometric function, which is displayed as the dotted curve. The 26 \times 26 table of probabilities of each one-letter response to each one-letter signal is the observer's letter-confusion matrix. The simulation used 3,000-trial letter-confusion matrices measured for each observer at each of three contrasts in noise. (For the ideal they were 100,000-trial matrices at four contrasts.) To prevent bias due to correlated sampling errors between the confusion matrices used to simulate the first and second stages of the model, each stage used an

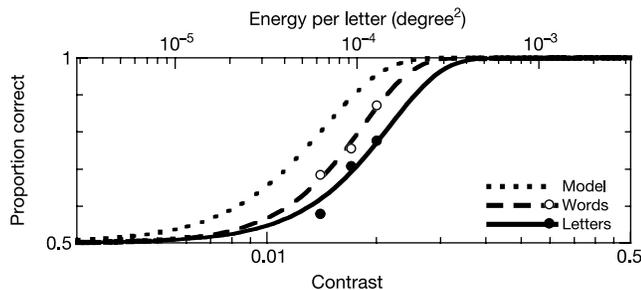


Figure 4 The word superiority effect. Proportion correct as a function of contrast and average energy per letter, for letters and words on a blank background. The dotted line represents the upper bound for strictly letter-based word identification, based on the observer's measured confusion probabilities at three contrasts. Unlike Fig. 3, only two response alternatives, differing by only one letter, were offered on each trial, for example, 'coin' versus 'join' or 'c' versus 'j'. The word superiority is slight, no greater than can be accounted for by strictly letter-based identification.

independent 1,500- (or 50,000-) trial subset of the empirical letter-confusion counts. The first stage receives a letter i_1 or a word i_1, i_2, i_3, i_4, i_5 and independently emits a letter j_1 or a letter at each position j_1, j_2, j_3, j_4, j_5 with each letter probability specified by the 26×26 confusion matrix $P(j | i)$. The best-possible second stage chooses the most probable 5-letter word i_1, i_2, i_3, i_4, i_5 given the independent first-stage letter identifications j_1, j_2, j_3, j_4, j_5 ; that is, it maximizes the posterior probability

$$P(i_1, i_2, i_3, i_4, i_5 | j_1, j_2, j_3, j_4, j_5) = \frac{P(i_1, i_2, i_3, i_4, i_5)P(j_1 | i_1)P(j_2 | i_2)P(j_3 | i_3)P(j_4 | i_4)P(j_5 | i_5)}{\sum_{i_1, i_2, i_3, i_4, i_5} P(i_1, i_2, i_3, i_4, i_5)P(j_1 | i_1)P(j_2 | i_2)P(j_3 | i_3)P(j_4 | i_4)P(j_5 | i_5)}$$

where $P(i_1, i_2, i_3, i_4, i_5)$ is the prior probability of the word i_1, i_2, i_3, i_4, i_5 . Concerned that the resulting 1,500 (3,000/2) trials per confusion matrix might not be enough, we simulated the two-stage model based on 100, 1,000, 3,000, 33,000 and 100,000 trials of the ideal observer. This revealed that the proportion correct is robust, only a few per cent lower for simulations using confusion matrices based on 3,000/2 rather than on 100,000/2 trials. Thus, our dotted curves in Figs 3 and 4 slightly underestimate the best-possible strictly letter-based performance, making our conclusion slightly more secure: human performance never clears the bar.

Word superiority

Following Reicher's¹⁰ elegant design, we began with a list of 288 pairs of 4-letter words that differed by only one letter within each pair. Equal numbers of words differed at each of the four letter positions. Our list was derived from that of ref. 30, replacing 18 obscure words (such as boll, lave, wile) by more common ones (ball, lake, mile). The observer was EG. In the word-identification task the observer was shown a low-contrast word, randomly selected from the list. Unlike our previous experiments, the response screen merely asked the observer to select between the correct word and its mate, which differed in only one letter position, as in 'c o i n' versus 'j o i n'. The letter-identification task drew from the same word list, but left blank all but the differing letters in each pair ('c ' versus 'j ') in both the stimulus and response screens. The ideal observer performs identically on both tasks, because the non-differing letters are irrelevant to the choice, so the human observer's word superiority implies that here the human is identifying words slightly more efficiently than letters. Thus, the word superiority effect is aptly named, but, as explained in the text, is consistent with strictly letter-based word identification.

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Control of dynamic CFTR selectivity by glutamate and ATP in epithelial cells

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Cystic fibrosis is caused by mutations in cystic fibrosis transmembrane conductance regulator (CFTR), an anion channel¹. Phosphorylation and ATP hydrolysis are generally believed to be indispensable for activating CFTR². Here we report phosphorylation- and ATP-independent activation of CFTR by cytoplasmic glutamate that exclusively elicits Cl⁻, but not HCO₃⁻, conductance in the human sweat duct. We also report that the anion selectivity of glutamate-activated CFTR is not intrinsically fixed, but can undergo a dynamic shift to conduct HCO₃⁻ by a process involving ATP hydrolysis. Duct cells from patients with ΔF508 mutant CFTR showed no glutamate/ATP activated Cl⁻ or HCO₃⁻ conductance. In contrast, duct cells from heterozygous patients with R117H/ΔF508 mutant CFTR also lost most of the Cl⁻ conductance, yet retained significant HCO₃⁻ conductance. Hence, not only does glutamate control neuronal ion channels, as is well known, but it can also regulate anion conductance and selectivity of CFTR in native epithelial cells. The loss of this uniquely regulated HCO₃⁻ conductance is most probably responsible for the more severe forms of cystic fibrosis pathology.

The molecular structure of CFTR is much more complicated than most ion channels. CFTR combines a regulatory domain consisting of numerous phosphorylation sites with two nucleotide-binding domains capable of ATP hydrolysis³ flanked by six transmembrane domains on each side⁴. Consistent with this structure, a consensus has evolved that the phosphorylation by protein kinase A and hydrolysis of ATP are essential for activating CFTR Cl⁻ channel². However, several discordant observations raised questions as to whether these requirements are absolute. We previously reported that CFTR Cl⁻ channels in the human sweat ducts are constitutively