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By presenting a Poisson process of flashes to observers who hit a button as quickly as possible after each, the authors identified the system involved in simple reaction time (RT). The nonlinear kernels up to 2nd order were measured from the stimulus and response point processes. The 1st-order kernel is analogous to a histogram of simple RTs. The 2nd-order kernel shows complex patterns of nonlinear suppression and facilitation between pairs of flashes. Simple RT measured as the lag of the 1st-order kernel’s peak agrees with RT from conventional discrete trial experiments. RTs are shorter and less variable when the flashes are separated by uniform rather than exponential delays, which shows that observers use the stimulus hazard function to become prepared to detect and respond to the flash.

Experimental psychologists present some stimulus to an observer and measure a behavioral response. Our task is one of system identification: We wish to express mathematically the relation between an input to the system and its output (Ljung, 1989). In the visual simple reaction time (RT) experiment, the input to the observer is some transient event such as a flashed spot, the output is a button press, and the system under study consists of the eye, the brain, and the hand. In this article, we identify the eye–brain–hand system using a novel method that also allows us to measure simple RT.

The aim of system identification is to recover the impulse response. For a stationary linear system, the impulse response is a full description that allows us to predict the system’s response to any input; the output is the convolution of the input and the impulse response. For noisy systems, we can measure the average impulse response. Norbert Wiener (1958) discovered that a system could be identified by presenting normal (Gaussian) white noise. If the system does not change over time (is stationary), the average impulse response is given by the cross-correlation of the input and the output waveforms (Cooper & McGillem, 1971, pp. 176–187). The technique delivers a continuous input and measures a continuous output. The method, in modified form, has been used to measure the spatial or temporal impulse response of sensory neurons. Modification is needed because the typical neuron has a point response—a spike. In one modification, the average response is found in a peri-stimulus-time histogram, and this histogram is cross-correlated with the white noise input. This technique has been applied to visual electrophysiology (Marmarelis & Naka, 1972) and to auditory electrophysiology (Eggermont, Johannesma, & Aertsen, 1983). Somewhat different white noise techniques have been used by Ohzawa to study visual electrophysiology (DeAngelis, Ohzawa, & Freeman, 1993) and by Sutter to study the electroretinogram (Sutter & Tran, 1992).

One important aspect of the white noise approach is its ability to discover the so-called higher order kernels. We have said that the impulse response gives a complete description of a linear system. For example, electrophysiologists present a flashed spot (a spatiotemporal impulse) while recording from a V1 simple cell, and obtain its receptive field or spatial impulse response. The simple cell’s behavior can be predicted quite well from its receptive field. A nonlinear system or cell, however, cannot be so neatly described by the impulse response. The impulse response is just the first-order kernel, and higher order kernels are required to describe the system’s nonlinearities (Lee & Schetzen, 1965; Schetzen, 1965). For example, the receptive field (spatial impulse response) of a V1 complex cell can be measured, but that would tell us little about the cell’s behavior. Second- and higher order kernels would be needed to describe some of the behavior that earns such cells the name complex (Szulborski & Palmer, 1990).

We use a point-process version of the white-noise approach to obtain the nonlinear kernels of the eye–brain–hand system in the simple RT experiment. A point process is a series of events spaced...
The first-order kernel shows us the response rate as a function of kernels. The zeroth-order kernel is simply the mean response rate. By analyzing the relationship of the stimulus and response times (see Appendix), we identify the system, obtaining zeroth-, first-, and second-order kernels. The zeroth-order kernel is simply the mean response rate. The first-order kernel shows us the response rate as a function of the lag after the stimulus and is analogous to the RT histogram in the classical experiment. The second-order kernel shows the response rate as a function of a pair of lags from each of two stimuli to the response; it allows us to see nonlinear suppression and facilitation between pairs of stimuli. (The nth-order kernel shows the response rate in relation to n lagged stimuli.)

Our primary aim in this article is to measure the nonlinear kernels of the eye–brain–hand system using the point-process method. We do this in Experiment 1. RT can also be measured using a Poisson process of flashes, and we examine RT in Experiments 2 and 3. In Experiment 2, we validate the Poisson process method of measuring RT by comparing the irreducible minimum RT, the limiting RT approached at high intensities, to that measured in a conventional discrete trial design. In the Poisson process, the delay between successive flashes is distributed according to an exponential distribution, and so we use the same delay distribution in the discrete trial experiment. To measure the irreducible minimum RT, we measure RT as a function of flash intensity. Finally, in Experiment 3, we assess the ability of the observer to use the form of the random delay between flashes to become prepared to detect each stimulus or to respond to it. Flashes in the Poisson process are completely unpredictable (Cox & Lewis, 1966, chapter 2); the hazard function is a constant (Cox & Oakes, 1984, p. 16). We compare the Poisson process results to those obtained using a point process of flashes whose delays are described by a uniform distribution. The uniform delay point process has an increasing hazard function, which observers might be able to use to become prepared for the next flash.

Experiment 1: Nonlinear Kernels
for the Eye–Brain–Hand System

By presenting a Poisson process of flashes and measuring the point process of button presses, we can measure the kernels of the eye–brain–hand system (see the Appendix). The kernel modelling approach is analogous to the familiar process of fitting a polynomial curve to a set of (x, y) points. In polynomial curve fitting, if there is no relationship between x and y, the best fit would simply be the line y = mean. If there is some relationship between x and y, the linear fit would be the line y = mean. If there is some relationship between x and y, the linear fit would be unsatisfactory. Even higher order terms could be brought in if necessary.

In our point-process approach, we use a set of kernels (zeroth-, first- and second-order) in an attempt to get a satisfactory fit to the observer's time-varying response rate (Brillinger, 1975a; Brillinger, Bryant, & Segundo, 1976). In the simplest possible case, the response rate would be constant. Then we would need only the zeroth-order kernel, the mean response rate, to describe it. Clearly the response rate will rise just after a stimulus has been presented. Therefore, we need to add another term, a first-order kernel, to describe that. The first-order kernel tells us the response rate at each possible lag after the stimulus. It may happen that when two flashes occur close together, the response rate is lower than the simple sum of the rates for each flash separately, or the response rate might be higher than the rates for each separately. To capture these nonlinear suppression and facilitation effects, we need to add the second-order kernel. The second-order kernel gives the response rate for pairs of stimuli at each possible pairing of lags. In principle, even higher-order kernels can be computed. We stop at the second-order kernel because large amounts of data are required to measure kernels of higher than second order, and the resulting estimates are noisy.

Our application of system identification methodology to the simple RT experiment is new, but others have used point-process stimuli. Egan, Greenberg, and Schulman (1961) used an auditory point process where the distribution of the delays between stimuli was uniform (so far as we can tell). Luce used a Poisson process auditory stimulus (Green & Luce, 1967; Luce & Green, 1970). The experimental results did not conform especially well to the parametric theory he presented (Luce, 1966). In the visual domain, Vaughan, Costa, and Gilden (1966) and Mansfield (1973) presented point processes where the distribution of the delays between stimuli was uniform (apparently). We consider such stimuli in Experiment 3. Broadbent and Gregory (1963) presented a non-Poisson point process in their study of vigilance.

We did the experiment with two designs: individual and pooled. In the individual design, two observers were run through many trials, and the individual data are presented. In the pooled design, each of several observers was only run through a small number of trials, and the data were pooled across observers.

Method

Observers

The individual data were obtained from the authors CB and AN. The pooled data were obtained from WS and 11 other observers. All observers had normal or corrected-to-normal vision in the tested eye.

Stimuli

Individual design. The stimulus parameters used in gathering the individual data and the pooled data were somewhat different, and so they are presented separately.

The stimulus was a Poisson process of flashes. The target was a very small spot, the size chosen mainly to bypass issues of spatial summation (Burrhardt, Gottesman, & Keenan, 1987, p. 538). The spot had a diameter of 0.5 min arc and was 7 min arc above a fixation dot. The viewing distance was 3.4 m.

The display was generated using a Tektronix 608 oscilloscope with P15 phosphor. The oscilloscope displayed points from a point plotter (Finley, 1985, describes an older version). The point plotter was controlled by an IBM clone computer running MSDOS. The display was refreshed at a rate of 6644.52 Hz.
To measure the retinal illuminance, the pupil diameter must be known. Therefore, we used a 3 mm diameter artificial pupil and monocular viewing. The pupil was placed as close as possible to the observer’s eye and was precisely centered on the viewer’s own pupil with an x-y positioner (Edmund Scientific). The observer’s eye was kept stationary behind the pupil by use of a bite bar (Kerr green impression compound Type I).

The fixation mark and the target dot had a steady illuminance of 940 photopic Td. Our main reason for using a nonzero background illuminance for the target dot was that it eliminated observer uncertainty about its spatial position. The rest of the display was black. The incremental flash had a duration of 1.023 ms. The flash duration can be stated quite precisely because the phosphor we used, P15, has extremely short persistence (Groner, Groner, Müller, Bischof, and DiLollo, 1993). The flash had one of several retinal illuminances.

The flashes were presented as a Poisson process with a rate of \( \frac{1}{5} \) flashes/s. This was a comfortable stimulus presentation rate for the observers. The time of each flash in the Poisson process was generated by summing exponential deviates. Each exponential deviate was produced by \(-3 \ln (1.0 - U)\), where \( U \) was a continuous uniform deviate between 0 and 1. The uniform deviates came from Marsaglia’s multiply-with-carry generator, a high-quality generator that has passed the Diehard test suite (http://stat.fsu.edu/~geo/diehard.html). To get the maximum sequence length (greater than \( 2^{99} \)) from the random number generator, the seeds were saved to disk at the end of each run and loaded in at the start of the next. Thus, the numbers used were from one long sequence. Because the maximum display duration for a flash was 1.023 ms, any delays shorter than this were discarded in the generation of the stimulus Poisson process.

There are two ways in which our experimental stimulus differed from an ideal Poisson process. First, the delays were created using a pseudorandom number generator. Any serial correlation among the numbers would translate into correlation in the resulting process. Brillinger’s formulas (see Appendix), especially for the second-order kernel, become meaningless in the presence of too much serial correlation. Our generator has passed stringent testing, but the best way around this problem is to use a hardware random number generator based on some truly random physical process. The second way in which our stimulus process differed from an ideal Poisson process was that our stimulus had a minimum delay (dead time) of about 0.001 s between events. A Poisson process has no dead time. However, the effects of our short dead time on cross-intensity estimates would be quite minor (a possible shifting of the function by less than 0.01 s).

The observer’s task was to press a button after each flash. The button box was attached to the computer, and the times of the stimuli and the responses were measured with a hardware \( \mu \)s timer. The button was hardware debounced.

**Pooled design.** The stimulus was a Poisson process with rate of \( \frac{1}{5} \) flashes/s. The target was a 0.5° square, formed by a tight raster of 300 dots. Viewing was monocular through a natural pupil from a forehead-and-chinrest 48.5 cm away from the oscilloscope. The flash duration was 0.9 ms; the minimum delay between the offset of one flash and the onset of another was 0.3 ms. The display was dark except for the fixation mark between flashes (unlike the dot display where the flash was an increment added to a nonzero background). The flash intensity was 1,680 cd/m².

**Procedure**

**Individual design.** Because the stimulus was delivered through a 3 mm artificial pupil, we had to ensure that the observer’s own pupil was larger. Therefore, the observer dark-adapted for 10 min before a set of runs started. After 10 min dark adaptation, the pupil diameter is about 5 mm (Alpem & Campbell, 1962). Our stimulus was foveal, and the fovea is fully dark-adapted after 10 min (Mote & Riopelle, 1951).

After the dark-adaptation period was over, a tone sounded, and the participants positioned themselves on the bite. The other eye was covered by an eye patch. Each experimental session consisted of two runs of 100 flashes. One run lasted about 5 min. In a given run, the observer fixated the fixation mark and pressed a button as quickly as possible after each flash. If multiple flashes occurred almost simultaneously, the observer pressed the button as many times as there seemed to be flashes. For example, if it seemed that 2 flashes occurred together, then the observer pressed the button twice. The times of the flashes and button presses were recorded by the computer.

The flash intensities were run in random order, with the constraint that each intensity was run once before beginning the second round of replication, etc. CB and AN ran 10 replications at each flash intensity, or in other words, 1,000 stimuli were presented at each flash intensity.

**Pooled design.** The stimulus was viewed monocularly with a natural pupil, and there was no bite bar or dark adaptation. A single flash intensity was used. A run consisted of 150 flashes in a session lasting about 5 min. Each observer participated in three experiments in random order. The results of the Poisson experiment are reported now, and the results of the other experiments are reported along with other results in Experiments 2 and 3.

**Data analysis.** A detailed description of system identification using point processes is given in the Appendix. We presented a Poisson process of flashes and recorded a point process of responses. The zeroth-order kernel is the mean response rate, computed as the number of responses divided by the time of the last response.

From the stimulus and response times, we computed the cross-intensity function (CIF), which is the point process analogue of the cross-correlation function. The CIF tells us the response rate (in presses/s) at each possible lag after a stimulus. It is analogous to the usual RT histogram. We find CIF(u) by looking forward \( u \) time units from each stimulus event and counting the responses that fall in a small bin (Figure 2). The first-order kernel is just the CIF minus the mean response rate. The data were gathered in a series of short runs, and prior to computation of the kernel these data were pooled within observers for the individual design or across observers for the pooled design. The data from all the runs to be pooled were pasted together to form one long bivariate sequence by adding the longest time in the first data set onto all the stimulus and response times in the second set, then by adding the longest time in this new combined set onto all the stimulus and response times in the third set, and so on. The first-order kernel was computed on this joined sequence using a bin width of 0.03 s; the second-order kernel used a bin width of 0.025 s.

**Results and Discussion**

In identifying the eye–brain–hand system, we seek to model the time-varying response rate. To do that we compute the zeroth-, first- and second-order kernels, which we now consider in turn.

**Zeroth-Order Kernel**

The zeroth-order kernel is the mean response rate. The mean response rate averaged across all 12 observers in the pooled design was 0.49 ± 0.03 button presses/s. This response rate is not statistically different from the stimulus rate of \( \frac{1}{5} \) flashes/s.

In the individual design, several flash intensities were used. Figure 3 shows the mean response rate as a function of the flash intensity. For a given flash intensity, the zeroth-order kernel is just

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**Figure 2.** The cross-intensity is found by counting the number of responses that fall in a small bin some lag after each stimulus event.
Figure 3. Mean response rate as a function of flash intensity for observers AN and CB.

The lag at which the peak occurs can be taken as a measure of the RT. This definition of RT as the location of a peak is the same as that used for latency of the visual evoked response (Vaughan et al., 1966). The location of the peak of the first-order kernel is analogous to the mode of the RT histogram in conventional studies. The observed values seem high. Mansfield (1973), using a flash size of 0.72°, found the RT at the highest intensities to be near 0.189 s; using a flash size of 0.5°, we find an RT of 0.27 s for our pooled data. Mansfield found an RT of 0.219 s for a flash size of 3 min; using a flash size of 0.5 min we find the fastest RTs to be 0.36 s (AN) and 0.42 s (CB). It is clear from Figure 5 that RT declines with flash intensity. We further examine these and other RT data in Experiments 2 and 3.

The flash detectability is related to the height of the kernel's peak (see Appendix). The first-order kernel is based on the CIF; both measure the association between the stimulus and response point processes (Brillinger, 1992, p. 262). If observers are detecting the stimulus, their responses will tend to occur shortly after each flash. Therefore, the height of the first-order kernel is related to the flash detectability. (The height of the peak conflates the effects of detectability and response time variability.) In Figure 6 the height of the first-order kernel peak (computed using a bin width of 0.01 s) is plotted as a function of the flash intensity. As one would expect, the height of the peak increases with flash intensity. The function appears to become saturated at about 7 button presses/s. That is about as fast as a person can hit a button. This statement is supported by the auto-intensity function (AIF) of the responses. The AIF is the same as the CIF, except it uses only one set of times (stimulus or response). Figure 7 shows the AIFs for the brightest flash for both observers. The AIF shows the rate of response some lag after a previous response. The AIF is zero up to a lag of about 0.15-0.175 s. Thus, the minimum lag between responses is about 0.15-0.175 s, which translates into a response rate of about 6-7 presses/s.

**First-Order Kernel**

Intuition tells us that each response will tend to occur shortly after a flash. The first-order kernels (Figures 4 and 5) confirm intuition. Each first-order kernel gives the response rate some lag after the stimulus onset. The first-order kernel is based on the cross-intensity function which is estimated by a form of histogram. The kernels for the pooled data (Figure 4) and for each flash intensity of the individual data (Figure 5) have the shape of a lowpass filter. Thus, in a simple RT task the eye-brain-hand system's response is somewhat sluggish and temporally smeared out. No negative lobe is present in either the pooled or individual kernels, which means that a response is always more likely after a flash. There is no evidence here of suppression. The first-order kernel is skewed rightward, as we would expect. The first-order kernel corresponds to the RT histogram in the conventional RT experiment, and the RT histogram is known to be skewed rightward (Wandell, Ahumada, & Welsh, 1984, Figure 3). We do not attempt to build a model of the processes in the observer that underlie simple RT; one task of such a model would be to reproduce the shape of the observed first-order kernel (Smith, 1995).
The response rate to a pair of flashes presented in close succession is lower than would be found by summing the response rate to each flash separately. Part of the explanation of the suppression lies in temporal summation: The two flashes are combined in the visual system, so the observer sees only one flash and presses the button only once. The second contributing factor is that the flashes mask each other, reducing the visibility of the pair. The cones have a biphasic temporal impulse response (Baylor, Nunn, & Schnapf, 1987, Figure 1) with a negative lobe that hits a minimum around 0.15 s. If two flashes are presented 0.15 s apart, the positive phase of the cone response to the second flash will be cancelled by the negative phase of the cone response to the first flash. Thus, the second of two flashes will not be seen and only one response will be given. A third possible explanation attributes the suppression to the minimum lag between responses. The AIF (Figure 7) shows that the minimum time between button presses is about 0.15 s. However, we can reject this explanation because it is the minimum delay between stimuli, not responses, that could cause a dark patch in the second-order kernel: The response rate would be low for short stimulus lag pairs because these pairs would not be presented and so no response could be given. In our experiment this minimum delay between flashes was 1 ms or less, and it is not the cause of the dark patch.

The second-order kernels also exhibit bright patches. These are regions of nonlinear facilitation; the response rate is higher than expected from linear summation. These facilitatory regions are less regular than the suppressive regions. They mainly occur where one lag is near the peak of the first-order kernel (about 0.3 s for the pooled data and about 0.4 s for the individual data) and the other lag is 0.1-0.3 s earlier or later. The dark patch is unlikely to have a sensory origin. Perhaps it reflects response preparation: Deecke, Scheid, and Kornhuber (1969) found that the (putative) readiness potential starts about 0.8 s before finger motion. At the two lowest flash intensities, both observers show facilitation for flashes that occur almost simultaneously (both lags equal to 0.6 s). Singly, these flashes were dim, and so the effect is

**Second-Order Kernel**

The second-order kernel allows us to see nonlinear effects between pairs of stimuli and the response rate. Each cell in the kernel shows the response rate for a pair of stimuli having a pair of lags. If the response rate is lower than expected from linear summation of the separate effects of the flashes, we have nonlinear suppression, and the cell is shown as dark; if the response rate is higher than expected, we have nonlinear facilitation, and the cell is shown as bright. Figures 8, 9, and 10 show the second-order kernels for the pooled data and for each flash intensity for observers CB and AN, respectively. The second-order kernels have contour lines superimposed (computed by the statistical language R’s contour() function). These lines show equal steps of response rate above and below zero.

The most obvious and consistent feature of the second-order kernels is a dark patch that occurs when one lag is near the peak of the first-order kernel (about 0.3 s for the pooled data and about 0.4 s for the individual data) and the other lag is 0.1-0.3 s earlier or later. The dark patch indicates nonlinear suppression:

**Figure 5.** First-order kernels for observers CB and AN for the flash intensities shown (in photopic Td/1000). Each successive kernel shifted upward by 1.0 for legibility. Bin width is 0.03 s.
that the two flashes temporally summate more-than-linearly and become quite visible.

One might wonder how reliable the observed patterns in the second-order kernels are. Figures 9 and 10 show quite similar patterns across the different flash intensities within each observer. We ran the Poisson process experiment with the same flash intensity and two stimulus rates, 1/3 and 1 flashes/s, and so we can compare the kernels obtained in the same observer with the two rates (Figure 11). The two kernels are broadly similar. There is suppression in the lag pair region (0.4, 0.3–0.6) and facilitation in the region (0.4, 0.0–0.3). The higher number of stimuli and responses collected for the higher stimulus rate gives a more detailed and less noisy picture of the kernel.

The second-order kernel allows us to see how flash pairs interact. Another method that has been used before is to present flash pairs with various delays between them and measure the RT to the second flash (Ueno, 1977). A large literature using this methodology has found that the RT to the second of two closely separated stimuli is slowed; this is termed the psychological refractory period (Luce, 1986, pp. 185–200). It could be argued that the psychological refractory period should show up as a combination of a bright and a dark patch in the second-order kernel. Let us say that the refractory period slows the RT by Δ s. This means that responses that would have otherwise occurred at the lag pair (lag 1, lag 2) are shifted to (lag 1, lag 2 + Δ). Therefore, the kernel will be dark at (lag 1, lag 2) and bright at (lag 1, lag 2 + Δ). In some of the kernels this explanation seems to apply. For example, observer AN for a flash brightness of 310,000 Td shows a dark spot at the lag pair (0.4, 0.5) and a bright spot at (0.4, 0.65). In this case it seems that the response to the second flash has been slowed by 0.15 s. In many cases the explanation does not apply, however. For example observer AN flash intensity of 180,000 Td shows a dark spot at about (0.4, 0.5) but a bright one at (0.4, 0.9)—this shift is far too large to be due to the psychological refractory period. Therefore, we conclude that our second-order kernels show more than just the psychological refractory period.

**Experiment 2: Point Process and Discrete Trial Measures of RT**

Most simple RT studies have used a discrete trial design. Each trial consists of a warning, a delay, and a response. Only after a response does the next trial proceed. In the Poisson process experiment, the stimuli keep coming at random times with no respite. RT can be measured in the point process experiment as the lag at which the first-order kernel reaches a peak. On the face of it the discrete trial and point-process experiments are quite different, and we wonder if the RTs measured with the two techniques are comparable. It could well be that the point-process stimulus delivery is unsettling for observers because of its nonstop nature, and so RT might be elevated. Very short delays between stimuli are common in the Poisson process, and these also might raise RT.

We compare the Poisson process data to those from a discrete trial design with an exponential delay. Successive delays in a Poisson process are distributed exponentially, and so by using a
discrete trial design with the same exponential delay distribution, we compare point process and discrete trial methods of stimulus delivery. We measure RT as a function of flash intensity to obtain the irreducible minimum RT (the limiting RT approached at the highest flash intensities). If the nature of the random delay is the important factor in determining the irreducible minimum RT, then the RTs from the discrete trial experiment should be similar to those from the Poisson process experiment.

**Method**

**Observers**

The observers were the same ones who served in Experiment 1.

**Stimuli**

These were as described in Experiment 1.

**Procedure**

**Individual design.** The procedure for the Poisson process experiment has been given before. These same Poisson process data are now compared with new discrete trial data.

For the discrete trial experiment, each run consisted of 50 trials. A trial was initiated by a button press. Then an exponential random delay with a mean of 3 s was given, followed by the flash. The exponential delays were generated in the manner earlier described. The delay distribution was not truncated. One quarter of the trials were catch trials containing no flash; thus, we used a go/no-go paradigm (Luce, 1986, p. 55). This paradigm was used to facilitate comparison with other simple RT experiments with catch trials. If the trial contained a flash, the observer hit a button. If not, the observer withheld a response, then initiated the next trial. Data from 5 runs or 250 trials per flash intensity were collected. The flash intensities were presented in blocked random order. The median RT was computed on correct responses only—premature responses and responses on catch trials were not used.

*Figure 9.* Second-order kernels for observer CB for the flash intensities shown (in Td/1,000). Bin width is 0.025 s.
The procedure for the Poisson process experiment was described in Experiment 1.

Each run in the discrete trial experiment consisted of 100 trials. A trial was initiated by a button press. Then the following sequence occurred: a beep, a fixed 1-s delay, an exponential random delay with a mean of 2 s, and finally the flash. The exponential delays were generated in the manner earlier described. No catch trials were used. Premature responses were not used in calculating RT.

Results and Discussion

The first-order kernels and RT histograms for the Poisson process and discrete trial data for each observer in the pooled design are shown in Figure 12. The discrete trial RTs were very well fit by a Gumbel probability density function (PDF) (Evans, Hastings, & Peacock, 1993), and the maximum likelihood fit to each data set is shown. Gumbel PDFs were also fitted to the first-order kernels by least squares. The Gumbel distribution has a location parameter (the mode) and a spread parameter. After fitting the individual curves, the resulting modes and spreads were compared for the discrete trial and Poisson process data. The 95% confidence interval for the (paired) difference in modes is $-0.0028 \pm 0.015$ s. The two methods both give an RT of about 0.28 s. The flash intensity was quite high (the highest we could produce), so we might be justified in thinking we are measuring the irreducible minimum RT. In Figure 3 of Pianta and Kalloniatis (1998) the irreducible minimum RT is between 0.224 and 0.324 s for their observers, and our value is in that range.

Although the point process and discrete trial experiments produce the same estimate of RT, the methods do differ in the shape of the RT histograms produced (the first-order kernel is a form of histogram). The spread of the Poisson process first-order kernel is slightly larger than the spread of the discrete trial histogram; the 95% confidence interval for the difference in spreads is $0.0076 \pm 0.0061$ s. Observers seem to be slightly less variable in the discrete
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\[ \text{RT} = \frac{a}{b + I} + c, \]

where \( I \) is the stimulus intensity and \( a, b, \) and \( c \) are fitted parameters. Inspection of the figure suggests that the irreducible minimum RT is the same for the discrete trial and point-process stimulus schedules, and the least squares fits of Equation 1 confirm this conclusion. For the Poisson data the 95% confidence intervals for the irreducible minimum RT are 0.30 ± 0.07 s (CB) and 0.37 ± 0.04 s (AN). For the discrete data the confidence intervals are 0.41 ± 0.02 s (CB) and 0.35 ± 0.02 s (AN). AN's shorter irreducible minimum RT in the discrete trial experiment can be explained by his higher false alarm rates (speed-accuracy trade-off). The irreducible minimum RTs we obtained are comparable to those found by other authors who used a flashed spot with discrete trials and exponential delay (Pianta & Kalloniatis, 1998). Our value for the irreducible minimum RT is slightly high, and this is probably due to our longer mean delay of 3.0 s, because RT increases as the mean delay increases (Nickerson & Burnham, 1969). Another factor raising our RTs is the small spot size.

In conclusion, the Poisson process experiment produces estimates of the irreducible minimum RT that are similar to those given by the discrete trial version of the experiment using exponential delays. Thus, the lag at which the peak of the first-order kernel occurs is a valid measure of RT. It seems that the form of the delay distribution is critical for RT, and it is irrelevant whether the stimuli are presented as a point process or in discrete trials.

Figure 11. Second-order kernels for observer CB for stimulus rates of 1 and \( \frac{1}{3} \) flashes/s, luminous energy 310,000 Td. Bin width is 0.025 s.

trial experiment, perhaps because the fixed foreperiod of 1 s prior to the variable delay gives them time to prepare for the stimulus. In the Poisson process experiment, they may be in various states of preparation when the stimulus arrives.

We now consider the individual data. Because we used catch trials for these observers, we were able to measure false alarms. For observer CB, the false alarm rates from the lowest to highest flash intensity were \( \frac{1}{64}, \frac{1}{65}, \frac{1}{66}, \frac{1}{67}, \frac{1}{68}, \frac{1}{69} \) (around 1% or lower); for AN they were \( \frac{1}{60}, \frac{1}{61}, \frac{1}{62}, \frac{1}{63}, \frac{1}{64}, \frac{1}{65} \) (declining from 20% for the dimmest flash to 2% for the brightest flash). Figure 13 plots the median RT (using only correct responses and no anticipations) from the discrete trial experiment as a function of flash intensity for both observers along with the RT found using the Poisson process method. The error bars in the figure show the standard errors, which for the Poisson data were computed by the following method. The first-order kernel was computed and the mode found for each run. The mean and standard error of the resulting modes were used to estimate the RT and its standard error. For the discrete trial data, the errors for RT were computed using a bootstrap method (Efron & Tibshirani, 1993, p. 47). We found the irreducible minimum by fitting, by nonlinear regression, the hyperbolic version of Piéron's law (Piéron, 1920, p. 60).

Figure 12. (a) First-order kernels with fitted Gumbel PDF for each observer for Poisson process of flashes. (b) Histograms of reaction times with fitted Gumbel PDF for discrete trial data. PDF = probability density function.
Experiment 3: The Role of the Delay Distribution

The point-process system identification technique presents a Poisson process of flashes. The delay between successive flashes has an exponential distribution. The exponential is what probabilists call a memoryless distribution—the hazard function is a constant. In other words, the chance of a flash occurring in the next instant does not depend on how long the observer has waited for it; the flashes occur completely at random. Many visual simple RT experiments have used discrete trials with a uniform distribution for the delays (Bartlett & MacLeod, 1954; Burkhardt et al., 1987; Klemmer, 1956; Minucci & Connors, 1964; Raab & Fehrer, 1962; Raab, Fehrer, & Hershenson, 1961; Roufs, 1974). The classic experiment of Mansfield (1973) used a point process of flashes where the delay between successive flashes was uniformly distributed. The uniform is not a memoryless distribution—the hazard function is increasing. The longer the observer waits, the more likely it is that the stimulus will occur in the next instant. If observers can use the information provided by the hazard function, they can become prepared to detect and respond to the stimulus. We compared visual simple RT using point processes of flashes where the random delay between flashes was either uniform (as in Mansfield's experiment) or exponential (the Poisson process) to see if observers are indeed sensitive to the form of the hazard function.

Method

Observers

The observers were the same ones who served in Experiment 1.

Stimuli

Individual design. First, we describe the Poisson process stimulus. For observer CB, the stimulus was as described in Experiment 1. For observer WS the target was a 0.8° square, formed by a tight raster of dots. The viewing distance was 57 cm. The display was dark except for the fixation mark between flashes (unlike the CB's dot display where the flash was an increment added to a nonzero background). The flash had a duration of 0.971 ms. Because the square was much larger than the single dot CB viewed, the square was visible at much lower intensities.

For the experiment using a uniform delay distribution, the stimulus times were formed by cumulating independent uniform random deviates between 2.5 and 5 s. Mansfield (1973) said that the delay in his experiment “varied irregularly” between these same limits. The point process with uniform delays is a form of what is called a renewal process (Ross, 1989, p. 294). The uniform delay distribution had a mean of 3.75 s, close to the mean delay of 3.0 s used in the Poisson process experiment.

Pooled design. The Poisson process stimulus was as described in Experiment 1. The flashes occurred at a rate of ½ flashes/s; the delays between successive flashes were exponential with mean 2 s.

The uniform renewal process presented flashes separated by a mean delay of 2 s. The delays were distributed according to a uniform distribution between 0.0012 and 3.9988 s.

Procedure

The procedure was described in Experiment 1.

Results and Discussion

When the delay between flashes is a uniform random variable, observers potentially can use the hazard function to become ever more prepared to detect and respond to the stimulus as they wait for the next flash. The hazard function for the exponential delays contains no such information. If observers can use the information that is present in the hazard function, the CIF for the uniform delay and the exponential delay stimuli will be different. We might expect the peak to occur earlier and for the CIF to be narrower if the observer is more prepared for the stimulus.

When the stimulus is a Poisson process, the CIF minus the mean response rate is the first-order kernel. That is no longer true for the point process with uniform random delays between flashes. We can still perform the same computation on the stimuli and responses, but the result is no longer the first-order kernel. Figure 14 compares the computed histograms for exponential and uniform delays for observer CB.

The CIFs (minus the mean response rate) from the uniform delay experiment are higher and narrower than those from the exponential delay experiment. This can be attributed to the predictability of the stimulus: Because the observers have a good idea of when the flash will occur, their responses are more tightly
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Figure 14. The cross-intensity function minus the mean response rate (first-order kernel in the case of exponential delays) for uniform and exponential random delays between flashes. Bin width is 0.03 s. The flash intensity (in Td/1000) is shown beside each curve. Each successive kernel is shifted upward by 1.0 for legibility. The observer was CB.

Figure 15. Reaction time as a function of flash intensity for experiments in which the delay between flashes was a uniform or exponential random variable. The standard errors are shown. The curves are least squares fits of Equation 1. Observers were CB and WS.

 delays the confidence interval is 0.234 ± 0.007 s. The irreducible minimum is significantly lower for the uniform delays compared with the exponential delays, p = 0.018.

The RT curves of Figure 15 all seem to reach an asymptote at high flash intensity values, but it would be helpful to know how bright these flashes were relative to the observer’s detection threshold. For observer WS a yes-no detection experiment using discrete trials and the same flashed square as in the RT experiments measured the threshold to be about 15 Td. The highest flash intensity was some 1,700 times detection threshold (3 logT units).

We also compared the Poisson process and uniform renewal process stimuli using the pooled RTs of 12 observers. As described in Experiment 2, the first-order kernels were computed for each observer’s data, then a Gumbel PDF was fitted to each (Figure 16). The mean paired difference between the modes of the kernels for the exponential and uniform delay experiments was 0.0154 ± 0.0152 s (95% confidence interval). Thus, the RT in the exponential experiment was slightly longer than that in the uniform delay
The 2D CIFs for exponential and uniform delays for the individual and pooled data are presented in Figure 17. The 2D CIFs for the individual data were computed on the responses obtained with the brightest flashes. For the uniform delay stimuli, the RT (lag 2 where the 2D CIF peak is maximal) is highest when the observer has been waiting a short time for the stimulus (lag 1 is short), and it declines toward an asymptote as the wait increases. The pattern holds for any arbitrary response rate, not just for the maximum. The overall form is a curved ridge. The 2D CIF plots for the uniform delay stimuli show that the observer can use the hazard function because the RT declines as the hazard function increases. The 2D CIF plots for the exponential delay stimuli also support the idea that the observer uses the hazard function. In the case of the exponential delay stimuli, the hazard function is a constant, and indeed the ridge in the 2D CIF is horizontal.

Other authors have found that RT declines as the observer waits for the stimulus. For example, Ollman and Billington (1972) used experimental paradigm, which is consistent with the individual data. The exponential delay experiment also produced a first-order kernel that was wider than that in the uniform delay experiment: The 95% confidence interval for the paired difference in spreads was 0.006 ± 0.005 s.

Both the individual and pooled data show that observers can use the information from the hazard function in the uniform renewal process experiment—their responses are marginally faster and have less spread than when Poisson process stimuli are delivered. We now give stronger evidence for observer use of the hazard function. For uniform delays, the hazard function rises as the observer waits for the next stimulus. We now show that the observer's RT declines as the hazard function increases moment by moment. We defined RT as the location of the peak of the CIF. We now compute a 2D CIF that shows the location of the peak as a function of the time elapsed since the last stimulus. The 2D CIF shows the response rate as a function of two lags: Lag 1 is the lag from the first of a pair of flashes to a response, and lag 2 is the lag from the second flash to a response. The wait since the last flash is lag 1, and so the RT for a given wait is the value of lag 2 at which a peak occurs. If the observer can use the hazard function from the uniform delay stimuli, the 2D CIF will show a ridge (bright line) with a negative slope. If the observer cannot use the hazard function, the ridge will be horizontal. In the exponential delay case, the hazard function is flat, so if the observer's performance depends on the hazard function the ridge in the 2D CIF should also be flat.

Figure 16. First-order kernels with fitted Gumbel PDF for each observer for (a) Poisson process of flashes and (b) point process of flashes with uniformly distributed delays. PDF = probability density function.

Figure 17. Cross-intensity functions for pairs of lags. The stimuli were point processes with exponential (left column) or uniform delays (right column) between flashes. The higher the response rate, the lighter the gray level in the plot; contour lines are superimposed. Bin width is 0.025 s. Individual data from CB and WS are shown as well as pooled data from 12 observers.
a discrete trial experiment with a uniform random delay that could take on one of four values. Their Figure 2 shows a decline in RT with delay duration. Our explanation is simply that the observer is using information contained in the stimulus—the hazard function. Ollman and Billington explain these results using a deadline model. The model as formulated by Ollman and Billington and also Kornblum (1973) contains a noisy internal clock, a signal detector, and a response generator. Both the internal clock and the signal detector are used to generate responses. At the warning stimulus (the model was formulated for discrete trial experiments), the clock pauses some variable duration. Detecting the signal takes a different variable duration. The response is generated by whichever of the two random variables—from the clock and from the detector—is smaller. According to the deadline model, on short delay trials most responses are due to the detector. On long delay trials, many responses are due to the clock; they are anticipations.

Can the deadline model explain our uniform renewal process results? With point-process stimuli there is no warning stimulus, so suppose that stimulus $i - 1$ serves as the warning for stimulus $i$. Figure 18 shows the results of simulations that compared the deadline model to a simple delayed response model (a model that contained no clock, only the detector). The simulations used normal distributions for the latencies from the clock and the detector, though other distributions produced the same results. Despite the extreme simplicity of the delayed response model, the CIF produced is quite similar to that produced by real observers (cf. top panel of Figure 14). The delayed response model gives a response to each stimulus, which is close to what happens when observers are presented with a bright flash (with a weak flash, many flashes produce no response). For the brightest flash, the CIF for observer CB has a peak of about 9 button presses/s, which is close to the simulation value. The deadline model, however, always produces a CIF height that is lower. Figure 18 shows the CIF for a mean deadline of 3 s; shorter deadlines produce lower CIF heights. The lowering of the CIF height is caused by the decorrelating effect of the clock-determined responses. Because such responses are anticipations, and because the observer is not psychic, the CIF betwee the anticipations and the corresponding stimuli is essentially zero. From the simulation results, we conclude that the deadline model does not underlie performance with the uniform renewal process stimuli. Recent experiments by Ruthruff (1996) suggest that the deadline model does not underlie choice RT performance either.

Although observers are not anticipating the stimulus in the way spelled out by the deadline model, they are using the stimulus hazard function. Three facts support this statement. First, the irreducible minimum RT tends to be lower for uniform delay stimuli. Second, the spread of the CIF is lower for uniform delay stimuli. Third, the 2D CIF for the uniform delay data shows that the RT declines as the duration that the observer has waited for the stimulus increases. The hazard function contains information about the chance of a stimulus arriving in the next instant, and observers are using this information to prepare themselves.

There are two possible kinds of preparation: preparation to detect the stimulus and preparation to make a response. Preparation to detect the stimulus is discussed as expectancy (Näätänen, 1970; Nickerson & Burnham, 1969) or time uncertainty (Klemmer, 1956) in the RT literature. Preparation to detect the stimulus is most clearly explained by signal detection theory. If the observer knows the exact waveform to be detected, including its time of arrival in the case of a flash, the ideal observer is a cross-correlator (Whalen, 1971, pp. 156–163). If the time of arrival is completely unknown, the ideal observer is an envelope detector (Whalen, 1971, pp. 222–223). The envelope detector is not as efficient as a cross-correlator. If the detection stage works better as the stimulus time of arrival becomes better known, this implies that the RT will decline likewise. In response preparation (Näätänen & Merisalo, 1977), the observer's motor system is getting ready to hit the button (whatever that may entail). Deecke et al. (1969), using scalp electrodes, found a readiness potential that precedes finger movement. We do not know whether perceptual preparation, motor preparation, or both are occurring when the observer uses the hazard function.

If visual simple RT is affected by the stimulus hazard function, clearly the mechanisms underlying RT are at quite a high level in the visual motor system. Therefore, previous attempts to link the main features of simple RT to the conduction speed of the optic nerve (Ueno, 1977, p. 591) or to the temporal response of the cones (Burkhardt et al., 1987; Mansfield & Daugman, 1978) are overly simplistic. The conduction speed of the optic nerve accounts for only a very small fraction of the total RT, and it is unaffected by flash intensity or hazard function. The cones have a response latency that does depend on the flash intensity (Baylor et al., 1987, Figure 1). However the peak of the cone impulse response occurs at about 0.05 s, which again is far too short to account for human simple RT.

Another fact about RT that implicates a high level of processing is its high variability. The temporal response of cones and the conduction time from the retina to brain have low variability. Studies of visual choice RT in monkeys using eye movements instead of button presses (Hanes & Schall, 1996) have been used to argue that the variability in RT is due to variability in the activity of the individual frontal eye field neurons that control the saccades. But our finding that the hazard function of the stimuli affects the RT seems to implicate strong involvement of a cogni-
tive area, not just a motor programming and execution area. This cognitive area is computing the hazard function of the stimulus.

In conclusion, observers will use information that prepares them to detect or respond to the stimulus. The fact that simple RT is affected by the stimulus hazard rate implies that the task taps the visual motor system at a high level.

Conclusions

The simple RT experiment can be viewed as an exercise in system identification. We used a Poisson process of flashes to characterize the eye–brain–hand system with a kernel expansion including terms up to second order. The second-order kernel reveals complex patterns of nonlinear facilitation and suppression between pairs of flashes. Some of these effects can be related to the psychological refractory period, but others cannot.

The RT can be measured as the lag at which the peak of the first-order kernel occurs. This measure of simple RT agrees with that from a traditional discrete trial RT experiment using an exponential delay with the same mean as the Poisson process. In addition, the RTs measured with the Poisson process method are comparable to those measured by other authors using similar visual targets in discrete trial experiments with exponential delay distributions.

Random uniform delays are commonly used in discrete trial RT experiments and have been used before in point-process experiments. However, it is the exponential, not the uniform, that has a constant hazard function. With a uniform delay distribution, the chance of a stimulus occurring in the next instant increases as the observer waits. Successive events are separated by exponential delays in the Poisson process; the flashes are completely unpredictable. We find that observers are able to use the information contained in the hazard function for uniform delays: The responses are faster, more tightly clustered, and become faster the longer the wait for the stimulus. These facts imply that simple RT involves the computation of the hazard function, which is a high level cognitive task.

References

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It is difficult to apply the standard system identification techniques in psychophysics because there is no continuous output waveform that can be measured. Our solution lies in using a point-process input and measuring the point-process output. In our experiments the stimulus point process is a set of light flashes occurring at random times. These flashes comprise a Poisson process, which is a form of white noise (Siebert, 1986, pp. 612–614). We instruct the observer to hit a button as quickly as possible after each stimulus event. Thus, at the end of the experiment we have a set of stimulus times \( S \) and a set of response times \( R \), where \( R \) events occurring from the beginning up to time \( T \) is denoted by \( N_R(T) \), with \( h_0 \) being the zeroth-order kernel, equivalent to the mean response rate.

The tendency for events to happen is constant. Another way to put this is that the hazard function is constant (Cox & Oakes, 1984, p. 16). Observers rate is a constant.

\[
\begin{align*}
&\text{System Identification and Reaction Time Using Point-Process Input and Output} \\
&\text{The hazard function is constant (Cox & Oakes, 1984, p. 16). Observers are presented with a Poisson train of stimuli, and they hit a button as quickly as possible after each stimulus event. Thus, at the end of the experiment we have a set of stimulus times } S \text{ and a set of response times } R. \text{ We seek to characterize the time-varying rate of response } m_R(t), \text{ using Brillinger's identification approach (Brillinger, 1975a, 1975b; Brillinger et al., 1976). The simplest possible characterization occurs when the response rate is a constant.}
\end{align*}
\]

\[
m_k(t) = m_k = h_0, \quad (A1)
\]

\[
h_k \text{ being the zeroth-order kernel, equivalent to the mean response rate } m_k. \text{ If the duration of the experiment is denoted by } T, \text{ and if the number of } R \text{ events occurring from the beginning up to time } T \text{ is denoted by } N_R(T), \text{ then for long } T, \text{ we can form the estimates}
\]

\[
h_k = \hat{h}_0 = N_R(T)/T, \quad (A2)
\]

where the hats denote estimators. The estimates are asymptotically normal (Brillinger, 1975b, p. 74). If we make the assumption that the successive event times are uncorrelated, the asymptotic variance is \( \hat{m}_k/T \).
intervals for the mean response rate could also be obtained with a bootstrap approach (Braun & Kulperger, 1998). One could also compute the estimate on each of several runs and find the confidence interval for the mean across the runs.

If the observer is in fact perceiving the stimulus, the responses will not just be emitted at a constant rate. Instead, responses will be most likely to occur shortly after the delivery of each stimulus. Therefore, we need an additional term in Equation A1 to reflect that

\[ m_0(t) = h_0 + \sum \int h_i(t - \sigma) dS(u) = h_0 + \sum \sum h_i(t - \sigma). \]  

(A3)

where \( h_i(u) \) is the impulse response or first-order kernel and \( \sigma_j \) is the time of the \( j \)th stimulus. The first-order kernel is the best linear predictor of the average change of the instantaneous response rate at time \( t \) in a response train \( R \), when a single stimulus occurs at time \( t - u \) in a stimulus train \( S \). If the stimulus train is a Poisson process, we have the simple relation

\[ h_1(u) = m_{sd}(u) - m_R, \]  

(A4)

where \( m_{sd}(u) \) is the cross-intensity function (CIF). The CIF is the response rate or intensity occurring some lag \( u \) after a stimulus is presented at time \( t \). The CIF is defined as

\[ m_{sd}(u) = \lim_{b \to 0} \frac{\sum \{ u - b/2 < \sigma_j < u + b/2 \} / \text{bin} \#}{bN_s(T)}. \]  

(A5)

where \( b \) is a bin width. The CIF is the point process analogue of the cross-correlation function. The average impulse response is equal to the CIF minus the mean response rate. We have already given an estimator for the mean response rate (Equation A2). Now we give an estimator for the CIF. Let \( \sigma_1, \sigma_2, \ldots \) and \( \rho_1, \rho_2, \ldots \) be the times of the stimulus and response events respectively that occur in the time interval \( 0 < t \leq T \). Let \# denote the number of events falling in a bin. Then we have the estimator

\[ m_{sd}(u) = \frac{\sum \{ u - b/2 < \sigma_j < u + b/2 \} / \text{bin} \#}{bN_s(T)}. \]  

(A6)

For each stimulus event, we look forward \( u \) time units and see how many responses fall in a small bin (Figure 2). This computation is done at a large number of lags to obtain the CIF estimate. For large \( T \), the distribution of \( m_{sd}(u) \) is approximately \( P(b)m_\text{sd} \), where \( P \) is a Poisson variate with mean \( bTm_\text{sd}(u) \) (Brillinger, 1975b, p. 75). Another approach would be to compute the estimate on each of several runs and find the confidence interval for the mean across the runs.

The first-order kernel is useful in predicting the response rate \( u \) time units after a single stimulus event. If the system under study is linear, the effects of the separate stimulus events are additive, and the first-order kernel will be all we need. However, real systems are often nonlinear, and so the effects of successive stimuli may not be simply additive. The second of two close stimuli may suppress or facilitate the response. To take account of such pairwise effects (using two stimulus times \( \sigma_j \) and \( \sigma_k \)), we need to add another term to Equation A3,

\[ m_k(t) = h_0 + \sum h_i(t - \sigma_j) + \sum \sum h_j(t - \sigma_j, t - \sigma_k). \]  

(A7)

Now we have the second-order kernel \( h_2(u, v) \). The second-order kernel measures the effects on the response rate of pairs of stimulus events with any relative timing. It will thus measure nonlinear suppression and facilitation. We saw that the first-order kernel was just the CIF minus the mean response rate. The situation is similar with the second-order kernel. We have

\[ h_1(u, v) = m_{sd}(u, v) - m_{sd}(u) - m_{sd}(v) + m_R. \]  

(A8)

where \( m_{sd}(u, v) \) is the 2D CIF,

\[ m_{sd}(u, v) = \lim_{b \to 0} \frac{\{ R \text{ point in } (t, t + b) \} / \text{bin} \#}{bN_s(T)}. \]  

(A9)

The 2D CIF can be estimated by a histogram method.

In principle, kernels of even higher order can be added. For example, a third-order kernel will look at the response rate in relation to triplets of stimuli. In practice, though, the computation of kernels higher than second order is problematic because of the large amount of data necessary and to the noisiness of the resulting kernel estimate. For a polynomial system, once we have obtained the various kernels, we have identified it (Palm & Pöpel, 1985). The kernels give us a complete characterization of the system.

The Poisson process experiment can be used to measure RT in addition to the kernels. We define RT as the lag at which the first-order kernel (or CIF) peak occurs. This is analogous to the mode of the conventional RT histogram. Other definitions of RT are possible. For example, one could use the centre of mass of the first-order kernel, which would be analogous to the mean of the conventional RT histogram. Or one could find the point that divides the area under the first-order kernel in half, which would be analogous to the median of the RT histogram.

Code for doing the necessary computations for point process system identification is available at http://fhis.gcal.ac.uk/VS/wsi/software. There are routes for joining sets of data and for computing and plotting estimates of the CIF, 2D CIF, and the zeroth-, first- and second-order kernels. Some of the code is written in C and the rest in the freeware language R (Ihaka & Gentleman, 1996), which runs on Macintosh, Windows, NT, and many variants of Unix (including Linux). R (http://cran.r-project.org/mirrors.html) is a free programming language specialized for statistical computation and graphics. All of the plots in this article were made using R. It is mostly compatible with the widely used commercial package S-Plus (Venables & Ripley, 1994). Some Matlab code, unused by us, is also available on our web page.