Decomposing skin conductance into tonic and phasic components

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Abstract

Overlapping phasic skin conductance responses (SCRs) obtained using short interstimulus interval (ISI) paradigms such as those employed in cognitive research, confound measurement of each discrete phasic SCR as well as the tonic skin conductance level (SCL). We report a method of resolving this problem using a modelling technique that takes advantage of the stereotyped nature of the within-subject SCR waveform. A four-parameter sigmoid-exponential SCR model that describes the entire response, was developed and extended to five-, six- and eight-parameter skin conductance SC models. These SC models were successfully curve-fitted to more than 60 SC segments, each containing one SCR or two overlapping SCRs on a sloping baseline obtained from 20 normal subjects. The SC segments were consequently decomposed into their components: the tail of the previous response, one or two SCRs and the SCL. The SCRs free of the complication of overlap were then quantified. The raw SCRs of the same data set were also measured using a standard method. The standard measurement showed a significant reduction of 15% in amplitude and 140 ms in peak latency compared to our method. The basic four SCR model parameters—onset time, rise time, decay time constant and gain—showed increasing inter-subject variability in that order. These SCR model parameters may be studied as variables in normal and patient groups and as indices of treatment response. This quantitative method also provides a means to assess the relationships between central and autonomic psychophysiological measures. © 1997 Elsevier Science B.V.

Keywords: Skin conductance response; Skin conductance level; Electrodermal activity modelling measurement scoring; Sympathetic autonomic response; Orienting reflex

1. Introduction

The skin conductance response (SCR) is an important autonomic nervous system (ANS) measure in psychophysiological research, probably more widely used than any other ANS measures. Its main attractions include its ease of recording, its simple waveform, its ability to indicate a response to single stimuli and its non-intrusive nature. Venables stated in his overview (1991) that by appropriate processing of the signal or the measurement of a critical portion of it, it may be
possible to provide a wanted index which would not be evident in the gross recording'. Despite its waveform simplicity, the SCR and skin conductance level (SCL) contain considerable information that may be associated with specific aspects of brain state and information processing.

A limitation in the use of these indices in cognitive research has partly been due to the response overlap in short inter-stimulus interval (ISI) paradigms conventionally employed in cognitive studies. These overlapping responses have limited efforts to study relationships between the ANS and the central nervous system (CNS) activity. Boucsein (1992) presented a good review of various scoring methods and their different degrees of success for use with long ISIs employed in traditional psychophysiological research. For short ISIs, SCR measurements have been made using a linear extension of the prestimulus baseline in the post-stimulus period (Barry et al., 1993), but this does not resolve the problem of delineating overlapping SCRs. For more accurate measurement, there is a need to analyze the SCR morphology and decompose skin conductance (SC) activity into its components. We have previously used exponential functions to characterise the SCL obtained in an habituation paradigm in our study of the relationship of prestimulus EEG and SCL (Lim et al., 1996). In this paper we report a four-parameter model of 'pure' SCR (excluding SCL) based on a combination of an asymmetrical sigmoid and an exponential function (Case 1: Eq. 1, Appendix). This model and its extensions can characterise a wide variety of response waveforms and sizes. Consequently, the composite SC activity is readily decomposed into its components, namely, the residuals from the previous SCR, the SCR(s) and the SCL. An accurate analytical estimate can be made of the peak latency and peak amplitude of each SCR free of the complication of response overlap and falling baselines.

2. Methods

2.1. Subjects

Normal adults (13 m, 7 f) aged between 20 and 49 years (mean = 29.9, SD = 9.0) were studied.

2.2. Apparatus and data acquisition

The subjects were seated comfortably in a quiet, dimly lit laboratory with air-conditioned ambient temperature set at 24 ± 1°C. Subjects sat facing a monitor screen and wearing a pair of headphones. An auditory oddball paradigm with a constant ISI of 1.32 s was used. Auditory stimulation consisted of tones at 80 dB SPL lasting 50 ms having rise and fall times of 10 ms, with a frequency of 1000 Hz for backgrounds and 1500 Hz for targets. A total of 40 target tones was presented pseudo-randomly with intertarget intervals (ITI) varying between 2.64 s and 15.84 s. Subjects were instructed to attend to the target tone and respond with a button press as quickly as possible. They were asked to fixate on a coloured dot on the screen. Skin conductance was recorded via a pair of silver–silver chloride electrodes, approximately 0.8 cm² in contact area, filled with 0.05 M sodium chloride gel placed on the volar surface of the distal phalanges of digits II and III of the non-dominant hand after the skin area was wiped with an alcohol swab. The electrode pairs forming part of the input circuit were excited by a constant voltage of 0.5 V (Lykken and Venables, 1971; Fowles et al., 1981) and the current change representing conductance was recorded using a DC amplifier with a low pass filter set at 50 Hz. SC and other signals were recorded continuously for 6.5 min using a 32-channel PC-based system. The signals were digitised at 256 Hz and stored to a hard disk. The SC digital signal with a magnitude resolution of 0.0265 μS was compressed by a factor of 5 giving an effective time-base resolution of 19.53 ms. This compression reduced the size of the data set but still retained a generous over-sampling since SCR frequency is less than 0.5 Hz (Fahrenberg et al., 1983). Although full head EEG and EOG were recorded simultaneously, only the SC data were studied for this exercise.

A large number of SC segments of 10-s epoch following target onset were visually inspected and categorised into three cases. They included simple SC segments with an SCR on a flat baseline
Case 2. Case 3 inclusion criteria were that the epoch contained a discrete SCR response on a sloping baseline (mainly the tail of the previous response) and that the response time course occurred within the epoch length. Case 4 consisted of complex SC segments containing two SCRs on a sloping baseline. Three SC models were developed as an extension of a four-parameter sigmoid-exponential ‘pure’ SCR model that describes the entire SCR response (see Appendix). A five-parameter SC model (Appendix, Eq. (2)) was adequate for Case 2, and this SC model was extended to a six-parameter model (Eq. (3)) to characterise signals of Case 3, and to an eight-parameter model (Eq. (4)) for Case 4 signals. In all the models throughout this paper (including the Appendix) the time unit is seconds (s) and the amplitude unit for the SC components is micro-Siemens (μS).

After a few preliminary tests of Case 2 using Eq. (2), this study used mainly the six-parameter model in relation to the 60 SC segments of Case 3. The signals were obtained largely from the first 10 targets and the rest from the first 20 targets and they were selected to represent a variety of shapes and sizes containing one discrete SCR superimposed on a range of sloping baselines. The parameters were obtained by curve-fitting using a standard non-linear least-squares method. They were then used to reconstruct three components: \( f_t \) describing the residual of the previous SCR, \( f_p \) describing the phasic SCR and \( c \) representing the tonic SCL. A few double responses were fitted using the eight-parameter model which included an additional term, \( f_{s2}(t) \), for the second SCR. The SCR peak latency and peak amplitude were then analytically obtained using Eq. (5) and Eq. (1) (Appendix). The SCR peak latency and peak amplitude were also measured from these raw SC signal using the standard traditional evaluation method B (pp. 136–137, Bousein, 1992).

Paired \( t \)-tests were used to compare the SCR peak latency and peak amplitude between the two scoring methods.

Those readers who are interested in the mathematical description and discussion of signal modelling should refer to the Appendix. Based on the mathematical concept and formulation outlined in the Appendix, we have developed a software package known as Skin Conductance Response Evaluation System (SCORES). Those who would like to use the software package, are invited to contact the corresponding author.

3. Results

The six-parameter asymmetrical sigmoid-exponential SC model successfully described all the 60 selected SC signals obtained from 20 subjects. The diversity of the signals and their analytically fitted waveforms are shown in Fig. 1. The middle two panels show two small SC signals at extremely high display sensitivity. The jagged raw SC signal is a direct consequence of reaching digitisation resolution (0.0265 μS) of the system. Note that the peak-to-peak noise magnitude is about 0.02 μS. Note also that the smooth fitted curve going through the mid-course at various regions of the raw signal. Figure 2 illustrates the raw (noiser) signal, the fitted curves and the residuals. The residuals were well below 5% of the signal amplitude. All the 60 SC signals were decomposed into three components: the tail of the previous response, SCR and SCL. Two examples of decomposition are shown in Fig. 3.

The four SCR parameter values and also those of two other parameters—initial SC amplitude at stimulus, \( a_0 \), and SCL, \( c \)—were obtained for every SC segment studied. Their across-subject means, SDs, coefficients of variation (CVs) and the maxima were also obtained, and are shown in Table 1. The table also shows the data of SCR peak latencies and the mean peak amplitudes obtained using our curve-fitted decomposed method and the standard method and the \( P \)-values of a comparison between them. The standard scoring method returned a significant reduction of amplitude by 15% and latency by 140 ms relative to the curve-fitted decomposed SCRs.

The means and SDs of the four SCR parameters (gain, \( T_{os1}, T_d \) and \( t_e \)) are used to reconstruct a family of curves, shown graphically in separate panels in Fig. 4, which demonstrate the form and extent of observed variations. Deviations from the mean by ±1 SD of gain cause dramatic changes in appearance, from an absent to a large response
(Fig. 4, gain). With a change in the time of onset, the whole waveform is shifted, as expected, along the time axis without any change in morphology (Fig. 4, $T_{on}$). A change in the decay time constant produces a dramatic change in the waveform shape, especially the recovery limbs (Fig. 4, $T_{off}$), and a change in the rise time affects mainly the rising slope (Fig. 4, $t_r$).

The variations of three of the four SCR parameters of the 20 subjects are shown in Fig. 5. Note the relatively stable response onset time, $T_{on}$, and rise time, $t_r$, and the relatively variable $T_{off}$.

Fig. 1. These are a few examples showing the diversity of the actual raw skin conductance traces and their fitted curves superimposed. The six-parameter SCR model handles a wide range of response sizes and shapes including (left to right, top to bottom) a large signal with fast recovery, a broad signal with slow rise and fall, two small noisy ones on steep slopes and two typical waveforms.
decay time constant, $t_d$. The parameter gain, $g_1$, which is most variable is not shown in the histogram.

The eight-parameter double response model yielded a good fit (Fig. 6) in the three double-SCR responses studied, and successfully decomposed each signal into four components. The SCR pairs were of the same morphology and their onset times were separated by 3.99 s, 2.87 s and 2.79 s, or roughly simple multiples of the ISI. As this was not the main thrust of this communication, no attempt was made to study a larger number of such cases.

4. Discussion

The six-parameter sigmoid-exponential SC model described adequately a wide variety of SC signal shapes and sizes on a range of sloping baselines (Fig. 1) with small residuals (Fig. 2). The signals were effectively decomposed into their components (Fig. 3). The significance of the four SCR parameters is best appreciated by reference to Fig. 4, which shows how each parameter modifies the SCR waveform and the extent of variations.

Extending from successful application of the six-parameter SC model, we also successfully applied the eight-parameter model to a more complex signal of two SCRs on a sloping baseline (Fig. 6). The results were encouraging and suggest that the basic methodological difficulty with the short ISI paradigm used in cognitive studies has been resolved, because all the complex overlapping SC signals can easily be classified into patterns corresponding to Case 2, 3 or 4, as de-
Fig. 3. Two sets of actual SC signals and the decomposed SCRs, the tails of the previous response and the SCLs (top to bottom). The ‘pure’ SCRs are far easier to score consistently.

scribed in the method section, and we have a working model for dealing with each of these SC patterns.

Discrepancies in peak latency and peak amplitude scoring between our method and the traditional method (Table 1) are no cause for concern,
because the traditional method operates on the apparent composite SC signal which is often a mixture of an SCR or two on a decaying limb of the previous response. The direction of these discrepancies is expected because of the additive effect of the decaying tail of the previous response and the current SCR. Although the discrepancy seems modest in this series, in some conditions conventional methods are ineffective (Barry et al., 1993); in the case of two closely spaced responses the conventional scoring methods would have resulted in even larger errors. This may have some impact on the nature of the recency effect on recovery phase (Bundy and Fitzgerald, 1975).

It must be pointed out that this sigmoid-exponential model is far from being a definitive SCR model. There can be a multitude of mathematical representations of varying complexity for the SCR (Schneider, 1987). Our method, which relies on the principle of superposition, is mathematically sound, and the principle allows us to consider each SC component independently, leading to signal decomposition. It is, however, not certain if this principle is physiologically valid for the autonomic electrodermal system in response to repeated stimuli. A few clues, however, are encouraging. Recommending conductance to be used to replace resistance on theoretical grounds, Lykken and Venables (1971) argued that SCR size was related to the number of parallel sweat gland conductance paths and hence was additive. This concept was confirmed by a recent report of positive correlation between the number of total and open sweat glands and SCR amplitude (Freedman et al., 1994). The system is far from being driven to saturation, which would have violated this principle, since our maximum SCR and SCL across subjects were, respectively, less than 2 $\mu S$ and 13 $\mu S$—well within the expected maximum range (Venables and Christie, 1980; Fowles et al., 1981) for standard recording techniques. All three electrical equivalent circuits proposed in the past involving combinations of serial and parallel resistors, with or without capacitors and potential sources (Boucsein, 1992), are based on lumped electric-circuit theory, in which this principle is known to be valid. The fact that the fitted decomposed SCRs summated almost exactly to the recorded overlapping composite SC signal (Figs. 1 and 2) suggests that the fitted decomposed SCR reflects underlying physiological SCR activity. The findings argue for the validity of the application of the superposition principle to electrodermal processes.

Apart from SCR, of equal importance in our

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*a* Paired $t$-test, $P < 0.0001$

*b* Paired $t$-test, $P < 0.00001$
Fig. 4. Four panels of the normal waveforms (solid lines) generated using the four-parameter SCR model taking the parameter mean values. Each panel shows the effect on the mean waveform caused by the parameter value deviating from the mean by \pm 1 SD (broken lines). Gain variation causes large amplitude changes including zero response. Changes in \( T_{\text{o}} \), the SCR onset time, cause shifts along the time axis without morphology changes. Variation of \( T_{r} \), the decay time constant, causes changes in the recovery limb of SCR. Note that the amplitudes were normalised to depict the decay differences more clearly. \( T_{\text{r}} \), the rise time, affects mainly the initial SCR incline.

method is its ability to measure SCL objectively. Previously, there has been no easy and consistent way of estimating the baseline, and hence SCL.

Our method, in another way, has an impact because of the advent of digital technology. A simple and inexpensive 12-bit analog-to-digital converter (ADC) offers a dynamic range of 4096 levels corresponding to 40 \( \mu \text{S} \), close to fulfilling the needs for representing the large tonic SCL and also the fine-grain changes of phasic SCR—the requirements set by committee guidelines for reporting electrodermal measurements (Fowles et al., 1981). A 16-bit ADC would have far exceeded the requirement without any need for tonic level control at the time of recording—a technique recommended by the committee mainly for the paper recorder—although the reporting of both the tonic and phasic activity has long been regarded as desirable (Grings, 1974). Digital recording is easier and the tonic information is not lost. In this context our method exploits the full advantages of digital recording by providing an effective method of accurately separating SCR from SCL, achieving greater efficiency and reliability.

In the absence of a physiological model of the SCR, it is difficult to interpret the model parameters with confidence. However, some plausible interpretations may be discussed here. As the gain parameter is able to modify the SCR from zero to any size, it may play a role in describing habituation. In the second order sigmoid function, the
Fig. 5. The inter-subject variations of the three important model parameters. $T_{on}$ (black) is most stable, followed by $t_r$ (grey) and $t_d$ (white).

rise time, $t_r$, is the time when the function reaches a quarter of its peak. This is equivalent to the half amplitude rise time of the first order symmetrical sigmoid function. This parameter determines the incline in the initial phase of the SCR. It probably reflects the cumulative effect of asynchronous sweat duct fillings mediated by responsiveness of the end-organs, i.e. the rate of recruiting increasing number of sweat glands into action (Freedman et al., 1994), and the effect of hydration of the stratum corneum. $T_d$ is the decay time constant of the exponential decline typical of the recovery phase of the SCR, which has long been recognised (Darrow, 1937; Edelberg, 1970). It is most probably associated with terminal sweat duct collapse (Edelberg, 1993) and reabsorption of sweat from the ducts (Fowles, 1974). $T_{on}$, the onset latency, has little effect on the waveform (Fig. 4, Panel $T_{on}$) and shows a remarkable level of stability within and across subjects (Table 1 and Fig. 5). Our mean onset latency was 1.51 s (SD = 0.37) giving a predicted upper limit (99%) of 2.62 s. This is in keeping with the range of 1–3 s recently advocated for the identification of stimulus-generated phasic electrodermal responses (Barry, 1990; Venables, 1991). Wider response onset latency criteria of 1–5 s and 1–4 s were popular in the literature between 1977 and 1982 (Levinson and Edelberg, 1985). The range has narrowed with time, perhaps reflecting advances in both our understanding of the SCR and its measurement.

The exact physiological processes leading to the SCR and SCL are yet to be determined, although the effector action is now better understood (Edelberg, 1993). It is hoped that more accurate measurement of SCR and SCL using a method such as this may promote studies that elucidate the psychophysiological processes involved, such as central drive, sympathetic outflow and effector action. This may lead to a more comprehensive model, including perhaps, the central processes.

Our model may have some contribution in cognitive research. Boucsein (1992) presented the view that two variables, the rate of habituation of the electrodermal response and its recovery time, were indicative of differential physiological involvement of the amygdala and the hippocampus, and these variables were given distinct psychological interpretations such as focussed versus distributed attention, or closed versus open gating of attention. As the gain parameter is capable of describing habituation in a continuum, it may improve on measurement of raw SCRs in this
context. $T_d$, the decay time constant, is a concise descriptor of the recovery phase, regardless of amplitude (Edelberg, 1970) but was not easily obtained previously. Our method makes this measurement more accessible and will hopefully promote its use. The other parameter in our SCR model, $t_r$, may also be of some psychophysiological research interest as this parameter dominates the initial incline, the region thought to warrant more detailed study (Venables et al., 1980). These SCR model parameters may be studied as variables in normal and patient groups and as indices of treatment response. This quantitative method also provides a means to assess the relationships between ANS and CNS in cognition.

Appendix A: Skin conductance signal modelling

A.1 Background

As a general strategy, we modelled incrementally the skin conductance (SC) signals in three cases of increasing complexity. A simple SC signal consists of a fixed baseline and skin conductance response (SCR) which has an initial rapid rise from the baseline to a peak and is followed by a recovery limb to the same baseline (Venables, 1991; Boucsein, 1992). When the baseline is fixed at zero the SC signal is an idealised SCR, which is most desirable for measurement. This ‘pure’ SCR waveform may be described mathematically by combining two distinct functions: a sigmoid function and an exponential decay function (Eq. (1)). We are not aware of previously published reports of the use of such a combination of the two functions to model the SCR. The exponential decay function is not new and is known to depict the recovery limb (Darrow, 1937; Edelberg, 1970; Venables, 1991) although there is no general consensus (Boucsein, 1992).

The use of an asymmetrical sigmoid function for the initial phase of SCR needs to be discussed. First let us assume that there is a fixed total number of sweat ducts that underlie the recording zone of the two surface electrodes. Following central drive, the sympathetic activation of the sweat glands supplying the sweat ducts must cause changes in conductance to follow a distribution curve of some sort because not all the sweat ducts will be filled at the same time. If the activation distribution function is known, one may integrate the function to obtain the cumulative action of sweat duct fillings. This would describe the rise of the SCR to a plateau when all the activated sweat glands are exerting their full influence. The sigmoid function is an approximation of this integral, as the hypothetical activation function is not known. The second order sigmoid function that we use was found to work adequately, satisfying the requirements of an abrupt
onset and then a slower rise to a plateau. Its beauty lies in its simplicity, needing only one descriptive parameter, the rise time, $t_r$.

$T_{ort}$ reflects the sum of a number of action times including afferent signal transmission time, relay times, decision time, efferent signal transmission time, electro-chemical conversion times, endorgan action time and sweat release time. Naturally, before arrival of the activation signal the effector endorgan will not respond, and hence the $f_{s1}(t)$ does not come into action until $T_{ort}$. As the two opposing terms in $f_{s1}(t)$ have unit amplitude, a combined gain factor, $g_f$, is used to scale the resultant of these terms to match the actual response size. Physiologically, this parameter is related to the actual number of sweat glands activated, their sweat ducts, their physical dimensions and the degree of activation synchrony. After considering physiological realities and having decided on these parameters to simulate the physiological dynamics, we use the mathematical formulation to describe the SCR and then three cases of commonly encountered SC signals in the following section. This is followed by some notes on how to use the models for SCR measurement.

### A.2 SCR and SC models

Based on the preceding considerations, and some trial and error, we propose a sigmoid-exponential four-parameter ‘pure’ SCR model (Case 1) as follows:

$$f_{s1} = \begin{cases} 0 & \text{for } t \leq T_{ort} \\ g_1 \exp[-(t-T_{ort})/t_d] & \text{for } t > T_{ort} \end{cases}$$

(1)

where the four parameters are: $g_1 =$ gain; $T_{ort}$ = response onset time; $t_r$ = rise time; and $t_d$ = decay time constant.

Following this ‘pure’ SCR case (Case 1), we considered three SC cases of increasing complexity: Case 2, a single SCR superimposed on a fixed SCL; Case 3, an SCR occurring on a decaying limb of a previous response; and Case 4, two overlapping SCRs on a decaying slope. Three SC models were developed to handle them. Other more complex signals can be considered as a combination of these three cases.

In applying the sigmoid-exponential four-parameter SCR model (Case 1) to the SC pattern of Case 2 we must add a term, $c$, representing the SCL to Eq. (1). Thus we have a five-parameter SC model:

$$f_s(t) = f_{s1}(t) + c.$$  

(2)

For Case 3 we needed only one extra parameter to accommodate the initial value ($a_0$) of the signal at stimulus onset by assuming the recovery process of each response to be similar sharing the same decay time constant $t_d$. This is a reasonable assumption for the endorgan behaviour during the recovery process, including sweat duct collapsing (Edelberg, 1993) and emptying of the sweat ducts (see Fig. 1 A of Edelbert and Müller, 1981). The recovery phase is considered by the group to follow the exponential decay, which is expected of many physical phenomena. Therefore, we needed an additional term, $f_d(t) = a_0 \exp(-t/t_d)$, leading to a six-parameter model:

$$f_s(t) = a_0 \exp(-t/t_d) + f_{s1}(t) + c.$$  

(3)

It turns out that sharing of the same time constants for adjacent SCRs does not cause appreciable error (see Fig. 2). Had the approximation not been good enough because of the sharing of $t_d$, we would see a systematic residual with a decay pattern.

For Case 4, we needed to accommodate a second SCR, which we assume to be similar to the first, but having its own gain $g_2$ and onset time $T_{ort2}$. We therefore have an eight-parameter model:

$$f_s(t) = a_0 \exp(-t/t_d) + f_{s1}(t) + f_{s2}(t) + c.$$  

(4)

### A.3 Curve-fitting

As our models are nonlinear, an iterative curve-fitting process is most appropriate. A stan-
The Marquardt–Levenberg method (Marquardt, 1963; Press et al., 1992) was chosen. The object of minimisation was the normalised chi-square and the convergence criterion was that at least two successive iterations did not alter the normalised chi-square, by more than a tolerance limit of 0.0001. This limit was chosen so that the algorithm does not ‘wander blindly’ in the minimum valley with insignificant terrain variations, and also to avoid problems due to floating point precision limits.

Inherent in any curve fitting method is the need for initial parameter values to be chosen appropriately to assure convergence to the global minimum. Two processes are used to determine the initial conditions. Firstly, the SCORES programme automatically scans the entire data file, and detects stimulus events (target or background) and SC trough and peak latencies and amplitudes to estimate roughly all the initial model parameter values. This is followed by visual inspection of the waveform and the opportunity to accept or to modify these automatically generated initial values before curve-fitting is committed. Convergence takes some ten to thirty iterations and only a few seconds using a processor running at 100 or 133 MHz in a standard IBM compatible PC. The success or otherwise of the fit is immediately apparent, and if it is not at first satisfactory the initial values may be modified until a satisfactory fit is achieved.

### A.4 SCR peak latency and amplitude

The SCR peak latency and amplitude are not explicit in the SCR model (Eq. (1)). However, the SCR peak amplitude and latency may be obtained by: (i) differentiating \( f_s(t) \) with respect to time, \( t \), to obtain the slope, \( df_s(t)/dt \), at any point on the curve; (ii) setting the slope to zero to define the response peak; and then (iii) solving for the peak time. \( df_s(t)/dt = 0 \) can be shown to be a simple cubic function:

\[
x^3 + x - 4t_g/t_r = 0; \quad \text{where } x = (t - T_{os1})/t_r.
\]  

(5)

A method for solving this function is readily available in many texts (e.g. Press et al., 1992, pp. 183–185). There is a single unambiguous solution for the peak time, which then enables calculation of the peak amplitude using Eq. (1).

### A.5 Application notes

We take the risk here of offending the experienced signal processing expert for the benefit of other researchers and clinicians. The foregoing paragraphs should be sufficient for a competent scientific programmer to develop a working software package. Others can buy a commercial software package with curve-fitting facilities. They then need to use any of Eqs. (2)–(4) together with Eq. (1) for the appropriate SC signal patterns (Case 2, 3 or 4 respectively). One important constraint in our model is that \( f_{st} = 0 \) prior to \( T_{os1} \). The time steps and SC data may be ASCII formatted and arranged column-wise in a spreadsheet. The time column starts with zero seconds (row 1) corresponding to the stimulus onset and ending with the epoch length say 10 s (in our case, row 512). The actual sample bin, i.e. the difference between successive time samples may vary from system to system. SCR is such a slowly varying signal that a sample bin between 30 and 100 Hz will be satisfactory. The accuracy of estimated peak latency will, of course, deteriorate with bin width increase. The epoch length need not be exactly 10 s. However, too short an epoch may fail to represent the entire SCR and too long an epoch may lead to extremely complex SC segments.

The parameter values are accepted when the curve-fitting process converges to a minimum. The obtained values of the four parameters: \( T_{os1}, g_1, t_s \) and \( t_g \) and the time steps \( t \) can be substituted in Eq. (1) to generate the decomposed SCR curve. This fitted decomposed SCR is then available for estimating the SCR peak latency and peak amplitude using either the analytical evaluation outlined earlier, visual inspection or graphical estimate. This ‘long-hand’ way of using our models is labour-intensive and slow and we would not recommend this approach for processing even moderate volumes of data.
References


