Title: A novel method for reliably measuring miniature and spontaneous postsynaptic

potentials/currents in whole-cell patch clamp recordings in the central nervous system

Abbreviated Title: Novel method for measuring mPSPs/mPSCs in the CNS

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Abstract

In chemical synapses of the central nervous system (CNS), information is transmitted via the presynaptic release of a vesicle (or 'quantum') of neurotransmitter, which elicits a postsynaptic electrical response with an amplitude termed the 'quantal size'. This key determinant of neural computation is hard to measure reliably due to its small size and the multiple sources of noise within neurons and electrophysiological recordings. Measuring amplitudes of miniature postsynaptic currents (mPSCs) or potentials (mPSPs) at the cell soma potentially offers a technically straightforward way to estimate quantal sizes, as each of these miniature responses (or 'minis') is elicited by the spontaneous release of a single neurotransmitter vesicle. However, a somatically recorded mini is typically massively attenuated compared with at its input site, and a significant fraction are indistinguishable from (or cancelled out by) background noise fluctuations. For minis to be accurately estimated, the noise component would need to be characterised independently. As the first step in devising such a method, we developed and described a novel mPSP/mPSC detection algorithm as part of our quantal analysis software called 'minis'. We tested its performance in detecting simulated minis in whole-cell recordings from pyramidal neurons in rat neocortical slices and compared it to two of the most-used mini detection algorithms. This benchmarking revealed superior detection by our algorithm. The release version of the algorithm also offers great flexibility via graphical and programming interfaces.

Significance statement

Accurately measuring the range of electrical 'sizes' of synapses in the brain is critical for understanding neural computations. As an important first step, we introduce a novel algorithm for detecting voltage or current transients ('minis') resulting from synapses spontaneously releasing vesicles containing neurotransmitters. We objectively evaluate this algorithm and compare it to other popular algorithms used for detecting spontaneous synaptic responses, setting an important methodological standard. Because of its superior performance and flexibility, our algorithm also offers a useful technological improvement for synapse researchers. The evaluation process we use highlights common methodological pitfalls bedevilling spontaneous synaptic signalling research, and points to potential solutions.

Abstract

Abbreviations

aCSF – artificial cerebrospinal fluid

AMPA – α-amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid

AP – action potential

API - application programming interface

AUC – area under the curve

CNS – central nervous system

CPP – (*RS*)-3-(2-carboxypiperazin-4-yl)-propyl-1-phosphonic acid

d' – sensitivity index 'd-prime' (defined in Methods)

FNR – false negative rate ('miss' rate)

FPR – false positive rate ('false alarm' rate)

GABA – gamma-aminobutyric acid

IPSC – inhibitory post-synaptic current

IPSP – inhibitory post-synaptic potential

mEPSC– miniature excitatory post-synaptic current

mEPSP– miniature excitatory post-synaptic potential

mIPSC– miniature inhibitory post-synaptic current

mIPSP– miniature inhibitory post-synaptic potential

mPSC – miniature post-synaptic current

mPSP – miniature post-synaptic potential

NBQX – 2,3-dioxo-6-nitro-1,2,3,4-tetrahydrobenzo[*f*]quinoxaline-7-sulfonamide

NMDA – N-methyl-D-aspartate

ROC – receiver operator characteristic

sEPSC– spontaneous excitatory post-synaptic current

sEPSP– spontaneous excitatory post-synaptic potential

sIPSC– spontaneous inhibitory post-synaptic current

sIPSP– spontaneous inhibitory post-synaptic potential

smEPSC – simulated mEPSC

smEPSP – simulated mEPSP

smPSC – simulated mPSC

smPSP – simulated mPSP

sPSC – spontaneous post-synaptic current

sPSP – spontaneous post-synaptic potential

TNR – true negative rate

TPR – true positive rate ('hit' rate, sensitivity)

TTX – tetrodotoxin

V_m – membrane potential

v-ROC – virtual ROC (ROC-like plot)

Introduction

Synaptic transmission in the CNS occurs in 'quanta' (Kuno, 1964; Larkman et al., 1991; Kraszewski and Grantyn, 1992; Kullmann and Nicoll, 1992; Stern et al., 1992; Jonas et al., 1993; Isaacson and Walmsley, 1995; Forti et al., 1997; Wall and Usowicz, 1998; Sahara and Takahashi, 2001; Hardingham et al., 2010) usually thought to correspond to the release of a single neurotransmitter vesicle (Heuser et al., 1979). The amplitude of the postsynaptic response to a quantum of transmitter, the quantal size, is a key parameter defining the efficacy of synaptic transmission (Vere-Jones, 1966; Katz, 1969) and, therefore, an important determinant of neural computation.

Quantal size measurements in the CNS are difficult due to multi-synaptic contacts, limited accessibility, significant quantal variance, temporal non-stationarity of synaptic properties, and low signal-to-noise ratios of somatic electrophysiological recordings of quantal events (Korn and Faber, 1991; Bekkers, 1994). For these reasons classical quantal analysis as done at the neuromuscular junction has run into problems in central synapses. More recent methods such as noise deconvolution, Variance-Mean analysis, and optical quantal analysis have not fared much better either (Edwards et al., 1976; Jack et al., 1981; Redman, 1990; Clamann et al., 1991; Reid and Clements, 1999; Yuste et al., 1999; Clements and Silver, 2000; Oertner et al., 2002; Clements, 2003; Silver, 2003; Biró et al., 2005; Enoki et al., 2009; Peled and Isacoff, 2011; Liu et al., 2022).

A complementary method of assessing synaptic function is to measure properties of mPSCs. Miniature PSC amplitude measurements are often taken as quantal size estimates across the population of active synapses onto a neuron, as the mPSC (under voltage clamp) or mPSP (under voltage recording) likely correspond to the response to a spontaneous release of a single neurotransmitter vesicle (Fatt and Katz, 1952; del Castillo and Katz, 1954; Brown et al., 1979; Isaacson and Walmsley, 1995; Wall and Usowicz, 1998). Measurements of mPSC amplitudes are

routine in the literature. However, they are likely overestimates due to small amplitude events being

difficult to detect and largely being missed.

The use of voltage clamp can be a major reason why mPSCs "go missing". Theoretical studies (Rall

and Segev, 1985; Major, 1993; Spruston et al., 1993) predicted and experimental findings (Williams

and Mitchell, 2008) confirmed that voltage clamp fails to clamp extended dendrites, and to capture

the current flowing in at electrically remote synapses. Amplitude attenuation can also be caused if

series resistance is not compensated (Williams and Mitchell, 2008). These issues can be somewhat

sidestepped by switching to voltage recording.

However, most mPSCs go undetected because of the electrophysiology of the neuron itself. Distal

minis leak charge via the dendritic membrane, but an even more significant amplitude attenuation,

40-fold or more, is inflicted by charging the membrane capacitance of dendritic trees (Stuart and

Spruston, 1998; Williams and Stuart, 2002; Nevian et al., 2007; Williams and Mitchell, 2008; Larkum

et al., 2009; Major et al., 2013). Such amplitudes, at the soma, are often indistinguishable from noise

fluctuations. Recording from thin dendrites close to synaptic input sites is technically challenging

(Nevian et al. 2007). Therefore, a reliable yet widely accessible quantal analysis method, based on

somatic whole-cell patch recording, would require taking account of the background noise

component in addition to measuring putative mPSPs (or mPSCs).

As an initial step in creating such a method, we developed a novel algorithm, called 'minis', to detect

miniature (and action potential-triggered) postsynaptic events. A novel algorithm was needed for

several reasons. Firstly, existing algorithms have not been described in sufficient detail in the peer-

reviewed literature. Popular algorithms like Mini Analysis and Clampfit are proprietary. Secondly,

because existing algorithms are not open, they are not modifiable. Thus, they cannot be automated

and integrated with other software. Lastly, existing algorithms have not yet, to our knowledge, been

benchmarked in peer-reviewed articles. To fill these gaps, we developed an algorithm that is

transparent, flexible, open-source, and objectively evaluated using standardised criteria.

Materials and Methods

Published values for amplitudes and frequencies of minis.

We searched the neuroscience literature between January 1, 2020 – January 31, 2022 for a

representative sample of recently reported amplitudes and frequencies of miniature excitatory

postsynaptic currents (mEPSCs) and potentials (mEPSPs) in cortical pyramidal cells, and common

data analysis practices in the CNS. We also compared reported mEPSC rates per second to a

predicted range of values. We limited our search to publications in English only that reported

research results on synaptic function in the CNS. We examined the title and abstract fields of studies

in MEDLINE database using the PubMed search engine with the following search keywords:

("spontaneous neurotransmission" OR "spontaneous neurotransmitter release" OR "spontaneous

transmitter release" OR "spontaneous postsynaptic" OR "miniature postsynaptic" OR "mEPSP" OR

"mEPSC" OR "mPSP" OR "mPSC" OR "mIPSP" OR "mIPSC" OR OR "sEPSP"[Title/Abstract] OR

"sEPSC"[Title/Abstract] OR "sPSP"[Title/Abstract] OR "sPSC"[Title/Abstract] OR

"sIPSP"[Title/Abstract] OR "sIPSC"[Title/Abstract]) AND ("cortex"[Title/Abstract] OR

"cortical"[Title/Abstract] OR "neocortex"[Title/Abstract] OR "neocortical"[Title/Abstract] OR

"hippocampus"[Title/Abstract] OR "hippocampal"[Title/Abstract] OR "thalamus"[Title/Abstract] OR

"thalamic"[Title/Abstract] OR "brain"[Title/Abstract] OR "cerebral"[Title/Abstract] OR "central

nervous system"[Title/Abstract] OR "pyramidal"[Title/Abstract] OR "CNS"[Title/Abstract]).

Abbreviations ending in PSP and PP stand for postsynaptic potentials, while PSC and PC stand for

postsynaptic currents and should not be confused with end-plate potentials and currents.

Animals and electrophysiology

All experimental procedures were carried out in accordance with the UK Animals (Scientific

Procedures) Act 1986 at Cardiff University under Home Office personal and project licenses.

19 to 27-day old Wistar rats (RRID:RGD_13508588; n = 11) of either sex were anaesthetised with

isoflurane and decapitated, and the brain removed under cold (0-2 °C) artificial cerebrospinal fluid

(aCSF), composed of (in mM) 125 NaCl, 26 $NaHCO_3$, 2.3 KCl, 1.26 KH_2PO_4, 1 $MgSO_4$, 10 glucose, and 2

$CaCl_2$ bubbled with 95% O_2 5%CO_2. Coronal somatosensory cortical slices 350 μm thick were cut and

held in an interface chamber with their surfaces kept moist for 1 to 3 hours by aCSF at room

temperature (21-23°C) under a 95% O_2 5% CO_2 atmosphere. Individual slices were then placed in the

recording chamber and held at 35-37°C with aCSF flowing over both surfaces. For recording

purposes at 35-37°C the aCSF solution contained (in mM) 125 NaCl, 24 $NaHCO_3$, 2.3 KCl, 1.26 KH_2PO_4,

1 $MgSO_4$, 10 glucose, and 2 $CaCl_2$.

Whole-cell recordings (n = 14) were obtained under visual control using infrared scanning gradient

contrast imaging with the imaging laser beam and a Dodt tube. Recordings were made with 4.5-9

MΩ borosilicate glass pipettes (Harvard Apparatus, 1.5 mm outside diameter and 0.86 mm, internal

diameter, omega-dot filament; Sutter P2000 puller), filled with (mM): 140 KGluconate, 10 HEPES, 2

$MgCl_2$, 3 ATP-Na_2, 0.3 GTP-Na, 0.1 Magnesium Green, 0.1 Alexa 594; 7.35 pH, 273 mOsm/L

osmolarity. Signals were amplified, low-pass filtered (5 KHz) and digitised (Axopatch-200B, custom

amplifier/filters, Digidata 1440, Clampex software; Molecular Devices). Pipettes and electrodes were

positioned with Sutter MP265 and 285 manipulators with a diagonal (axial) mode, using

parallelogram trajectories.

The electrophysiological recordings consisted of two phases. During the first phase we recorded

mEPSPs against the background of physiological noise ('noise + minis' condition) by applying aCSF

with action potential and inhibitory postsynaptic potential blockers added: 0.5 or 1 μM tetrodotoxin

(TTX; selective, potent Na^+ channel blocker), and 12.5 μM gabazine (selective, potent $GABA_A$

receptor antagonist to block (fast components) of inhibitory synaptic inputs – IPSCs and resulting

IPSPs). Action potential (AP) blockade by TTX was explicitly tested for with long current pulses

pushing membrane potential (V_m) well above normal AP threshold levels, to around -20 mV. The

average duration of this phase of the recordings was 21.8 (± s.d. 0.9) minutes. During a second

phase, we recorded noise with mEPSPs blocked ('noise-alone' condition). This recording was carried

out after further adding 40 µM 2,3-dioxo-6-nitro-7-sulfamoyl-benzo[f]quinoxaline (NBQX) (selective,

potent α-amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid (AMPA) receptor antagonist) and 50

µM CPP (competitive, non-use dependent selective N-methyl-D-aspartate (NMDA) receptor

antagonist) to the solution used in the 'noise + minis' condition, to block all excitatory glutamatergic

synaptic inputs (and thus EPSPs), verified by inspecting and analysing the traces across a number of

recordings with the same flow rates. The average duration of this phase of the recordings was 44.8

(± s.d. 2.9) minutes.

Experimental design

The goal of this benchmarking study was to compare mEPSP detection performance by three

different detection algorithms, mainly in terms of standard signal detection theory measures. Two of

them were the most popular software products used in the field of synaptic function research in the

CNS, while the third one was our novel algorithm called 'minis'.

Current clamp whole-cell patch recordings obtained during the initial recording phase ('noise +

minis' condition) were not used in this benchmarking study. The current clamp recordings obtained

during the second recording phase ('noise-alone' condition) served as the background data in the

mEPSP ('simulated minis') computer simulations (n=14 cells). Computationally simulated mEPSPs

(smEPSPs) were added onto segments of these V_m noise recordings (2 of them 200 seconds, while

the remaining 12 were 100 seconds long) and the resultant hybrid waveforms (noise + simulated

minis) were then subjected to mEPSP detection analyses using 'minis', Mini Analysis (Bluecell;

RRID:SCR_002184), and Clampfit (part of the pClamp software suite, Molecular Devices;

RRID:SCR_011323) software. Detection performance was quantified using signal detection theory

measures and compared between the three algorithms.

Simulations

Simulating distributions of miniature excitatory postsynaptic potentials with a range of amplitudes

and rise times

All simulations were carried out within the 'minis' software environment which is based on Matlab

(Mathworks; RRID:SCR_001622). Simulation of minis-like events was based on an analytical solution

to the passive cable equation for a transient current (Rall, 1977) using 100 lumped terms with a

double exponential synaptic current with τ_1= 0.1 ms and τ_2 = 2 ms (Major et al., 1993).

For a given membrane time constant, an initial cable segment was constructed with an electrotonic

length l/λ = 0.6, where l is the physical length of a dendrite (μm) and λ is the length (μm) constant

(Rall, 1977). Charge (Q) was injected at a location (x μm) along this cable and the resulting simulated

postsynaptic V_m was measured at one end of this cable segment. The precise location of the injected

charge was varied systematically, depending on the desired shape of the simulated event. Increasing

the distance of the injected charge along the cable away from the measurement site gradually

increased the rise time of the simulated event. To further increase the rise time, electrotonic length

was gradually increased until the required rise time was obtained. Increasing the amount of injected

charge increased the amplitude of the simulated event. Therefore, one was able to construct a

simulated postsynaptic potential of any rise time or amplitude, for the particular membrane time

constant used. A pool of simulated events could be created having any kind of distribution of

amplitudes and rise times, for a given decay time constant, with individual events' onsets

timed/placed pseudo-randomly along the time axis of the V_m recording.

Simulations used to construct full receiver operating characteristic (ROC)-like curves, using relatively

fixed but realistic ('moderately-sized') mini amplitudes

All simulated mEPSPs were drawn from a two-dimensional normal distribution (independent

amplitude and rise time dimensions) with the following amplitude parameters: mean μ_1 = 0.3 mV

and standard deviation σ_1 = 0.05 mV (i.e., amplitudes relatively constant, with a relatively small

amount of variation). The following (independent) 10-90% rise time parameters were used: μ_2 = 0.05

ms and σ_2 = 2.5 ms (with a minimum rise time of 0.05 ms; i.e., only upper half of normal distribution

used). Simulated events were drawn pseudo-randomly from a distribution at one of the following

frequencies (minis/second): 640, 320, 160, 80, 40, 20, 10, 5, 2.5, 2.5, 2.5, 2.5, and 2.5.

Corresponding noise amplitude scale factors for these 14 frequency conditions were as follows: 1, 1,

1, 1, 1, 1, 1, 1, 1, 1.2, 1.4, 1.8, 2.6, and 4.2. The simulated events were then positioned at pseudo-

randomly determined times along the V_m noise recording epochs obtained during the second

recording phase ('noise-alone' condition). Two of the noise-alone epochs were 200 seconds long,

while the remaining twelve were 100 seconds long. Four different simulation traces per recording,

each of them having different pseudo-random event timings, were generated for every

frequency/noise scale condition, resulting in a total number of 14×4×14 = 784 traces.

Simulations of miniature excitatory postsynaptic potentials using a range of biologically realistic

amplitudes at realistic frequencies

The simulation parameters used to construct full ROC-like curves cover only a part of the likely

biological range. In reality, in cortex, minis vary far more in their amplitudes, with large numbers of

smaller minis, but a minority of bigger minis too - some much bigger. Therefore, we set out to

compare all three algorithms using a range of plausible simulated mini amplitudes, within the

restricted range of what we deemed to be realistic frequencies based on our estimation (from

recent peer-reviewed publications) in the first Results subsection.

All simulated events were drawn from a two-dimensional distribution with the following

parameters: amplitudes were chosen from twelve discrete values (0.05, 0.1, 0.15, 0.2, 0.25, 0.3,

0.35, 0.4, 0.45, 0.5, 0.55 and 0.6 mV) with equal probabilities, rise times were independently chosen

from the upper half of a normal distribution with mean $\mu_2 = 0.05$ ms, and standard deviation $\sigma_2 = 2.5$

ms (i.e., no rise time shorter than 0.05 ms). Three 'realistic' mini frequencies were used: either 53,

33, or 13 minis/s. The simulated events were positioned at pseudo-random times along the same

noise recording epochs as used in the previous subsection. Four different simulation traces per

recording, each of them with different random event timings, were generated for every frequency

condition, resulting in a total number of 3×4×14 = 168 traces.

Detection of spontaneous and miniature postsynaptic potentials

'minis' detection algorithm

We developed a new algorithm to detect postsynaptic potentials and currents, that we have

incorporated into a data analysis software package called 'minis', coded in Matlab (Mathworks). It is

distributed as an application programming interface (API) in the form of a packaged Matlab app or a

Python (Python Software Foundation; RRID:SCR_008394) package or as a compiled standalone

desktop application with a graphical user interface. In brief, the detection algorithm takes a filtered

V_m or clamp current trace in the Axon Binary File (ABF) format and detects peaks and rising phases

and estimates their amplitudes and rise and decay times after applying certain processing steps.

These steps are outlined below (with parameter values tailored for detecting smEPSPs in cortical

pyramidal neurons). A schematic illustration of the key steps is shown in Figure 1:

A. Steps to find minis:

1. The data can be band-stop filtered to remove mains noise (e.g., small integer multiples of

301   50 Hz frequency components: optional). For this, a Butterworth filter (Matlab's 'butter'

302   function) is used with a stopband attenuation of 10 dB and a passband 'ripple' of 0.05 dB.

The stopband size is 1 Hz, and the passband is the entire remaining frequency range except

for the ±3 Hz window either side of the stopband frequency.

2. The recording trace can be smoothed using a Gaussian window (optional). We use a 1.5-

millisecond window (with standard deviation of the Gaussian of 0.53 ms). This step removes

high frequency noise.

3. Peaks (local maxima) are identified in the filtered, smoothed recording trace. Each peak is

then examined consecutively, starting with the initial peak.

4. Going through all the peaks one by one, any peak within the "Peak Integration Period"

('duration') following the current ('working') peak of interest is discarded if it is *smaller*

(lower) than the peak of interest. For the analysis in this paper, we use a Peak Integration

Period of 2.5 ms; this can be matched to the different 'sharpnesses' or 'breadths' of peaks

in different data.

5. If there is a larger peak within the peak integration period, the 'working' peak of interest is

moved to this new peak, and the old peak and all intervening peaks between it and the new

'working' peak of interest are discarded.

6. The baseline of the peak is positioned asymmetrically around the lowest value (local

minimum) before the peak. Because of the faster upstroke of minis, compared with their

decays, 80% of the baseline period falls before the lowest voltage (local minimum) and the

remaining 20% after it (see Figure 1, inset). The interval from the baseline to the peak is

limited by the *Maximum Time-to-Peak* parameter (10 ms used here). The last 20% of the

baseline cannot start earlier than this.

7. The length in time of the baseline is controlled by the *baseline duration* parameter. We

used 2-ms. (N.B. a baseline, or indeed an entire mini, can occur during the summated decay

'tails' of previous minis, particularly when the minis frequency is high relative to their decay

time, as often seen with mPSPs under voltage recording at body temperature – but also

under voltage clamp).

8. If the baseline overlaps with or falls before the previous peak, its start is delayed till immediately after the previous peak (to stop the baseline being pulled down by the previous rising phase), but the end time is kept the same.

9. To reject any large artefactual 'glitches', or small events that are putative noise, if the amplitude of the peak is outside of the range of acceptable amplitudes, between a detection threshold and a maximum, the peak is discarded. We allowed a range of amplitudes of 0.1-10 mV in detection conditions used to construct full 'virtual' receiver operating characteristic (ROC) curves. In other conditions we applied a range of 0.05-10 mV. (N.B. 0.02 or 0.03 mV detection thresholds are useful for real whole-cell patch recording data from neocortical pyramidal neurons, under our experimental conditions, guided by the range of amplitudes of dendritically detected, somatically recorded mEPSPs in Nevian et al. (2007) from layer 5 pyramidal neurons from rat somatosensory cortex; in general, detection thresholds will need to be adjusted to the cell type and experimental conditions).

B. Steps against multiple small minis being erroneously lumped together (merged):

10. Rising phase asymmetries: if the first half of the rise time (10-50% or 20-50%, depending on the rise time duration of choice) is longer than the second half (50-90% or 50-80%) by a factor of 5 or more (an asymmetry incompatible with typical single, non-summating EPSP or EPSC rising phases), the end of the baseline is extended slightly into the 'take-off' of the rising phase. (This correction can be repeated one more time).

11. The amplitude range test is applied again (Step 9).

12. If the second half of the rise time is longer than the first half by a factor of 5 or more, the peak is shifted to a previously discarded smaller peak, if exists. (Two minis could be summating on their rising phases, which is treated as a single mini, or the second mini could occur just after the peak of the first, which is treated as two minis, if two peaks are distinguishable).

13. The amplitude range test is applied again (Step 9).

14. If the 10% or 20% rise time mark (depending on whether 10-90% or 20-80% rise time is

measured) is later than the end of the baseline by more than a half of the baseline duration

(1 ms in our case), a new baseline is established closer to the peak (by moving the baseline

to the next local minimum).

15. Finally, the amplitude range test is applied again (Step 9).

16. A mini (mPSP/mPSC) is established.

Detection using Mini Analysis software

Mini Analysis software version 6.0.7 was used to detect mEPSPs for a benchmarking purpose. We

used the following detection parameters: As with the 'minis' program, an amplitude threshold of 0.1

mV (when constructing the full ROC-like curve) or 0.05 mV (all other simulated conditions), in both

cases somewhat matched to the simulated data, a "Period to search for a Local maximum" of 12.5

ms, "Time before a peak for baseline" of 10 ms, a "Period to search a decay time" of 30 ms, a

"Fraction of peak to find a decay time" of 0.37 (one effective time constant for exponential decay), a

"Period to average a baseline" of 2 ms, an "Area threshold" of 0 mV×ms (i.e., not used), a "Number

of points to average for peak" of 1, and using the "Detect complex peak" option (to avoid missing

close-together events). The chosen detection parameters closely resembled similarly named

parameters in the 'minis' detection algorithm with minor deviations to improve performance.

Arrived by trial and error, these parameters were also found to give the most optimal detection

performance of the Mini Analysis software in comparison to other tested parameter sets. Event

detection was carried out on the recording data that was filtered and smoothed in the same way as

described in steps 1 and 2 of the previous sub-section.

Detection using Clampfit

Clampfit software, part of the pClamp 11.0.3.03 software suite, was used to detect real and

simulated mEPSPs and mEPSCs for a benchmarking purpose. Recordings were band-stop filtered as

described in step 1 of the 'minis' detection algorithm. Data was not smoothed. A template search

algorithm was used with 9 templates. The mEPSP template set was constructed based on the

simulated events. Events having 0.5 ms, 1.5 ms, 3.5 ms, and 6.5 ms 10-90% rise times were selected

to produce 4 distinct mEPSP templates (with the correct decay time constants). An additional 5

single-peaked templates were constructed in a way that made them potentially a mix of multiple

simulated waveforms. They were constructed to have extra-fast, fast, intermediate, slow, and extra-

slow rise times corresponding to 2 ms, 2.75 ms, 6 ms, 7 ms, and 8 ms 0-100% rise times and 8 ms,

9.25 ms, 17 ms, 23 ms, and 37 ms duration full decays, respectively. Combining single and mixed

waveforms gave better detection performance than having waveforms based only on any one of

these types alone. Template match threshold was set to the default of 4 noise standard deviations

with the rest of the detection parameters being set to their default values as well. The same set of

templates was used to analyse all simulated current clamp data.

Detection algorithm response classification

At the outset we identified prominent noise events in the V_m noise recordings (the 2nd recording

phase: 'noise-alone' condition) that could potentially be confused for true minis (mEPSPs) by any of

the algorithms (noise traces in Figures 2A and B). All noise recordings were filtered and smoothed as

in Steps 1 and 2 of the 'minis' detection algorithm. The data was further smoothed by a rectangular

'box-car' moving average window of 20 ms. Then all peaks larger than 0.01 mV and having a half-

width of at least 0.5 ms were identified. These peaks were classed as (notional) noise 'events' (for

the purpose of generating 'sensible' true negative rates, TNRs, which do not 'swamp' false positive

rates across the entire virtual ROC; see below). Subsequently we simulated mEPSPs and added them

at pseudo-random times to a zero-trace having the same length as the noise recording of interest

(Simulation traces in Figures 2A and B). The peaks of these events were classed as signal events. The

simulated trace was then added to the noise recording ("Simulation + noise" traces in Figures 2A and

B). Locations of signal and designated noise events formed the 'ground truth' information.

Following the detection process, all detected events were associated with one of the signal and

noise events depending on their proximity to these predefined 'ground truth' events. A detected

event was classed as a true positive (a 'hit') if it was the closest detection event within 5ms of a

signal (simulated mEPSP/mini) event. If no detection event occurred within the 10 ms symmetrical

window surrounding a signal (simulated mini) event (-5 to 5 ms), the signal event was classed as a

false negative (a 'miss'). If no detection event (except correct detections) occurred within the same

duration window surrounding a noise event, the noise event was classed as a true negative ('correct

rejection'). Although in theory there could potentially be a much higher number of possible time

points which could be labelled as correct rejections, or true negatives, in this situation, because of

their inherently somewhat arbitrary nature, we wanted to keep the maximum number comparable

to the maximum number of true positives (simulated minis), so the ROC plot had a reasonable

chance of being relatively 'square' (i.e. having a useful dynamic range). The remaining detection

events were classed as false positives ('false alarms'). Examples of classified detection events are

shown in Figure 2 separately for all three detection algorithms.

Detection response time to the nearest neighbour

The time to the peak of the nearest smEPSP was available for every classified response. Detection

performance was then evaluated as a function of the time to the nearest neighbour.

Membrane potential 'phase' (trend) classification

We attempted to address common detection errors, in particular missed minis on the decaying

phase of a previous mini (causing second peak to drop relative to its baseline), or on the rising phase

of another mini (so the rises of both minis get lumped together). Algorithm detection performance

was assessed not only for full recordings but also separately for periods when the 'underlying'

simulated V_m (before adding the noise) was rising, decaying, or remained roughly stable (Figure 3).

The 'decaying phases' (downward trend) of the purely simulated V_m were set to be a) the period

from 0.0625 ms after the peak until the purely simulated V_m trace dropped to the ratio of 0.3/e mV

(0.11 mV) (amplitudes of simulated minis were ~0.3 mV in the full virtual-ROC curve conditions, so

this would be about one membrane time constant after an 'average' simulated mini) or b) until the

V_m started rising again to reach a new peak that was above the initial peak (at the start of this decay

phase). If the new peak was lower than the initial one, the entire new peak was classified as part of

the ongoing decay phase. Peaks occurring on the decay phase of the V_m were assigned the V_m decay

rate of change that was present 0.25 ms (5 sample points) prior to the appearance of the V_m

inflection points associated with the start of the rise of a new mini (indicated by the blue arrow in

Figure 3A). The rising 'phase' was treated essentially somewhat as a decay phase in reverse. The only

difference was that the ratio of 0.3/e mV was replaced by the ratio of 0.3/10 mV (0.03 mV). Peaks

occurring on a V_m rise phase (upward trend) were assigned a V_m rate of rise value that was present

0.125 ms *after* the appearance of an upward V_m inflection point following the initial decay of the

previous peak (indicated by green arrows in Figure 3A). Periods that were already classified as decay

phases could not be reclassified as rising phases. Periods of relatively slowly-changing simulated V_m,

outside of the rise and decay phases were classed as "stable" (or a flattish phase). The classification

of purely simulated membrane potentials into three different trend phases was used to assign

phases to the combined noise recordings + simulated minis (Figure 3B). The detection performance

during rise and decay trend phases was evaluated as a function of the V_m rate of change.

Data Analyses

Performance of the three algorithms was compared using measures from signal detection theory. All

detection responses were classified as described in the *Detection algorithm response classification*

subsection. True positive ('hit') rate (TPR) was calculated as follows:

457
$$TPR = \frac{True\ positive\ count}{True\ positive\ count + False\ negative\ count}.$$

459 Throughout this text we use TPR, detection probability, and sensitivity interchangeably. False

460 positive ('false alarm') rate (FPR) was calculated as follows:

461
$$FPR = \frac{False\ positive\ count}{False\ positive\ count + True\ negative\ count}.$$

The true negative count we have used is perforce notional, as explained above, but still useful for

standardised, non-subjective comparisons and benchmarking. Throughout we use FPR and 'false

alarm rate' interchangeably.

Calculation of TPR and (notional) FPR allowed us to produce ROC-like curves and to calculate area

under the curve (AUC; area under the ROC curve, for each complete ROC curve, with 0.5 indicating

chance performance (the area of the triangle under the diagonal from (0,0) to (1,1) and 1 indicating

perfect performance, i.e., the area of a right angle starting at (0,0), vertical to (0,1) then going

horizontal to (1,1)) as detection performance indicators. These are the most commonly used

performance indicators for classifiers, in addition to sensitivity (TPR), and d' (discriminability or

sensitivity index) which we often use in parallel throughout this text. The d' statistic was calculated

as follows:

475
$$d' = z(TPR) - z(FPR),$$

where z is the z-score defined as the inverse of the normal cumulative distribution function, i.e.

z(arg) is the number of sd's from the mean giving the area equal to its argument arg under the

standard unit normal distribution (mean 0, sd 1), starting from -∞. TPR and FPR values are essentially

treated as cumulative probabilities as explained in (Macmillan and Creelman, 2005). So d' tells us

how many standard deviations 'apart' the TPR and FPR are, assuming they are cumulative

probabilities (areas under curve) of a standard normal distribution. N.B. If FPR is 0, z(FPR) is -∞ so d'

is undefined, but arbitrarily large and positive (as occurs in some of our figures below). These plots

are truncated for the detection method in question, but the performance is still superior to any plots

with finite values.

The above detection performance indicators were calculated for full recordings, as well as separately

for rising and decaying periods of V_m.

In addition, we also looked at cumulative (left-to-right over the x-axis) TPR and cumulative FPR. The

cumulative TPR was defined as follows, for each detection algorithm and simulated waveform:

$$Cumulative\ TPR = \frac{Cumulative\ true\ positive\ count}{Total\ unbanded\ true\ positive\ count} * Overall\ unbanded\ TPR.$$

Likewise, the cumulative FPR was defined as:

$$Cumulative\ FPR = \frac{Cumulative\ false\ positive\ count}{Total\ unbanded\ false\ positive\ count} * Overall\ unbanded\ \ FPR.$$

The latter two measures were not only useful for measuring cumulative hits and false alarms over a

range of time intervals and V_m rates of change, but also provided overall estimates of TPR and FPR.

Statistical analyses

All inferential statistics were based on the assumption that distributions of all measures were

normal. All mean distribution values are stated/depicted with 95% confidence limits of the mean.

Data accessibility

All data analysed in this study is publicly available (Dervinis, 2023a). The available data include

'noise-alone' whole-cell patch membrane potential recordings that were used in computer

simulations. The hybrid V_m traces containing smEPSPs added to noise recordings are also available.

All electrophysiological recordings were stored in Axon Binary File (ABF) format.

mEPSP templates used for detecting real and simulated events via Clampfit are also in the same

dataset in the form of Axon Template Files (ATFs).

Code accessibility

All analyses were carried out in Matlab and the analysis code is publicly available on GitHub

(Dervinis, 2023b). The code is complete with instructions on how to reproduce all figures reported in

this study.

Software accessibility

The present study reported the use of a novel mEPSP/mEPSC detection algorithm that is part of

'minis' open-source software available on GitHub (Dervinis, 2023c).

Results

Research literature measuring minis in the central nervous system

There were 107 studies in total that matched our criteria. All of these studies used voltage clamp as the electrophysiological method for recording spontaneous and miniature postsynaptic events. We surveyed the software they used to detect these events. The biggest group, ~48%, reported using Mini Analysis. 26% reported using Clampfit, while 13% used a custom algorithm. The remaining 13% did not specify. We compared the performance of the two most popular detection algorithms, Mini Analysis and Clampfit, both commercially available, with our new algorithm 'minis'.

35 studies (ca. 32%) reported using a current amplitude detection threshold of which 19 studies specified actual numeric value used (-6.8 ± s.d. 0.44 pA, range of -3 to -20 pA). It is likely that a higher fraction of studies made use of amplitude thresholds as only two explicitly reported not using any detection thresholds. Most of the studies did not give enough details (65% of all studies) to judge one way or the other. However, studies that used Mini Analysis for detection must have used a detection threshold, as this software requires it.

Out of all the studies, 18 carried out research in neocortical pyramidal cells looking at mPSCs only (spontaneous PSCs excluded). 12 studies reported a mean mEPSC amplitude value of -11.74 ± s.d. 0.77 pA (range of -6.0 to -20.9 pA). 13 studies reported a mean frequency value of 3.6 ± s.d. 0.34 per second (range of 1.0 to 8.0 per second).

The total putative excitatory synapse count on a single cortical pyramidal cell can number in the tens of thousands (Eyal et al., 2018b). Layer 2/3 pyramidal cells in rats are thought to have 5,000 to 30,000 putative excitatory synapses (Larkman, 1991; Eyal et al., 2018b). Large-thick-trunk/tufted layer 5 pyramidal cells would have an even larger number of contacts (Larkman, 1991). Therefore,

we can roughly assume that for most cortical pyramidal cells the number of putative excitatory

synapses ranges between 5,000 and 50,000. Conservatively, we could assume that only a minority,

roughly 40%, of them are functional ('non-silent') synapses with active zones and post-synaptic

densities containing AMPA receptors (Motta et al., 2019; Holler et al., 2021). Given that a

spontaneous vesicle release at a single release site has been estimated to occur with an approximate

frequency of 0.0021 per second (Murthy and Stevens, 1999) and given that there may be at least 2.7

release sites per cortical synapse (Holler et al., 2021), the lower bound frequency estimate of such

events within a single cortical pyramidal neuron might be expected to range somewhere between

ca. 10 minis/s and 100 minis/s (5,000*0.4*0.0021*2.7– 50,000*0.4*0.0021*2.7). Frequency values

reported in the recent literature are below this predicted range by an order of magnitude,

suggesting a significant fraction of smaller minis may commonly be 'missed' under some recording

conditions. This problem has been observed directly (Nevian et al., 2007), using paired dendritic and

somatic whole-cell patch recordings, albeit using voltage recording rather than voltage clamp,

recording from large layer 5 neocortical pyramidal neurons.

Algorithm performance comparison for detecting moderately-sized (~0.3 mV) simulated miniature

excitatory postsynaptic potentials

Detection under a wide range of frequency conditions: overall performance

In the Results subsection 'Research literature measuring minis in the central nervous system', we

reported that detection of spontaneous postsynaptic events is typically carried out using an

amplitude threshold. This approach implies that the range of amplitudes of spontaneous

postsynaptic events is somewhat known and that, on the smaller end, the amplitudes are

moderately-sized and sufficiently larger than pure noise fluctuations. Leaving aside the question of

the empirical validity of this (somewhat dubious?) assumption, we evaluated automated detection

of moderately-sized (0.3 ± s.d. 0.05 mV) smEPSPs added to whole-cell patch clamp noise recordings

(the 2nd recording phase: 'noise-alone' condition).

We compared our novel 'minis' algorithm with Mini Analysis and Clampfit. We created 14 simulation

frequency conditions with different effective signal-to-noise ratios that loosely mimicked the effects

of varying the signal detection threshold. On the one hand, increasing the frequency of smEPSPs

tended to decrease TPR as simulated events started to merge. On the other hand, increasing the

noise amplitude (scaling up the noise that was added to the simulated minis) tended primarily to

increase the FPR.

We plotted the detection performance in terms of TPRs against FPRs, as 'virtual' (notional) Receiver

Operator Characteristic (v-ROC) curves, for all 14 conditions and all three algorithms in Figure 4A.

We found that in the first six conditions (high minis frequencies), the v-ROC curve for 'minis' had

minimal overlap with any other curve and was positioned furthest away from the diagonal (starting

from left to right; 640, 320, 160, 80, 40, and 20 minis/s with x1 noise scaling), indicative of a superior

performance in this (relatively high) frequency range (the highest frequencies were used to create

the full v-ROC; higher frequencies increase overlaps, i.e. temporal summation, between minis, which

are particularly challenging to detect). The same observation was supported by another measure,

the sensitivity index d', shown in Figure 4B. Detection performance in the remaining 8 conditions

(10, 5, 2.5, 2.5, 2.5, 2.5, 2.5, and 2.5 minis/s with noise scaling factors of x 1, 1, 1, 1.2, 1.4, 1.8, 2.6,

and 4.2, respectively) was very similar for both 'minis' and Mini Analysis: neither of the two showed

a clear superiority on both performance measures simultaneously: v-ROC and d' curves overlapped.

In contrast, Clampfit consistently performed worst across all 14 conditions, particularly with high

amplitude noise. Clampfit becomes progressively 'confused' as noise increases, placing templates on

noise events, but ignoring 'swamped' smEPSPs.

When overall performance was assessed averaging across individual frequency and signal-to-noise

ratio conditions, we found that 'minis' showed the best performance with the mean Area Under the

(v-ROC) Curve (AUC) value of 0.960 ± 0.002 (95% confidence interval here onwards; Figure 4C). A

paired samples t-test comparing to Mini Analysis which had a mean AUC value of 0.937 ± 0.0022

gave t(13) = 12.4 and p = $1.37×10^{-8}$. Clampfit showed the poorest overall performance with the mean

AUC value of 0.706 ± 0.0043, t(13) = 33.1, and p = $6.14×10^{-14}$ when compared to the Mini Analysis

mean AUC value in a paired samples t-test. These differences in detection performance were further

corroborated by the d' measure averaged across all signal-to-noise ratio conditions (Figure 4D). A

paired samples t-test comparing mean d' values from 'minis' (2.45 ± 0.045) versus Mini Analysis

(2.11 ± 0.04) gave t(13) = 14.0 and p = $3.24×10^{-9}$. The same test comparing the mean d' from Mini

Analysis and Clampfit (1.23 ± 0.024) gave t(13) = 13.3 and p = $6.07×10^{-9}$. In summary, these findings

clearly demonstrated that our 'minis' detection algorithm outperformed the other two algorithms,

for ~0.3 mV simulated minis added to real recording noise, at frequencies above 10 minis/s, while

Clampfit consistently showed the poorest detection performance across the entire frequency and

signal-to-noise range examined, for these mPSP shapes and templates.

Detection under a wide range of frequency conditions: common errors

Both 'minis' and Mini Analysis were fairly good at detecting moderately-sized (0.3 ± s.d. 0.05 mV)

smEPSPs added to our noise-alone recordings. Yet all three algorithms, including 'minis', missed a

sizeable proportion. Figure 5 shows examples of common mistakes. One type of mistake was missing

simulated events that occurred very close to other events (Figures 5A, B, C, D, E, F, and G).

Unsurprisingly, none of the three algorithms could deal with events that overlapped nearly perfectly,

always lumping them together. Detecting peaks in the data using thresholds or fitting templates to

the data cannot offer a way of identifying overlaps. Another common error type was missing events

with peaks on the rising phase of another mEPSP (Figures 5A, B, C, D, E, and F; green arrowheads).

Unlike perfect or near-perfect overlaps, these events had a clear but brief decay period that was

quickly upended by the rising phase of the next mini. Because these decays were brief, they were

often lumped with a subsequent mEPSP or they could not be adequately fit with a template by

Clampfit and, therefore, were discarded. The 'minis' program (but not Mini Analysis) does offer a

way to minimise these errors by reducing the peak integration period, but this comes at the expense

of noise fluctuations on the rising phase increasingly passing as postsynaptic potentials (a type of

false positive; Figure 5H, red arrowheads). An effective solution to this problem would, therefore,

require isolating and measuring the noise component in whole-cell patch clamp recordings - which

currently is not implemented in either Mini Analysis or Clampfit (but is in 'minis').

An even more common error type was to miss (smaller) mEPSPs that occurred on the decay phase of

another, often larger, earlier mEPSP (Figures 5D and G; blue arrowheads). The amplitude of mEPSPs

occurring on decays is effectively reduced (as the peak drops relative to the baseline, due to the

underlying decay of V_m) and the steeper the decay, the more the amplitude is reduced. The

amplitude of such a reduced mini may fall below the detection threshold and/or shape distortions

may prevent fitting a template. As a result, such mEPSPs were occasionally discarded (this turns out

to be a significant problem with real minis recorded from cortical pyramidal neurons, which exhibit

significant temporal summation, because of their relatively high frequencies and slow decays). There

is no easy way of correcting these errors, as it would (for example) require estimating the underlying

decaying potential and subtracting it from the overall V_m or estimating the fall in the peak and

adding it back to the amplitude before deciding whether to accept that candidate putative mini.

mEPSPs that neither occurred during the rise nor decay phases were also occasionally missed

(Figures 5A, D, E, and F; black arrowheads). This could have happened due to a failure to fit a

template (Clampfit) or due to the amplitude being reduced below threshold by *downward*

background noise fluctuations. In recordings of real mEPSPs, these errors would mainly affect small

amplitude mEPSPs. Again, an effective solution to this problem would require isolating and

measuring the noise component in whole-cell patch clamp recordings similarly to previously

discussed errors occurring on the V_m rise phase.

A whole other class of detection errors appeared in the form of false alarms (false positives)

occurring on the rising (Figure 5E; red arrowhead) or decaying phases (Figures 5A, B, and H; red

arrowheads) of underlying mEPSPs or in the absence of any other minis in the vicinity (Figures 5B

and H; red arrowheads). These mistakes were often caused by *upward* background noise

fluctuations passing as real minis and might have been 'enabled' by low amplitude detection

thresholds or an inability to discern shapes of real minis from mini-like noise. Just like the previously

discussed error type, a solution would require isolating and measuring properties of the noise

component. In addition, there were errors that uniquely affected only one of the algorithms, like the

misplacement of detected events (peaks) by Mini Analysis (Figure 5C; green arrowheads).

We saw that distinct detection errors could be made depending on how close they were to

neighbouring mEPSPs and whether they occurred on the rise or decay phases of other nearby

mEPSPs or in the absence of any other mEPSPs in the background. All three algorithms occasionally

committed these errors, but their incidence was uneven.

Detection under a wide range of frequency conditions: the membrane potential 'slope trend' effect

In order to quantify the detection performance in different circumstances, for the same ~0.3 mV

smEPSPs, we evaluated the probability of making errors in relation to the *proximity* to neighbouring

minis and the phase (*trend*) of the background V_m: rising or decaying. We looked at TPR as a function

of time interval to the nearest-neighbour mini (Figure 6A) taken together for all minis frequency

conditions used above (but excluding conditions where noise was scaled): i.e., 640, 320, 160, 80, 40,

20, 10, 5, and 2.5 minis/s conditions (9 in total). We found that detection was superior for our 'minis'

program across the entire inter-mini interval range. Mini Analysis came second, with Clampfit

consistently worst. These differences in detection performance were also reflected in the *cumulative*

TPR (Figure 6D). As for the FPR (Figure 6B), 'minis' was superior at detecting ~0.3 mV smEPSPs that

were within 10 ms of the nearest neighbour (peak-to-peak). This performance edge over Mini

Analysis was not maintained for larger inter-mini peak intervals, while Clampfit again showed

consistently the worst performance across the entire interval range. These performance differences

were also reflected in the *cumulative* FPR (Figure 6E). Taken together, true and false positive rates

allowed as to calculate a combined performance indicator, sensitivity index d', as a function of time

to the nearest neighbour (Figure 6C). The combined measure indicated that 'minis' had the superior

detection performance within 10 ms of the nearest neighbour while Clampfit showed the worst

performance across the entire inter-mini interval range.

During the V_m rise phase performance differences were unequivocal. There were very few events

and, therefore, positive detections when the background V_m was rising at 200 µV/s or faster (Figure

7D). Most of the detected events coinciding with the rise phase actually occurred when V_m was

changing at the rate of 10 to 100 µV/s. In this range 'minis' showed the best detection performance

with d' between 1 and 2 (Figure 7C). Mini Analysis was the second best, while Clampfit showed the

worst performance. This order of performance was maintained for rates below 10 µV/s with overall

performance improving for all algorithms. The performance edge of 'minis' over the other

algorithms was primarily due to low FPR (Figure 7B). The TPR of 'minis' was also superior to the

other two algorithms but, in terms of sensitivity, Mini Analysis was not far behind (Figure 7A). In the

range between 15 and 35 µV/s 'minis' actually fell slightly behind Mini Analysis. The cumulative rates

clearly supported the observation that 'minis' was superior to the other two algorithms with Mini

Analysis coming second and Clampfit having the worst performance (Figures 7D and E).

The same behaviour of the three algorithms was also observed for detecting ~0.3 mV smEPSPs

occurring on the decay phase of the background V_m (caused by summation of other smEPSPs). Most

of the detected simulated events were associated with rates of V_m change in the range of -100 and -

10 µV/s (Figure 8D). In this range and above, 'minis' demonstrated the best performance relative to

the other two algorithms with d' ranging between 1.5 and 2.5 (Figure 8C). Mini Analysis again came

second, while Clampfit showed very poor performance. Clampfit often had a d' that was close to 0,

meaning that its performance was often not different from chance level when background V_m was

decaying. This was mainly due to the large FPR for this algorithm (Figure 8B); 'minis' had

unequivocally the highest TPR and the lowest FPR (Figures 8A and B) with cumulative rates very

clearly reflecting this (Figures 8D and E). The overall performance of the runner-up, Mini Analysis,

was substantially poorer.

Detection under realistic frequency conditions (20, 40, 80 minis/s)

Data points used to construct the full virtual ROC curve include frequency and noise conditions that

were not necessarily realistic. Based on our calculations, the range of mEPSP frequencies one might

commonly expect during real recordings from neocortical pyramidal neurons is likely to be between

10 and 100 minis/s (see above; also G.M., unpublished experimental observations); In Figures 4A and

B, 20, 40 and 80 minis/s (from right to left) are highlighted by open circles. Just as across the entire

ROC curve, the performance of 'minis' was superior in this frequency range compared to the other

two algorithms with Mini Analysis coming second, and Clampfit being worst, by a substantial margin.

Other measures like true positive and false positive rates as functions of the time to the nearest

neighbour and V_m rate of change during the rise or decay phases pointed to a very similar conclusion

made regarding the full ROC curve. First, we found that 'minis' performed better than other

algorithms at detecting mEPSPs that were within 10 ms of other mEPSPs and that at longer delays

Mini Analysis performed just as well (Figure 9). Meanwhile, Clampfit performed consistently worst

across the range of inter-mini intervals, whether measured by d' (Figure 9C) or true positive and

false positive rates (Figures 9A, B, D, and E). When it came to V_m rate of change, 'minis' consistently

showed the best performance at detecting smEPSPs occurring with the background V_m rate of

change ranging between -40 and 100 µV/s (Figures 10 and 11). This is the range where the vast

majority of simulated events occurred (Figures 10D and 11D). In terms of individual TPR and FPR

(Figures 10A and B and 11A and B) and cumulative rates (Figures 10D and E and 11D and E), the

conclusions are much the same as those made regarding the full virtual ROC curve. Namely, that

'minis' had the largest TPR and the smallest FPR with an exception being the TPR in relation to rising

background (simulated) membrane potential trends (Figures 10A and D), with there being a range

(45-100 µV/s) where Mini Analysis had a slightly higher TPR, but not overall performance measured

as d' (Figure 10C). Similar to conditions used to construct the full ROC curve, Clampfit showed

consistently the worst performance by all measures. The performance of all three algorithms was

better with realistic smEPSP frequencies (Figures 10C and 11C) than over the full 'virtual' ROC curve

(Figures 7C and 8C). In summary, evaluation of detection of mEPSPs simulated at realistic

frequencies supported conclusions made regarding detection performance under a much broader

range of simulation frequencies.

Algorithm performance comparison for detecting simulated excitatory postsynaptic potentials

with a wide set of discrete amplitudes, at realistic frequencies

So far, we have only tested performance of the three algorithms when detecting moderately-sized

(0.3 mV ± s.d. 0.05 mV) mEPSPs with a relatively narrow range of amplitudes. The existing evidence

does not indicate that either mPSPs or mPSCs form a distinct amplitude distribution that can be

separated from the amplitude distribution of noise fluctuations. Therefore, here we aimed to test

the performance of detecting smEPSPs of a wide range of amplitudes, to evaluate the three

algorithms in more realistic settings.

We used three frequency conditions: 13, 33, and 53 minis/s. Within each of these conditions

smEPSPs were drawn pseudo-randomly from a uniform distribution of the following twelve discrete

amplitudes: 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, and 0.6 mV (4 different

simulations per noise trace per frequency conditions; see Methods for shapes). Just like in previous

simulations, we positioned these smEPSPs pseudo-randomly over noise recordings and detected

them using the three algorithms. The overall performance of these algorithms is shown in terms of

true and false positive rates in Figure 12A and d' in Figure 12B. A few things are prominent in these

graphs. First of all, the detection performance of all algorithms was considerably worse than when

detecting moderately-sized (~0.3 mV) mEPSPs. Secondly, 'minis' again had the edge over two other

algorithms, especially at higher mini frequencies. Third, Clampfit's performance was consistently the

poorest, in our hands.

Performance was also assessed pooling the frequency conditions. We found 'minis' to have the best

performance with the mean AUC value of 0.827 ± 0.003 (95% confidence interval from here on;

Figure 12C). A paired samples t-test comparing to Mini Analysis with the mean AUC value of 0.809 ±

0.003 gave p = 1.0×10^{-6}. Clampfit showed the poorest performance, with the mean AUC value of

0.665 ± 0.004, p = 2.2×10^{-10} when compared to the Mini Analysis mean AUC value in a paired

samples t-test. These differences in detection performance were further corroborated by the d'

measure averaged across all frequency conditions (Figure 12D). The d' discriminability index scores

of 'minis' (1.5 ± 0.05) and Mini Analysis (1.33 ± 0.04) were significantly different (p < 10^{-5}), as were

the d' from Mini Analysis and Clampfit (0.61 ± 0.02) (p < 4×10^{-6}) The conclusion based on combined

measures was in line with the assessment based on Individual frequency conditions.

Other measures like true positive and false positive rates as functions of the interval to the nearest

neighbour and V_m rate of change during the rise or decay phases using more realistic settings

pointed to a very similar conclusion to that made with the full virtual ROC curve. First, we found that

'minis' performed better than the other algorithms at detecting mEPSPs that were within 10 ms of

other mEPSPs, and that at larger intervals, Mini Analysis performed just as well (Figure 13).

Meanwhile, Clampfit performed consistently the worst across the range of inter-mini intervals

whether in terms of d' (Figure 13C) or true and false positive rates (Figures 13A, B, D, and E). When it

came to V_m rate of change, 'minis' performed better than Mini Analysis, which in turn performed

better than Clampfit when detecting smEPSPs occurring during rise and decay phases of background

simulated V_m (Figures 14 and 15). One difference compared to the full virtual ROC curve analysis was

that the detection performance of 'minis' and Mini Analysis overlapped in the range of 15-25 μV/s

when detecting smEPSPs occurring on the rise phase of the background V_m (Figure 14C). This is

largely caused by an increased FPR of 'minis' in this rate range (Figure 14B). The overall performance

of all algorithms was better (Figures 14C and 15C) compared to the full virtual ROC curve analysis

(Figures 7C and 8C), but still worse when compared to detecting moderately-sized (~0.3 mV)

smEPSPs with realistic frequencies (Figures 10C and 11C), as described in the previous subsection. In

summary, 'minis' had a substantial advantage when detecting minis in close proximity to

neighbouring minis, as well as during rising or falling background V_m, with Clampfit severely

underperforming.

Discussion

Our analysis suggests that 'mini' (mEPSC/P) frequencies typically reported in neocortical slices in the CNS synaptic function literature may be underestimated, by up to an order of magnitude. Minis are missed in part because of voltage clamp errors – a combination of space clamp errors and failures to adequately compensate series resistance – allowing charge to escape from the voltage clamp and spread to other parts of the dendritic and axonal trees, and the resulting amplitude attenuation due to filtering by the resistive and capacitive properties of dendritic membranes (Rall and Segev, 1985; Major, 1993; Spruston et al., 1993; Stuart and Spruston, 1998; Williams and Stuart, 2002; Nevian et al., 2007; Williams and Mitchell, 2008). This and other evidence (overlapping noise and minis histograms, many dendritically-detected minis being undetectable at the soma, Nevian et al. 2007) indicates there is no objective cut-off between the amplitude distributions of real mEPSP/Cs and noise fluctuations from other sources. Although using voltage recording (current clamp) addresses voltage clamp errors, the amplitude of mPSPs is also attenuated by dendritic trees (Williams and Stuart, 2002; Nevian et al., 2007; Larkum et al., 2009) as charge spreads away from the input site (synapse). These observations are a serious problem for the standard approach of using direct amplitude measurements of somatic mPSPs or mPSCs, by themselves, as an estimate of quantal size distributions in the CNS. The method essentially becomes a 'beauty contest', as arbitrary decisions have to be made about what is noise and what is a real mini, further confounded by the issue of a substantial fraction of missed minis.

The same method could, however, be used to objectively measure the properties of pure noise fluctuations (with minis blocked). This would allow one, in principle, to separate 'signal' (minis) from noise components in traces of minis recorded in the presence of noise. As the first step, we developed an effective mPSP/C detection algorithm, called 'minis'. We quantified the performance of 'minis' using standard measures from signal detection theory – namely, ROC (receiver operating

characteristic) curves and sensitivity index d', alongside measures of sensitivity – true positive rate

(TPR) and false positive rate (FPR = 1 – specificity) – and demonstrated superior performance of our

algorithm relative to the other two most popular algorithms in the field of minis research: Mini

Analysis and Clampfit. Our algorithm had a performance edge over the other two algorithms not

only for detecting moderately-sized (~0.3 mV) mEPSPs, but also across a wide range of realistic

mEPSP amplitudes, shapes and frequencies. Crucially, the latter included the higher mini frequencies

observed in neocortical slice experiments at body temperature, 13-80 minis/s, where temporal

summation becomes an increasing challenge for detection. As a necessary step in building a reliable

quantal size estimation method, we succeeded in developing an algorithm for detecting postsynaptic

events that is transparent, systematically evaluated, and flexible.

Notwithstanding its good performance, the 'minis' algorithm has important limitations. First, the

'minis' algorithm, just like the other two detection algorithms, cannot by itself alone be used to

estimate quantal sizes. Due to amplitude attenuation of spontaneous postsynaptic events and the

need to use amplitude detection thresholds, the estimated amplitude will generally only be an upper

limit on the actual population mean amplitude. We have also demonstrated that mini detection is

impaired on rising and decaying trends of V_m. The severity of this problem worsens with the rate of

change of V_m. The problem is exacerbated as the time between neighbouring minis gets shorter.

Therefore, the mean amplitude estimate is not only affected by the presence of noise and by

amplitude attenuation, but also by the presence of other miniature postsynaptic events. All the

above limitations also apply to estimating the frequency of postsynaptic events. All the mentioned

factors reduce event detectability and, therefore, result in an underestimated frequency. However,

'detecting' noise events as false minis can cause errors in the other direction if too low a detection

threshold is set. Despite these limitations, our program 'minis' fares better on this front compared to

the other two algorithms: 'minis' performance is also superior on rising and decaying trends in V_m,

and for closely-spaced events. To our knowledge, this is the first time these problems have been

addressed, and their impact quantified in a systematic manner, and their implications discussed.

Other caveats concern the method for assessing the performance of detection algorithms. We did

not use the full plausible range of realistic distributions for simulating mEPSPs in terms of their

frequencies, amplitudes, and their rise and decay times. However, the shapes of these distributions

are not entirely known, and this is an empirical question that remains unanswered. Because of this

reason, we refrained for trying to address this question here and avoided making empirically

dubious assumptions. Instead, we explored a range of scenarios where simulation frequencies

ranged from more to less realistic. We explored the effects of varying signal/noise ratios. We believe

that the large size of the parameter space we have explored does allow us to conclude that the three

algorithms differ systematically in their performance, with our algorithm – 'minis' – being superior to

the other two (in our hands at least).

We have not constructed ROC curves in the usual fashion by varying a detection threshold of each

algorithm. Unfortunately, we were limited by the nature of the algorithms, specifically Clampfit

which does not use a pure amplitude detection threshold but uses convolution of the data trace with

each of the templates. However, our manipulations of varying the frequency of simulated events, as

well as varying the amplitude of noise, allowed us to mimic effects of varying the detection

threshold. We are also aware of one particular issue regarding the classification of correct rejections

(true negatives). One could argue that a proper definition of correct rejections would require

treating every data sample point as a potential noise event that could either be falsely detected as a

signal event or correctly rejected as a noise event. Unfortunately, such a definition would result in

large numbers of correct rejections (true negatives) swamping the number of other detection

measures (true positives, false alarms (false positives), and misses (false negatives)) and, therefore,

would make the detection performance analysis essentially meaningless. Alternatively, treating

every 10 ms noise window as a basis for correct rejection would still produce a relatively large

number of correct rejections, as would similar, more complicated schemes. There is also no reason

why a single noise event should be limited to a single 10 ms window. Therefore, we thought that a

reasonably practical definition of correct rejections as rejected prominent noise fluctuations fared

better than the alternatives. Having explicit, transparent, and reproducible, methods to benchmark

the performance is better than relying on subjective examination of recording traces.

Finally, we would like to address the question of whether we used optimal detection settings for

each algorithm. Mini Analysis settings were similar to those of 'minis'. The two algorithms are

somewhat similar and chosen settings were observed to give the best performance for both

algorithms when detecting simulated mPSPs, after considerable exploration. In case there is any

doubt about our method, we have made our recorded and simulated data and Matlab analysis code

publicly available. With regards to using Clampfit to analyse simulated data, we used 9 templates

(the maximum allowed) constructed in a typical fashion by averaging a number of waveforms with

similar shapes but separating qualitatively different shapes. These templates have also been made

available publicly. We tested different detection regimes with templates based on both smoothed or

unsmoothed traces and comparing detection of smoothed and unsmoothed recording traces and

chose the best regime. However, we did not construct new templates for every new recording or

every new simulation condition, because this is extremely time-consuming and is not an efficient

way to conduct this type of analysis, although Clampfit detection performance might have improved

marginally. Clampfit might perform better if the number of templates was not limited to 9, and if a

wide range of inbuilt templates was available. These issues are, however, outside the scope of this

study. Given these considerations, we are confident in the validity of our approach.

In the discussion of errors made by different detection algorithms, we alluded to the usefulness of

being able to estimate properties of V_m noise fluctuations. Noise events could potentially be

'removed' from the combined signal and noise event distribution by direct histogram subtraction,

although in practice it turns out one needs to compensate for the decay of the underlying waveform,

following minis (MD & GM, unpublished observations). Alternatively, noise traces can be used to

more accurately 'reverse-engineer' the signal distribution via simulations, by iteratively adjusting the

shapes, amplitudes, and frequencies of simulated minis, and adding these to real noise, under the

control of an optimisation algorithm to match up the distributions of *simulated* minis plus real noise

to *real* minis plus real noise. A future paper will explore this and present a quantal analysis method

based on the 'minis' spontaneous postsynaptic event detection algorithm.

References

Bekkers JM (1994) Quantal analysis of synaptic transmission in the central nervous system. Curr Opin Neurobiol 4:360–365.

Biró ÁA, Holderith NB, Nusser Z (2005) Quantal Size Is Independent of the Release Probability at Hippocampal Excitatory Synapses. The Journal of Neuroscience 25:223–232.

Brown TH, Wong RKS, Prince DA (1979) Spontaneous miniature synaptic potentials in hippocampal neurons. Brain Res 177:194–199.

Clamann HP, Rioult-Pedotti MS, Luscher HR (1991) The influence of noise on quantal EPSP size obtained by deconvolution in spinal motoneurons in the cat. J Neurophysiol 65:67–75.

Clements JD (2003) Variance–mean analysis: a simple and reliable approach for investigating synaptic transmission and modulation. J Neurosci Methods 130:115–125.

Clements JD, Silver RA (2000) Unveiling synaptic plasticity: a new graphical and analytical approach. Trends Neurosci 23:105–113.

del Castillo J, Katz B (1954) Quantal components of the end-plate potential. J Physiol 124:560–573.

Dervinis M (2023a) Intracellular membrane potential noise recordings and mEPSP simulations in cortical pyramidal cells used to benchmark "minis" software. G-Node. https://doi.org/10.12751/g-node.inpx5x.

Dervinis M (2023b) dervinism/minis-benchmarking. Zenodo. https://doi.org/10.5281/zenodo.8336130.

Dervinis M (2023c) dervinism/minis. Zenodo. https://doi.org/10.5281/zenodo.8336025.

Edwards FR, Redman SJ, Walmsley B (1976) Statistical fluctuations in charge transfer at Ia synapses on spinal motoneurones. J Physiol 259:665–688.

Enoki R, Hu Y, Hamilton D, Fine A (2009) Expression of Long-Term Plasticity at Individual Synapses in Hippocampus Is Graded, Bidirectional, and Mainly Presynaptic: Optical Quantal Analysis. Neuron 62:242–253.

Eyal G, Verhoog MB, Testa-Silva G, Deitcher Y, Benavides-Piccione R, DeFelipe J, de Kock CPJ, Mansvelder HD, Segev I (2018) Human Cortical Pyramidal Neurons: From Spines to Spikes via Models. Front Cell Neurosci 12:1–24.

Fatt P, Katz B (1952) Spontaneous subthreshold activity at motor nerve endings. J Physiol 117:109–128.

Forti L, Bossi M, Bergamaschi A, Villa A, Malgaroli A (1997) Loose-patch recordings of single quanta at individual hippocampal synapses. Nature 388:874–878.

Hardingham NR, Read JCA, Trevelyan AJ, Nelson JC, Jack JJB, Bannister NJ (2010) Quantal Analysis Reveals a Functional Correlation between Presynaptic and Postsynaptic Efficacy in Excitatory Connections from Rat Neocortex. The Journal of Neuroscience 30:1441–1451.

Heuser JE, Reese TS, Dennis MJ, Jan Y, Jan L, Evans L (1979) Synaptic vesicle exocytosis captured by
quick freezing and correlated with quantal transmitter release. Journal of Cell Biology 81:275–
300.

Holler S, Köstinger G, Martin KAC, Schuhknecht GFP, Stratford KJ (2021) Structure and function of a
neocortical synapse. Nature 591:111–116.

Isaacson JS, Walmsley B (1995) Counting quanta: Direct measurements of transmitter release at a
central synapse. Neuron 15:875–884.

Jack JJ, Redman SJ, Wong K (1981) The components of synaptic potentials evoked in cat spinal
motoneurones by impulses in single group Ia afferents. J Physiol 321:65–96.

Jonas P, Major G, Sakmann B (1993) Quantal components of unitary EPSCs at the mossy fibre
synapse on CA3 pyramidal cells of rat hippocampus. J Physiol 472:615–663.

Katz B (1969) The Release of Neural Transmitter Substances. Liverpool: Liverpool Univ. Press.

Korn H, Faber DS (1991) Quantal analysis and synaptic efficacy in the CNS. Trends Neurosci 14:439–
445.

Kraszewski K, Grantyn R (1992) Unitary, quantal and miniature gaba-activated synaptic chloride
currents in cultured neurons from the rat superior colliculus. Neuroscience 47:555–570.

Kullmann DM, Nicoll RA (1992) Long-term potentiation is associated with increases in quantal
content and quantal amplitude. Nature 357:240–244.

Kuno M (1964) Quantal components of excitatory synaptic potentials in spinal motoneurones. J
Physiol 175:81–99.

Larkman A, Stratford K, Jack J (1991) Quantal analysis of excitatory synaptic action and depression in
hippocampal slices. Nature 350:344–347.

Larkman AU (1991) Dendritic morphology of pyramidal neurones of the visual cortex of the rat: III.
Spine distributions. Journal of Comparative Neurology 306:332–343.

Larkum ME, Nevian T, Sandler M, Polsky A, Schiller J (2009) Synaptic Integration in Tuft Dendrites of
Layer 5 Pyramidal Neurons: A New Unifying Principle. Science (1979) 325:756–760.

Liu Z et al. (2022) Sustained deep-tissue voltage recording using a fast indicator evolved for two-
photon microscopy. Cell 185:3408-3425.e29.

Macmillan NA, Creelman CD (2005) Detection theory: A user's guide, 2nd ed. Mahwah, NJ, US:
Lawrence Erlbaum Associates Publishers.

Major G (1993) Solutions for transients in arbitrarily branching cables: III. Voltage clamp problems.
Biophys J 65:469–491.

Major G, Evans JD, Jack JJ (1993) Solutions for transients in arbitrarily branching cables: I. Voltage
recording with a somatic shunt. Biophys J 65:423–449.

Major G, Larkum ME, Schiller J (2013) Active Properties of Neocortical Pyramidal Neuron Dendrites.
Annu Rev Neurosci 36:1–24.

Motta A, Berning M, Boergens KM, Staffler B, Beining M, Loomba S, Hennig P, Wissler H,
Helmstaedter M (2019) Dense connectomic reconstruction in layer 4 of the somatosensory
cortex. Science (1979) 366:eaay3134.

Murthy VN, Stevens CF (1999) Reversal of synaptic vesicle docking at central synapses. Nat Neurosci
2:503–507.

Nevian T, Larkum ME, Polsky A, Schiller J (2007) Properties of basal dendrites of layer 5 pyramidal
neurons: a direct patch-clamp recording study. Nat Neurosci 10:206–214.

Oertner TG, Sabatini BL, Nimchinsky EA, Svoboda K (2002) Facilitation at single synapses probed with
optical quantal analysis. Nat Neurosci 5:657–664.

Peled ES, Isacoff EY (2011) Optical quantal analysis of synaptic transmission in wild-type and rab3-
mutant Drosophila motor axons. Nat Neurosci 14:519–526.

Rall W (1977) Core Conductor Theory and Cable Properties of Neurons. In: Handbook of physiology,
cellular biology of neurons (Kandel ER, Brookhardt JM, Mountcastle VM, eds), pp 39–97.
Bethesda, MD: American Physiological Society.

Rall W, Segev I (1985) Space-clamp problems when voltage clamping branched neurons with
intracellular microelectrodes. In: Voltage and Patch Clamping with Microelectrodes (T. G. Smith
Jr, Lecar H, Redman SJ, Gage P, eds), pp 191–215. Bethesda, MD: American Physiological
Society.

Redman S (1990) Quantal analysis of synaptic potentials in neurons of the central nervous system.
Physiol Rev 70:165–198.

Reid CA, Clements JD (1999) Postsynaptic expression of long-term potentiation in the rat dentate
gyrus demonstrated by variance-mean analysis. J Physiol 518:121–130.

Sahara Y, Takahashi T (2001) Quantal components of the excitatory postsynaptic currents at a rat
central auditory synapse. J Physiol 536:189–197.

Silver RA (2003) Estimation of nonuniform quantal parameters with multiple-probability fluctuation
analysis: theory, application and limitations. J Neurosci Methods 130:127–141.

Spruston N, Jaffe DB, Williams SH, Johnston D (1993) Voltage- and space-clamp errors associated
with the measurement of electrotonically remote synaptic events. J Neurophysiol 70:781–802.

Stern P, Edwards FA, Sakmann B (1992) Fast and slow components of unitary EPSCs on stellate cells
elicited by focal stimulation in slices of rat visual cortex. J Physiol 449:247–278.

Stuart G, Spruston N (1998) Determinants of Voltage Attenuation in Neocortical Pyramidal Neuron
Dendrites. The Journal of Neuroscience 18:3501–3510.

Vere-Jones D (1966) SIMPLE STOCHASTIC MODELS FOR THE RELEASE OF QUANTA OF TRANSMITTER
FROM A NERVE TERMINAL. Australian Journal of Statistics 8:53–63.

Wall MJ, Usowicz MM (1998) Development of the quantal properties of evoked and spontaneous
synaptic currents at a brain synapse. Nat Neurosci 1:675–682.

Williams SR, Mitchell SJ (2008) Direct measurement of somatic voltage clamp errors in central
neurons. Nat Neurosci 11:790–798.

Williams SR, Stuart GJ (2002) Dependence of EPSP Efficacy on Synapse Location in Neocortical
Pyramidal Neurons. Science (1979) 295:1907–1910.

Yuste R, Majewska A, Cash SS, Denk W (1999) Mechanisms of Calcium Influx into Hippocampal
Spines: Heterogeneity among Spines, Coincidence Detection by NMDA Receptors, and Optical
Quantal Analysis. The Journal of Neuroscience 19:1976–1987.

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Figure 1: A Schematic representation of key steps in 'minis' detection algorithm.

An illustration of a step-by-step application of the mPSP/C detection algorithm using simulated data.

Numbered steps dealing with mini peaks/amplitudes are shown in red, steps used to determine the

baseline are shown in blue. Briefly, the steps are:

1. Bandstop filter (against mains).

2. Lowpass filter to remove high frequency noise.

3. Find peaks.

4. Discard smaller peaks with the peak integration period represented by the length of the

    bracket and the union symbol (∪).

5. Move to a higher peak (if exists) within the peak integration period discarding the earlier

    peak.

6. Position the baseline at a local minimum located within the time-to-peak period prior to the

    peak.

7. Position the baseline asymmetrically (80:20) around the minimum (colour change at the

inset).

8. Correct the start of the baseline if it overlaps with the previous peak.

9. Discard the peak if it falls outside the acceptable amplitude range (repeated three more

times).

10. Compare rise time halves to correct the baseline (can be repeated once more).

11. Repeat Step 9.

12. Compare rise time halves to correct the peak.

13. Repeat Step 9.

14. Correct the baseline if it significantly deviates from the 10%/20% rise time mark.

15. Repeat Step 9.

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Figure 2: Simulation and detection performance.

(A) An example of simulated membrane potential recording with average simulated mEPSP

frequency of 20 minis/s. The top voltage trace shows a brief segment with randomly timed smEPSPs

with random, normally-distributed amplitudes (μ_1= 0.3 mV, σ_1 = 0.05 mV) and 10-90% rise times

(drawn from the upper half of the distribution with $\mu_2 = 0.05$ ms, $\sigma_2 = 2.5$ ms); see Methods. Dotted

green vertical lines mark signal events corresponding to smEPSP peaks. The paler shaded colour

demarcates a 10-ms (± 5 ms) window for accepting the detection of a signal event. The second

traces from the top are corresponding recordings of V_m noise fluctuations (the 2nd recording phase:

'noise-alone' condition, in TTX and transmitter blockers), after initial filtering and smoothing (steps 1

and 2 of the 'minis' detection algorithm). Dotted vertical cyan lines indicate noise events; the shaded

colour demarcates a window of exclusion for correctly rejecting these events (see Methods). The V_m

third from the top trace is a hybrid one with smEPSPs added to the noise recording and with signal

events and noise 'events' indicated. The coloured V_m traces below show detection performance for

the three different algorithms.

(B) An example of simulated V_m recording with mEPSP frequency of 40 minis/s.

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Figure 3: Membrane potential rising, steady-ish and falling 'trend phases'.

(A) A short segment of a V_m trace showing five smEPSPs. Different V_m 'trend phases', based on the

overall upward or downward trend in *simulated* voltage, are marked in colour. Green arrows

indicate V_m points where the V_m rate of increase is assigned to the preceding mEPSP peak. The blue

arrow indicates a V_m point where the V_m rate of decay is assigned to the following mEPSP peak.

(B) Simulated V_m trace in (A) added to a noise recording. V_m 'trend phases' were determined in (A)

and are used to classify detected events in (B).

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Figure 4: Overall performance for detecting 'moderately'-sized smEPSPs (~0.3 mV).

(A) 'virtual' ROC (Receiver Operator Characteristic)-like curve showing performance for detecting

'moderately'-sized smEPSPs in terms of True Positive Rate TPR (sensitivity) and False Positive Rate

FPR (1 – specificity) for all three algorithms, averaged across all 14 cells. In each case, dataset varies

from point to point, as opposed to detection threshold itself (which is varied systematically in a

traditional ROC, using one dataset). Ideal performance would be a right-angle plot going vertically up

TPR-axis at FPR=0, then horizontally along the top of the plot at TPR=1; minis is close to ideal, and

superior to Mini Analysis, which is not too far from ideal (despite its 'missed minis' problems).

Clampfit is far from ideal. Different points represent 14 different frequency/signal-to-noise ratio

conditions, averaged across all 14 cells. Moving (generally) from bottom to top/left to right,

simulated minis rates and signal-to-noise ratio are decreasing. Vertical and horizontal bars indicate

95% confidence interval around each mean. The dotted diagonal line indicates chance performance.

The hollow circles mark three realistic smEPSP frequencies (80, 40, and 20 minis/s).

(B) Sensitivity (discriminability) index (d') in the same 14 conditions as in (A) for all three algorithms,

averaged across all 14 cells.

(C) 'Violin' plots for Area under the virtual-ROC curve in (A) for all three algorithms. Individual data

points represent the 14 individual recordings (cells), horizontally 'swarmed' to avoid overlaps. AUC

(Area Under Curve) is averaged across all 14 frequency/signal-to-noise conditions for each cell for

each detection algorithm. The mean is marked by a solid line over the 'violin' centre. The dashed line

indicates the 95% confidence limits of the mean, and coloured shapes indicate the approximate

(smoothed) probability densities (wider = higher probability of those values).

**** indicates (highly) significantly different at $p \leq 10^{-5}$ level, paired t-test.

(D) Similar plot for sensitivity index d' averaged across all 14 frequency/signal-to-noise conditions for

each cell and each detection algorithm.

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Figure 5: Moderately-sized (~0.3 mV) smEPSPs (40 minis/s): detection errors made by the three

algorithms.

(A-H) Examples of smEPSP detection errors commonly committed by the three algorithms. Traces in

blue, red, and magenta represent detection performance for 'minis', Mini Analysis, and Clampfit,

respectively. The top black trace shows actual smEPSPs. Vertical green dotted lines mark actual

individual (i.e., non-summated) smEPSP peak locations with the fainter shaded colour demarcating a

10-ms window for accepting the detection of an mEPSP. Arrowheads indicate common detection

errors made by the three algorithms. (Details in text).

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Figure 6: Performance when detecting moderately-sized (~0.3 mV) smEPSPs as a function of time to

the nearest neighbour (mean inter-mini peak-to-peak interval). Pale shaded colours indicate 95%

confidence intervals.

(A) True positive rate (TPR).

(B) False positive rate (FPR).

(C) Sensitivity index d' (undefined but arbitrarily high for TPR > 0 and FPR = 0, e.g. for inter-mini

intervals below 1 ms, for minis algorithm).

(D) Cumulative true positive rate (TPR) (cumulative true positives normalised by the total unbanded

true positive count and scaled by the overall unbanded TPR; see text for details).

(E) Cumulative FPR (cumulative false positives normalised by the total unbanded false positive count

and scaled by the overall unbanded FPR).

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Figure 7: Performance when detecting moderately-sized (~0.3 mV) smEPSPs on a rising trend V_m as a

function of the V_m rate of change. Paler shaded colours indicate 95% confidence intervals.

(A) True positive rate (TPR).

(B) False positive rate (FPR).

(C) Sensitivity index d'.

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 8: Performance when detecting moderately-sized (~0.3 mV) smEPSPs on the membrane

potential decaying trend phase as a function of the membrane potential rate of change. Paler

shaded colours indicate 95% confidence intervals.

(A) True positive rate (TPR)

(B) False positive rate (FPR).

(C) Sensitivity Index d'.

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 9: Performance when detecting moderately-sized (~0.3 mV) smEPSPs as a function of time to

the nearest neighbour with realistic mini rates (20, 40, 80 minis/s). Paler shaded colours indicate

95% confidence intervals.

(A) True positive rate (TPR).

(B) False positive rate (FPR).

(C) Sensitivity index d' (undefined but arbitrarily high for TPR > 0 and FPR = 0, e.g. for inter-mini

intervals below 1 ms, for minis algorithm).

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 10: Performance when detecting moderately-sized (~0.3 mV) smEPSPs on the rising trend V_m

phases with realistic mini rates (20, 40, 80 minis/s, as in Fig. 9), as a function of the rate of change of

V_m. Pale shaded colours indicate 95% confidence intervals.

(A) True positive rate (TPR)

(B) False positive rate (FPR).

(C) Sensitivity index d'.

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 11: Performance when detecting moderately-sized (~0.3 mV) smEPSPs on the membrane

potential decay phase with realistic minis rates (20, 40, 80 minis/s, as in Figs. 9 and 10). Pale shaded

colours indicate 95% confidence intervals.

(A) True positive rate (TPR) when detecting moderately-sized smEPSPs on the V_m decay phase as a

function of the V_m rate of change.

(B) False positive rate (FPR).

(C) Sensitivity index d'.

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 12: Overall performance for detecting smEPSPs of various (realistic) discrete amplitudes at

'realistic' mini rates (details in text).

(A) Partial virtual "ROC" curve showing performance for detecting small-to-large-sized smEPSPs (0.05

to 0.6 mV in increments of 0.05 mV selected and added at random to a noise trace from each of the

14 cells) in terms of TPR (sensitivity) and FPR (1 – specificity) for all three algorithms. Moving from

left to right different data points represent 3 different biologically realistic frequency conditions: 53,

33, and 13 minis/s. Vertical and horizontal bars indicate 95% confidence interval around the mean.

The dotted diagonal line indicates chance performance.

(B) Sensitivity index (d') when detecting smEPSPs in the same 3 conditions as in (A) for all three

algorithms.

(C) Area under the virtual-ROC curve in (A) for all three algorithms. Individual data points represent

individual recordings (n=14 cells), averaged over the three simulated minis frequencies. The mean is

marked by a solid line over the violin centre. The dashed line indicates the 95% confidence limits.

**** indicates (highly) significantly different at $p \leq 10^{-5}$ level, paired t-test.

(D) Sensitivity index d' averaged across all three simulated minis frequencies, for each cell (n=14),

separately for each detection algorithm.

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Figure 13: Performance for detecting smEPSPs of various (realistic) discrete amplitudes as a function

of the time to the nearest neighbour.

(A) True positive rate (TPR) when detecting smEPSPs of various discrete amplitudes (0.05 to 0.6 mV

in increments of 0.05 mV) added at random to noise waveforms, as in previous figure, as a function

of the time to the nearest neighbour. Pale shaded colours indicate 95% confidence intervals.

(B) False positive rate (FPR).

(C) d' (undefined but arbitrarily high for TPR > 0 and FPR = 0, e.g. for inter-mini intervals below 1 ms,

for minis algorithm).

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 14: Performance for detecting smEPSPs of (realistic) discrete amplitudes on the membrane

potential rise phase.

(A) True positive rate (TPR) when detecting smEPSPs of various amplitudes (0.05 to 0.6 mV in

increments of 0.05 mV, added at random to noise waveforms, as in the previous figure), on the V_m

rise phase as a function of the V_m rate of change. Pale shaded colours indicate 95% confidence

intervals.

(B) False positive rate (FPR).

(C) d'.

(D) Cumulative TPR.

(E) Cumulative FPR.

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Figure 15: Performance for detecting smEPSPs of (realistic) discrete amplitudes on the membrane

potential decay phase under realistic frequency conditions.

(A) True positive rate (TPR) when detecting smEPSPs of various amplitudes (0.05 to 0.6 mV in

increments of 0.05 mV, as in previous figure) on the V_m decay phase, as a function of the V_m rate of

change. Pale shaded colours indicate 95% confidence intervals.

(B) false positive rate (FPR).

(C) d'.

(D) Cumulative TPR.

(E) Cumulative FPR.