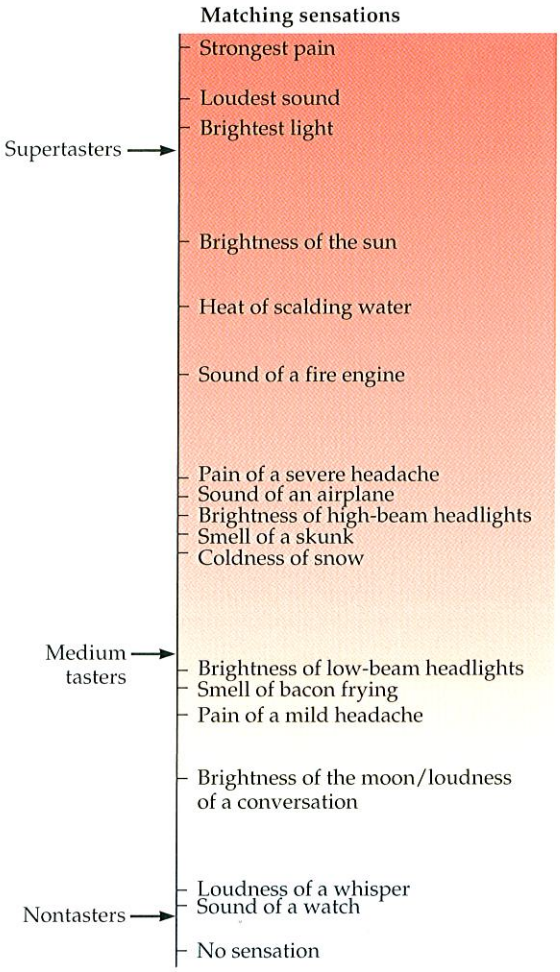


FIGURE 1.9 Cross-modality matching. The levels of bitterness of concentrated PROP perceived by nontasters, medium tasters, and supertasters of PROP are shown on the left. The perceived intensities of a variety of everyday sensations are shown on the right. The arrow from each taster type indicates the level of sensation to which those tasters matched the taste of PROP. (Data from Fast, 2004.)

- *Stevens' power law* describes rating data quite well, but notice that rating data are qualitatively different from the data that supported Weber's law. We can record the subjects' ratings and we can check whether those ratings are reasonable and consistent, but there is no way to know whether they are objectively right or wrong.

A useful variant of the scaling method can show us that different individuals can live in different sensory worlds, even if they are exposed to the same stimuli. The method is **cross-modality matching** (J. C. Stevens, 1959). In cross-modality matching, an observer adjusts a stimulus of one sort to match the perceived magnitude of a stimulus of a completely different sort. For example, we might ask a listener to adjust the brightness of a light until it matches the loudness of a particular tone. People can do this and, for the most part, everyone with "normal" vision and hearing will produce the same pattern of matches of a sound to a light. We still can't examine someone else's private experience, but at least the relationship of visual experience and auditory experience appears to be similar across individuals.

Not so when it comes to the sense of taste. There is a molecule called propylthiouracil (PROP) that some people experience as very bitter, while others experience it as almost tasteless. Still others fall in between. This relationship can be examined formally with cross-modal matching (Marks et al., 1988). If observers are asked to match the bitterness of PROP to other sensations completely unrelated to taste, we do not find the sort of agreement that is found when observers match sounds and lights (Figure 1.9). Some people—we'll call them nontasters—match the taste of PROP to very weak sensations like the sound of a watch or a whisper. A group of **supertasters** assert that the bitterness of PROP is similar in intensity to the brightness of the sun or the most intense pain ever experienced. Medium tasters match PROP to weaker stimuli, such as the smell of frying bacon or the pain of a mild headache (Bartoshuk, Fast, and Snyder, 2005). As we will see in Chapter 15, there is a genetic basis for this variation, and it has wide implications for our food preferences and, consequently, for health. For the present discussion, this example shows that we can use scaling methods to quantify what appear to be real differences in individuals' taste experience.

cross-modality matching The ability to match the intensities of sensations that come from different sensory modalities. This ability enables insight into sensory differences. For example, a listener might adjust the brightness of a light until it matches the loudness of a tone.

supertaster An individual whose perception of taste sensations is the most intense.

signal detection theory A psychophysical theory that quantifies the response of an observer to the presentation of a signal in the presence of noise. Measures obtained from a series of presentations are sensitivity (d') and criterion of the observer.

Signal Detection Theory

Let's return to thresholds—particularly to the fact that they are not absolute. An important way to think about this fact and to deal with it, experimentally, is known as **signal detection theory** (D. M. Green and Swets, 1966). Signal detection theory holds that the stimulus you're trying to detect (the "signal") is always being detected in the presence of "noise." If you sit in the quietest place you can find and you wear your best noise-canceling headphones, you will find that you can still hear *something*. Similarly, if you close your eyes in a

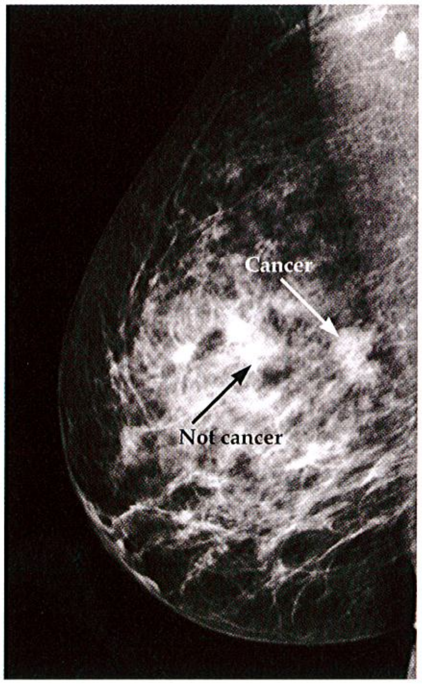


FIGURE 1.10 Mammograms, X-rays of the breast, are used to screen women for breast cancer. Reading such images is a difficult perceptual task, even for a trained radiologist. (Courtesy of Dr. Robyn Birdwell, Harvard Medical School.)

dark room, you still see something—a mottled pattern of gray with occasional brighter flashes. This is internal noise, the static in your nervous system. When you're trying to detect a faint sound or flash of light, you must be able to detect it in the presence of that internal noise. Down near threshold, it will be hard to tell a real stimulus from a particularly vigorous surge of internal noise.

There is external noise too. Consider that radiologist, introduced earlier, reading a mammogram looking for signs of breast cancer. In **Figure 1.10**, it is the marked fuzzy white region that is the danger sign. As you can see, however, the mammogram contains lots of other similar regions. We can think of the cancer as the signal. By the time it is presented to the radiologist in an X-ray, it is a signal plus noise. Elsewhere in the image, and in other images, are stimuli that are just noise. The radiologist is a visual expert, trained to find these particular signals, but sometimes the signal will be lost in the noise and missed, and sometimes some noise will look enough like cancer to generate a false alarm (Nodine et al., 2002).

Of course, sometimes neither internal nor external noise is much of a problem. When you see this dot, •, you are seeing it in the presence of internal noise, but the magnitude of that noise is so much smaller than the signal generated by the dot that it has no real impact. Similarly, the dot may not be exactly the same as other dots, but that variation, the external noise, is also too small to have an impact. If asked about the presence of a dot here, •, and its absence here, , you will be correct in your answer essentially every time. Signal detection theory exists to help us understand what's going on when we make decisions under conditions of uncertainty.

Since we are not expert mammographers, let's introduce a different example to illustrate the workings of signal detection theory. You're in the shower. The water is making a noise that we will, imaginatively, call *noise*. Sometimes the noise sounds louder to you; sometimes it seems softer. We could plot the distribution of your perception of noise as shown in **Figure 1.11***a*.

Now the phone rings. That will be our *signal*. Your perceptual task is to detect the signal in the presence of the noise. What you hear is a combination of the ring and the shower. That is, the signal is added to the noise, so we can imagine that now we have two distributions of responses in your nervous system: a noise-alone distribution and a signal-plus-noise distribution (Figure 1.11*b*).

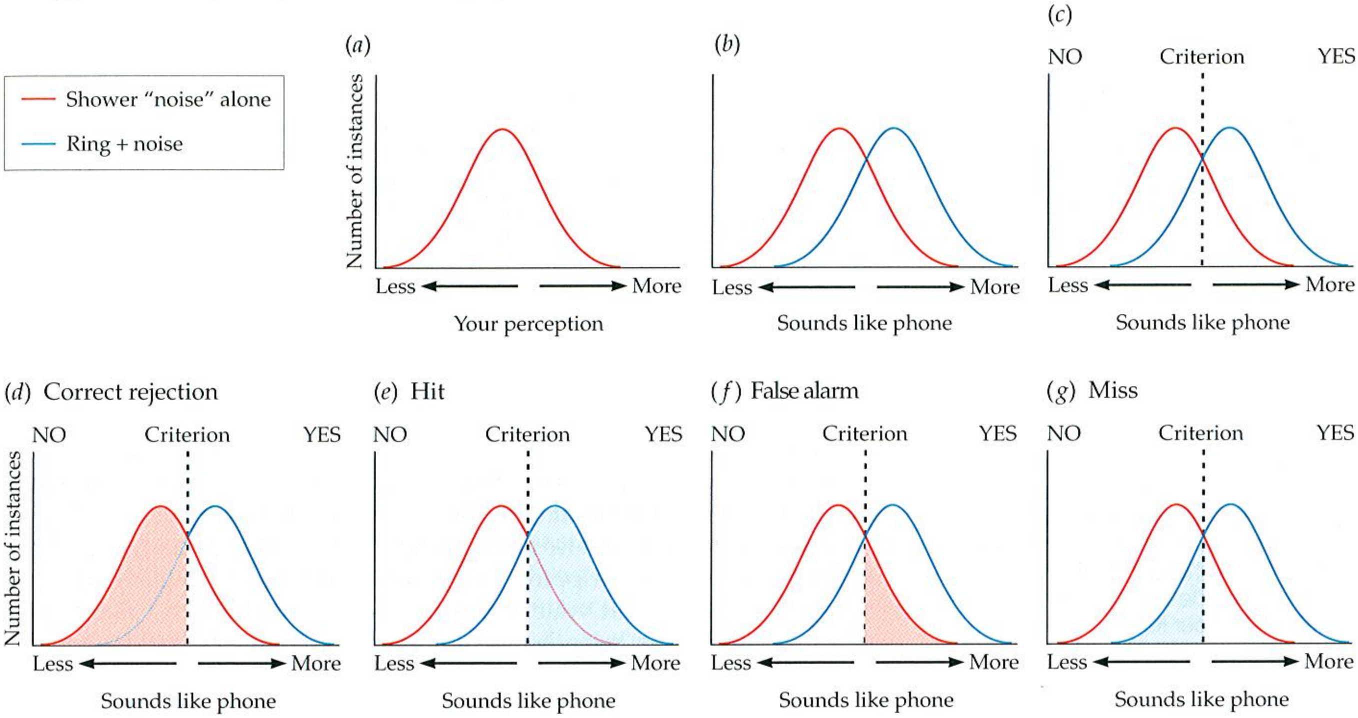
For the sake of simplicity, let's suppose that "more" response means that it sounds more like the phone is ringing. So now your job is to decide whether it's time to jump out of the shower and answer what might be the phone. The problem is that you have no way of knowing at any given moment whether you're hearing noise alone or signal plus noise. The best you can do is to decide on a **criterion** level of response (Figure 1.11*c*). If the response in your nervous system exceeds that criterion, you will jump out of the shower and run naked and dripping to find the phone. If the level is below the criterion, you will decide that it is not a ring and stay in the shower. Note that this "decision" is made automatically; it's not that you sit down to make a conscious (soggy) choice. Thus a criterion, in signal detection theory, is a value that is somehow determined by the observer. A response, inside the observer, above criterion will be taken as evidence that a signal is present. A response below that level will be treated as noise.

criterion In signal detection theory, an internal threshold that is set by the observer. If the internal response is above criterion, the observer gives one response (e.g., "yes, I hear that"). Below criterion, the observer gives another response (e.g., "no, I hear nothing").

There are four possible outcomes (Figure 1.11*d*–*g*): You might say "no" when there is no ring; that's a correct rejection (Figure 1.11*d*). You might say "yes" when there is a ring; that's known as a hit (Figure 1.11*e*). Then there are the errors. If you jump out of the shower when there's no ring, that's a false alarm (Figure 1.11*f*). If you miss the call, that's a miss (Figure 1.11*g*).

How sensitive are you to the ring? In the graphs of Figure 1.11, the sensitivity is shown as the separation between the noise-alone and signal-plus-noise

FIGURE 1.11 Detecting a stimulus using signal detection theory (SDT). (*a*) SDT assumes that all perceptual decisions must be made against a background of noise (the red curve) generated in the world or in the nervous system. (*b*) Your job is to distinguish nervous system responses due to noise alone (red) or to signal plus noise (blue). (*c*) The best you can do is establish a criterion (dotted line) and declare that you detect something if the response is above that criterion. SDT includes four classes of responses: (*d*) correct rejections (you say "no" and there is, indeed, no signal); (*e*) hits (you say "yes" and there is a signal); (*f*) false alarm errors (you say "yes" to nothing); and (*g*) miss errors (you say "no" to a real signal).



distributions. If the distributions are on top of each other (**Figure 1.12***a*), you can't tell noise alone from signal plus noise. A false alarm is just as likely as a hit. By knowing the relationship of hits to false alarms, you can calculate a **sensitivity** measure known as d' (*d*-prime), which would be about zero in Figure 1.12*a*. In Figure 1.12*c* we see the case of a large d'. Here you could detect

sensitivity In signal detection theory, a value that defines the ease with which an observer can tell the difference between the presence and absence of a stimulus or the difference between stimulus 1 and stimulus 2.

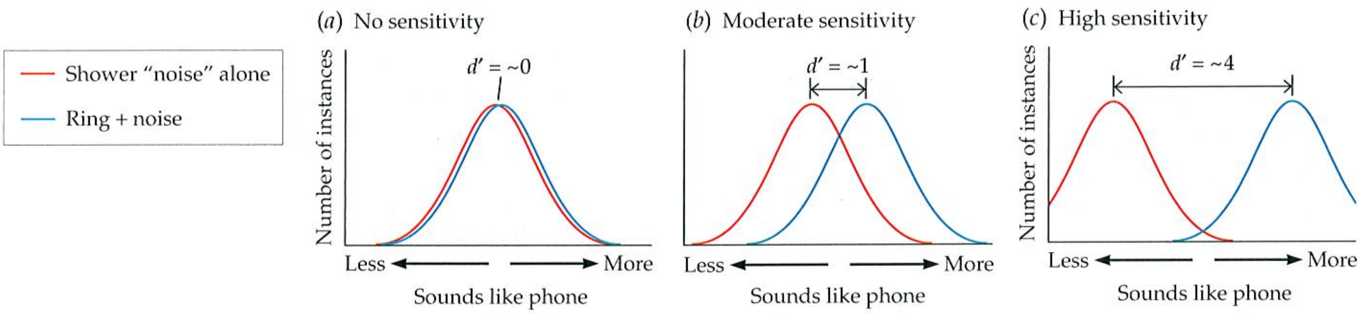


FIGURE 1.12 Your sensitivity to a stimulus is illustrated by the separation between the distributions of your response to noise alone (red curve) and to signal plus noise (blue). This separation is captured by the measure d' (*d*-prime). (*a*) If the distributions completely overlap, $d' = 0$ and you have no ability to detect the signal. (*b*) If d' is intermediate, you have some sensitivity but your performance will be imperfect. (*c*) If d' is big, then distinguishing signal from noise is trivial.

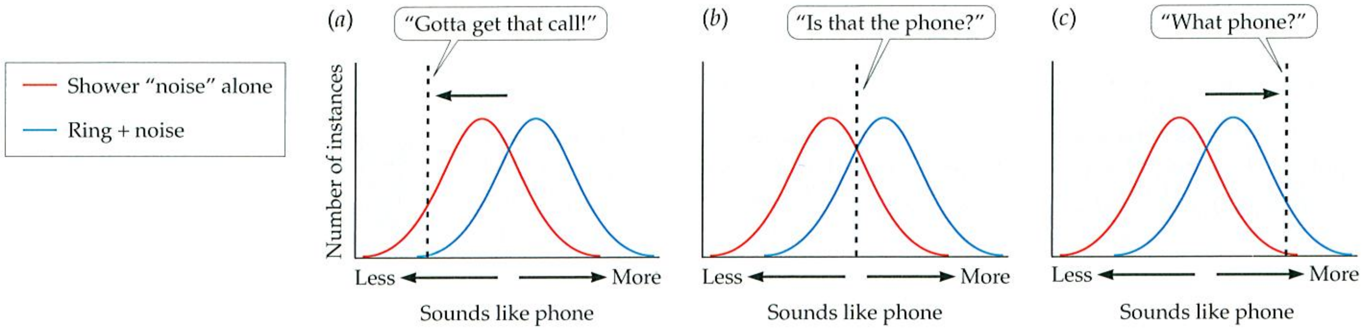


FIGURE 1.13 For a fixed *d′*, all you can do is change the pattern of your errors by shifting the response criterion. If you don't want to miss any signals, you move your criterion to the left (*a*), but then you make more false alarms. If you don't like false alarms, you move to the right (*c*), but then you make more miss errors. In all these cases (*a*–*c*), your sensitivity, *d′*, remains the same.

receiver operating characteristic (ROC) curve In studies of signal detection, the graphical plot of the hit rate as a function of the false-alarm rate. If these are the same, points fall on the diagonal, indicating that the observer cannot tell the difference between the presence and absence of the signal. As the observer's sensitivity increases, the curve bows upward toward the upper left corner. That point represents a perfect ability to distinguish signal from noise (100% hits, 0% false alarms).

essentially all the rings and never make a false alarm. The situation we've been discussing is in between (Figure 1.12*b*).

Now suppose you're waiting for an important call. Even though you really don't want to miss the call, you can't magically make yourself more sensitive. All you can do is move the criterion level of response, as shown in **Figure 1.13*a***. If you shift your criterion to the left, you won't miss many calls, but you will make lots of false alarms (Figure 1.13*a*). That's annoying. You're running around naked, dripping on the floor, and traumatizing the cat for no good reason. If you shift your criterion to the right, you won't make those annoying false alarms, but now you will miss most of the calls (Figure 1.13*c*). For a fixed value of *d′*, changing the criterion changes the hits and false alarms in predictable ways. If you plot false alarms on the x-axis of a graph against hits on the y-axis for different criterion values, you get a curve known as a **receiver operating characteristic (ROC) curve** (**Figure 1.14**).

Suppose you were guessing (the Figure 1.12*a* situation), then you might guess "yes" on 40% of the occasions when the phone rang, but you would also guess "yes" on 40% of the occasions when the phone did not ring. If you moved your criterion and guessed "yes" on 80% of phone-present occasions, you would also guess "yes" on 80% of phone-absent occasions. Your data would fall on that "chance performance" diagonal in Figure 1.14. If you were perfect (the Figure 1.12*c* situation), you would make 100% hits and 0% false alarms and your data point would lie at the upper left corner in Figure 1.14. Situations in between (Figure 1.12*b*) produce curves between guessing

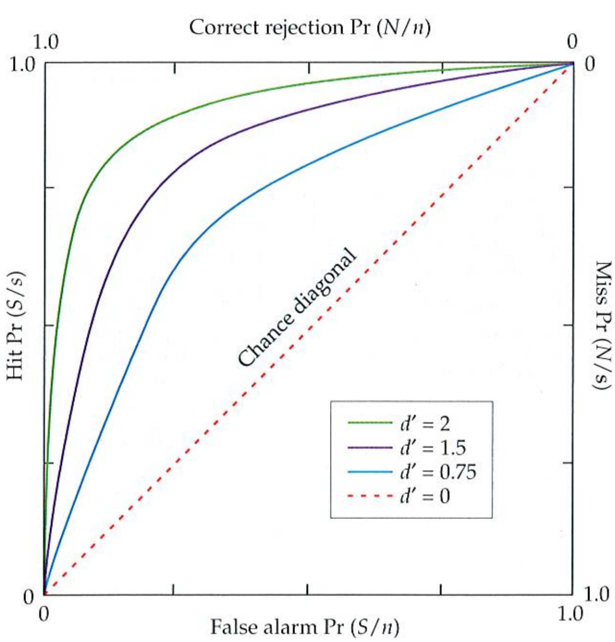


FIGURE 1.14 Theoretical receiver operating characteristic (ROC) curves for different values of *d′*. Note that *d′* = 0 when performance is at chance. When *d′* increases, the probability of hits and correct rejections increases, and the probability of misses and false alarms decreases. Pr(*N*/*n*) = probability of response "no signal present" when no signal is present (correct rejection); Pr(*N*/*s*) = probability of response "no signal present" when signal is present (miss); Pr(*S*/*n*) = probability of response "signal present" when no signal is present (false alarm); Pr(*S*/*s*) = probability of response "signal present" when signal is present (hit).

FIGURE 1.15 Joseph Fourier was a French mathematician and physicist who first showed how very complex signals could be understood more easily as a combination of simple sine wave components.

and perfection (the green, purple, and blue curves in Figure 1.14). If your data lie below the chance line, you did the experiment wrong!

Let's return to our radiologist. She has an ROC curve whose closeness to perfection reflects her expertise. On that ROC, her criterion can slide up and to the right, in which case she will make more hits but also more false alarms, or down and to the left, in which case she will make fewer false alarms but more misses. Where she places her criterion (consciously or unconsciously) will depend on many factors. Does the patient have factors that make her more or less likely to have cancer? What is the perceived "cost" of a missed cancer? What is the perceived cost of a false alarm? You can see that what started out as a query about the lack of absolute thresholds can become, quite literally, a matter of life and death.

Signal detection theory can become a rather complicated topic in detail. To learn about how to calculate *d′* and about ROC curves, there are many useful websites and several texts (e.g., Macmillan and Creelman, 2005; see Burgess, 2010, if you're interested in the application to radiology).

Fourier Analysis

While we're on the topic of signals, there's just one more tool in the researcher's arsenal that will prove helpful to you as you learn about sensation and perception. French mathematician **Joseph Fourier** (1768–1830) (**Figure 1.15**) developed analyses that permit modern perception scientists to better understand how complex sounds such as music and speech, complex head motions, and complex images such as objects and scenes can be decomposed into a set of simpler signals. To understand Fourier's analytical technique, let's begin with sounds, because they're easy to describe.

One of the simplest kinds of sounds is a **sine wave** (or, in hearing, a *pure tone*). The air pressure in a sine wave changes continuously (sinusoidally) at one frequency (**Figure 1.16**). The time taken for one complete cycle of a sine wave is the **period**, or **wavelength**, of the sine wave. The height of the wave is its amplitude. The **phase** of the wave is its position relative to a fixed marker. Phase is measured in degrees, with 360 degrees of phase across one period, like the 360 degrees around a circle. Thus, in Figure 1.16 the red and blue sine waves differ by 90 degrees in phase.

Sine waves are not common, everyday sounds, because few vibrations in the world are so pure. If you've taken a hearing test or used tuning forks, you may have heard sine waves. Flutes can produce musical notes that are close

sine wave 1. In hearing, a waveform for which variation as a function of time is a sine function. Also called *pure tone*. 2. In vision, a pattern for which variation in a property like brightness or color as a function of space is a sine function.

period or wavelength The time (or space) required for one cycle of a repeating waveform.

phase 1. In vision, the relative position of a grating. 2. In hearing, the relative timing of a sine wave.

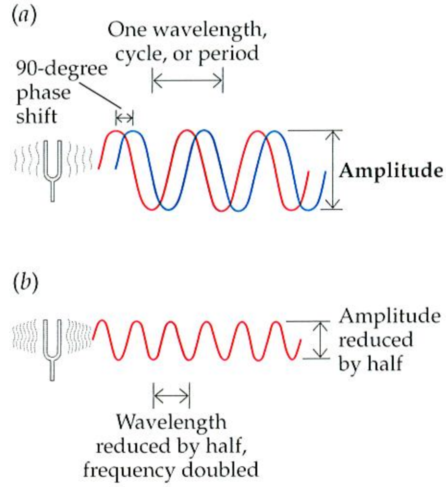


FIGURE 1.16 Sine waves. (*a*) A vibrating tuning fork produces sinusoidal variations in air pressure—variations that are the stimulus for hearing. We can plot those variations as sine waves. The period, or wavelength, is the time taken for one complete cycle (marked by the gray box). The amplitude is the height of the wave. The position of the wave relative to a fixed marker is its phase—measured in degrees out of a total of 360 degrees, like the 360 degrees around a circle. The red and blue sine waves shown here are separated by 90 degrees of phase. (*b*) This tuning fork produces a sine wave that has half the amplitude and half the wavelength of the waves in (*a*). In hearing, the frequency of a sine wave is the number of cycles per second. In vision, you might have sinusoidal variation of light over space; then the frequency would be in cycles per degree of visual angle (see Chapter 3).