MEArec: a fast and customizable testbench simulator for ground-truth extracellular spiking activity

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Abstract

When recording neural activity from extracellular electrodes, both *in vivo* and *in vitro*, spike sorting is a required and very important processing step that allows for identification of single neurons' activity. Spike sorting is a complex algorithmic procedure, and in recent years many groups have attempted to tackle this problem, resulting in numerous methods and software packages. However, validation of spike sorting techniques is complicated. It is an inherently unsupervised problem and it is hard to find universal metrics to evaluate performance. Simultaneous recordings that combine extracellular and patch-clamp or juxtacellular techniques can provide ground-truth data to evaluate spike sorting methods. However, their utility is limited by the fact that only a few cells can be measured at the same time. Simulated ground-truth recordings can provide a powerful alternative mean to rank the performance of spike sorters. We present here `MEArec`, a Python-based software which permits flexible and fast simulation of extracellular recordings.

`MEArec` allows users to generate extracellular signals on various customizable electrode designs and can replicate various problematic aspects for spike sorting, such as bursting, spatio-temporal overlapping events, and drifting. We expect `MEArec` will provide a common testbench for spike sorting development and evaluation, in which spike sorting developers can rapidly generate and evaluate the performance of their algorithms.

keywords: Spike sorting; Benchmark data; Extracellular recordings simulator; Open-source software

Introduction

Extracellular neural electrophysiology is one of the most used and important techniques to study brain function. It consists of measuring the electrical activity of neurons from electrodes in the extracellular space, that pick up the electrical activity of surrounding neurons. To communicate with each other, neurons generate action potentials, which can be identified in the recorded signals as fast potential transients called *spikes*.

Since electrodes can record the extracellular activity of several surrounding neurons, a processing step called spike sorting is needed. Historically this has required manual curation of the data, which in addition to being time consuming also introduces human bias to data interpretations. In recent years, several automated spike sorters have been developed to alleviate this problems. Spike sorting algorithms [40, 28] attempt to separate spike trains of different neurons (units) from the extracellular mixture of signals using a variety of different approaches. After a pre-processing step that usually involves high-pass filtering and re-referencing of the signals to reduce noise, some algorithms first detect putative spikes above a detection threshold and then cluster the extracted and aligned waveforms in

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a lower-dimensional space [38, 41, 8, 22, 25]. Another approach consists of finding spike templates, using clustering methods, and then matching the templates recursively to the recordings to find when a certain spike has occurred. The general term for these approaches is template-matching [37, 43, 10]. Other approaches have been explored, including the use of independent component analysis [24, 3] and semi-supervised approaches [27].

The recent development of high-density silicon probes both for *in vitro* [2, 13] and *in vivo* applications [35, 26] poses new challenges for spike sorting [42]. The high electrode count calls for fully automatic spike sorting algorithms, as the process of manually curating hundreds or thousands of channels becomes more time consuming and less manageable. Therefore, spike sorting algorithms need to be be capable of dealing with a large number of units and dense probes. To address these requirements, the latest developments in spike sorting software have attempted to make algorithms scalable and hardware-accelerated [37, 25, 43].

The evaluation of spike sorting performance is also not trivial. Spike sorting is unsupervised by definition, as the recorded signals are only measured extracellularly with no knowledge of the underlying spiking activity. A few attempts at providing ground-truth datasets, for example by combining extracellular and patch-clamp or juxtacellular recordings [21, 19, 35, 43, 31, 1] exist, but the main limitation of this approach is that only one or a few cells can be patched at the same time, providing very limited ground-truth information with respect to the number of neurons that can be recorded simultaneously from extracellular probes.

Biophysically detailed simulated data provide a powerful alternative and complementary approach to spike sorting validation [11]. In simulations, recordings can be built from known ground-truth data for all neurons, which allows one to precisely evaluate the performance of spike sorters. Simulators of extracellular activity should be able to replicate important aspects of spiking activity that can be challenging for spike sorting algorithms, including bursting modulation, spatio-temporal overlap of spikes, unit drifting over time, as well as realistic noise models. Moreover, they should allow users to have full control over these features and they should be efficient and fast.

In the last years, there have been a few projects aiming at developing neural simulators for benchmarking spike sorting methods [6, 18, 33]: Camunas et al. developed `NeuroCube` [6], a MATLAB-based simulator which combines biophysically detailed cell models and synthetic spike trains (a so called "hybrid approach") to simulate the activity of neurons close to a recording probe, while noise is simulated by the activity of distant neurons. `NeuroCube` is very easy to use with a simple and intuitive graphical user interface (GUI). The user has direct control of parameters to control the rate of active neurons, their firing rate properties, and the duration of the recordings. The cell models are shipped with the software and recordings can be simulated on a single electrodes or a tetrode. It is relatively fast, but the cell model simulations (using `NEURON` [7]) are re-simulated for every recording.

Hagen et al. developed `ViSAPy` [18], a Python-based simulator that uses multi-compartment simulation of single neurons to generate spikes, network modeling of point-neurons in NEST [9] to generate synaptic inputs onto the spiking neurons, and experimentally fitted noise. `ViSAPy` does not use a hybrid approach, as it runs a full network simulation in `NEURON` [7] and computes the extracellular potentials using `LFPy` [29, 17]. `ViSAPy` implements a Python application programming interface (API) which allows the user to set multiple parameters for the network simulation providing the synaptic input, the probe design, and the noise model generator. Cell models can be freely chosen and loaded using the `LFPy` package. Further, 1-dimensional drifting can be incorporated in the simulations by shifting the electrodes over time [12]. Learning to use the software and, in particular, tailoring the specific properties of the resulting spike trains, for example burstiness, requires some effort by the user. As the running of `NEURON` simulations with biophysically detailed neurons can be computationally expensive, the use of `ViSAPy` to generate long-duration spike-sorting benchmarking data is boosted by access to powerful computers.

Mondragon et al. developed a Neural Benchmark Simulator (`NBS`) [33] extending the `NeuroCube` software. `NBS` extends the capability of `NeuroCube` for using user-specific probes, and it combines the spiking activity signals (from `NeuroCube`), with low-frequency activity signals, and artifacts libraries shipped with the code. The user can set different weight parameters to assemble the spiking, low-

frequency, and artifact signals, but these three signal types are not modifiable.

Despite the existence of such tools for generating benchmarking data, their use in spike sorting literature has until now been limited, and the benchmarking and validation of spike sorting algorithms non-standardized and unsystematic. A natural question to ask is thus how to best stimulate the use of such benchmarking tools in the spike sorting community.

From a spike sorting developer perspective, we argue that an ideal extracellular simulator should be *i)* fast, *ii)* controllable, *iii)* biophysically detailed, and *iv)* easy to use. A fast simulator would enable spike sorter developers to generate a large and varied set of recordings to test their algorithms against and to improve their spike sorting methods. Controllability refers to the possibility to have direct control of features of the simulated recordings. The ideal extracellular spike simulator should include the possibility to use different cell models and types, to decide the firing properties of the neurons, to control the temporal and spatio-temporal synchrony of extracellular spikes, to generate recordings on different probe models, and to have full reproducibility of the simulated recordings. A biophysically detailed simulator should be capable of reproducing key physiological aspects of the recordings, including, but not limited to, bursting spikes, drifting between the electrodes and the neurons, and realistic noise profiles. Finally, to maximize the ease of use, the ideal extracellular simulator should be designed as an accessible and easy to learn software package. Preferably, the tool should be implemented with a graphical user interface (GUI), a command line interface (CLI), or with a simple application programming interface (API).

With these principles in mind, we present here `MEArec`, an open-source Python-based simulator. `MEArec` provides a fast, highly controllable, biophysically detailed, and easy to use framework to generate simulated extracellular recordings. In addition to producing benchmark datasets, we developed `MEArec` as a powerful tool that can serve as a testbench for optimizing existing and novel spike sorting methods. To facilitate this goal, `MEArec` allows users to explore how several aspects of recordings affect spike sorting, with full control of challenging features such as bursting activity, drifting, spatio-temporal synchrony, and noise effects, so that spike sorter developers can use it to help their algorithm design. Moreover, `MEArec` has an extensive documentation `https://mearec.readthedocs.io/` and the code is tested with a continuous integration platform[1].

Results

Getting started with `MEArec`: a simple tetrode dataset generation

One of the key goals of `MEArec` is to ease the simulation of extracellular recordings and make it fully reproducible. In order to demonstrate this, we first show and break down the commands used to generate a simple tetrode recording that we will to further characterize in the rest of the paper.

`MEArec`, at installation, comes with 13 layer 5 cortical cell models from the Neocortical Microcircuit Portal [39, 4]. This enables the user to dive into simulations without the need to download and compile cell models. On the other hand, the initial cell models can be easily extended by downloading more cell models and placing them in the cell models folder.

To generate 30 extracellular spikes (also referred as templates) per cell model recorded on a shank tetrode probe, the user can simply run this command:

```
>> mearec gen-templates -prb tetrode-mea-l -n 30 --seed 0
   ...
   Saved templates in path-to-templates-file.h5
```

The `-prb` option allows for choosing the probe model, `-n` controls the number of templates per cell model to generate, and the `--seed` option is used to ensure reproducibility and if it is not provided, a random seed is chosen. In both cases, the seed is saved in the `HDF5` file, so that the same templates can be perfectly replicated.

[1] `https://travis-ci.org/`

Once the templates are generated, recordings can be generated as follows:

```
>> mearec gen-recordings -t path-to-templates-file.h5 -d 30 -ne 4 -ni 2
   --st-seed 0 --temp-seed 1 --noise-seed 2
   ...
   Saved recordings in path-to-recordings-file.h5
```

The `gen-recordings` command combines the selected templates from 4 excitatory cells (`-ne 4`) and 2 inhibitory cells (`-ni 2`), that usually have a more narrow spike waveform and a higher firing rate, with randomly generated spike trains. The duration of the output recordings is 30 seconds (`-d 30`). In this case, three random seeds control the spike train random generation (`--st-seed 0`), the template selection (`--temp-seed 1`), and the noise generation (`--noise-seed 2`). Figure 1 shows one second of the generated recordings (A), the extracted waveforms and the mean waveforms for each unit on the electrode with the largest peak (B), and the principal component analysis (PCA) projections of the waveforms on the tetrode channels.

`MEArec` also implements a convenient Python API, which is run internally by the CLI commands. For example, the following snippet of code implements the same commands shown above for generating templates and recordings:

```python
import MEArec as mr

# generate templates
templates_params = mr.get_default_templates_params()
cell_models_folder = mr.get_default_cell_models()
templates_params['probe'] = 'tetrode-mea-l'
templates_params['n'] = 30
templates_params['seed'] = 0
tempgen = mr.gen_templates(cell_models_folder=cell_models_folder,
                           params=templates_params)
mr.save_template_generator_templates(tempgen, 'path-to-templates-file.h5')

# generate recordings
recordings_params = mr.get_default_recordings_params()
recordings_params['spiketrains']['n_exc'] = 4
recordings_params['spiketrains']['n_inh'] = 2
recordings_params['spiketrains']['duration'] = 30
recordings_params['spiketrains']['seed'] = 0
recordings_params['templates']['seed'] = 1
recordings_params['recordings']['seed'] = 2
recgen = mr.gen_recordings(params=recordings_params,
                           templates='path-to-templates-file.h5')
mr.save_recording_generator(recgen, 'path-to-recordings-file.h5')
```

Moreover, the Python API implements plotting functions to visually inspect the simulated templates and recordings. For example, Figure 1 panels were generated using the `plot_recordings()` (A), `plot_waveforms()` (B), and `plot_pca_map()` (C) functions.

`MEArec` overview

After having shown how to generate a recording in `MEArec`, we introduce here an overview of the software (Figure 2). The simulation is split in two phases: *templates generation* (Figure 2A) and *recordings generation* (Figure 2B).

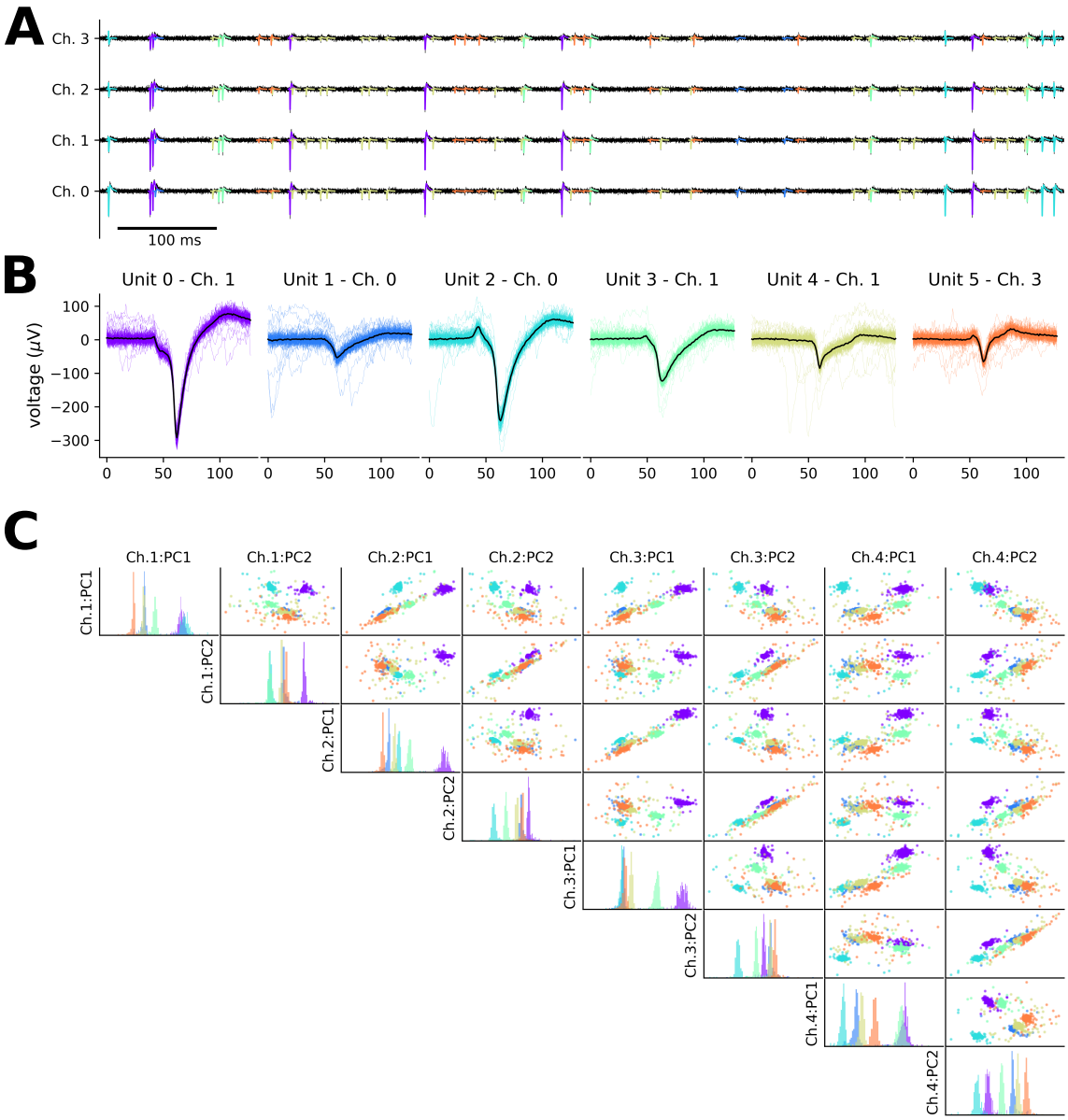

Figure 1: Example of simulated tetrode recording. (A) One second of the recording timeseries on the four tetrode channels. The templates for the different units are overlapped to the recording traces in different colors. (B) Extracted waveforms on the channel with the largest amplitude for the six units in the recordings. (C) PCA projections on the first two PC components of the four tetrode channels. Each color corresponds to a neuron. The diagonal plots display the histograms of the PC projection on the corresponding channel.

Templates (or extracellular action potentials) are generated using biophysically realistic cell models which are positioned in the surroundings of a probe model. The templates generation output is a library of a large variety of extracellular templates, which can then be used to build the recordings. The templates generation phase is the most time consuming, but the same templates library can be used to generate a virtually infinite number of different recordings.

Recordings are then generated by combining templates selected with user-defined rules (based on minimum distance between neurons, amplitudes, spatial overlaps, and cell-types) and by simulating spike trains. Selected templates and spike trains are assembled using a customized (or modulated) convolution, which can replicate interesting features of spiking activity such as bursting and drifting. After convolution, additive noise is generated and added to the recordings. Finally, the output recordings can be optionally filtered with a band-pass or a high-pass filter. For a full description of the templates and recordings generation, please refer to the Materials and Methods section.

`MEArec` is designed to allow for full customization, transparency, and reproducibility of the simulated recordings. Parameters for the templates and recordings generation are accessible by the user and documented, so that different aspects of the simulated signals can be finely tuned (see Materials and Methods for a list of parameters and their explanation). Moreover, the implemented command line interface (CLI) and simple Python API, enables the user to easily modify parameters, customize, and run simulations.

Finally, `MEArec` permits to manually set several random seeds used by the simulator to make recordings fully reproducible. This feature also enables one to study how separate characteristics of the recordings affect the spike sorting performance. As an example, we will show in the next sections how to simulate a recording sharing all parameters, hence with exactly the same spiking activity, but with different noise levels or drifting velocities.

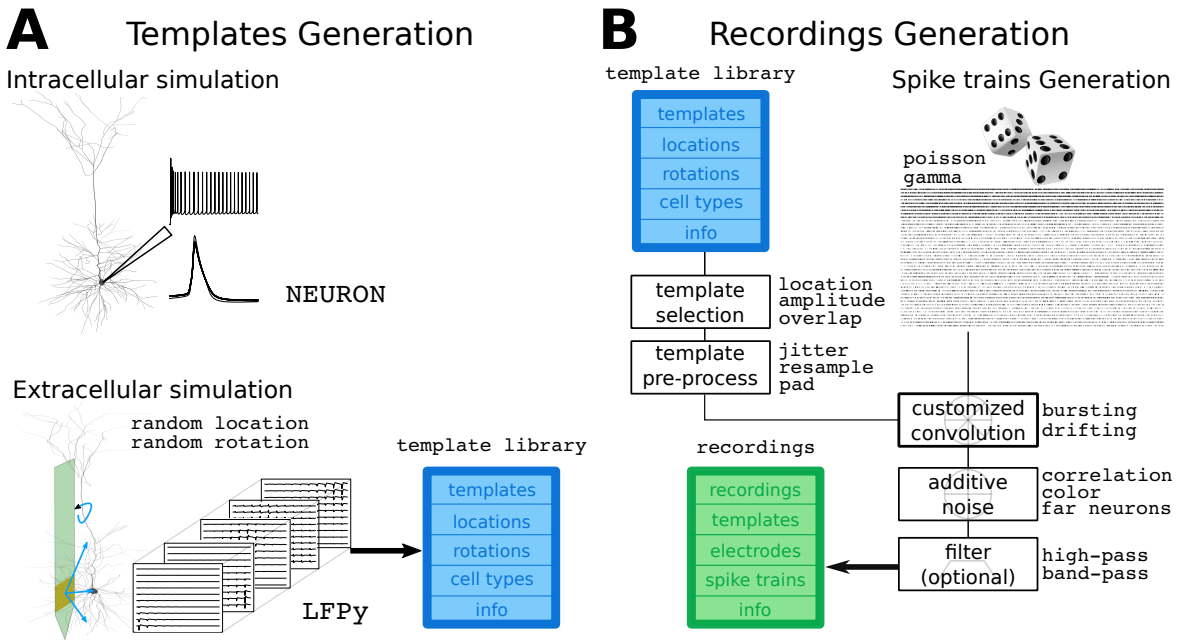

Figure 2: Overview of the `MEArec` software. The simulation is divided in two phases: *templates generation* and *recordings generation*. (A) The *templates generation* phase is split in an intracellular and extracellular simulation. The intracellular simulation computes, for each available cell model, the transmembrane currents generated by several action potentials. In the extracellular simulation, each cell model is randomly moved and rotated several times and the stored currents are loaded to the model to compute the extracellular action potential, building a *template library*. (B) The *recordings generation* phase combines templates selected from the *template library* and randomly generated spike trains. Selected templates are pre-processed before a customized convolution with the spike trains. Additive noise is added to the output of the convolution, and the recordings can be optionally filtered.

Generation of realistic Multi-Electrode Array recordings

The recent development of Multi-Electrode Arrays (MEAs) enables researchers to record extracellular activity at very high spatio-temporal density both for *in vitro* [2, 13] and *in vivo* applications [35, 26]. The large number of electrodes and their high density can result in challenges for spike sorting algorithms. It is therefore important to be able to simulate recordings from these kind of neural probes.

To deal with different probe designs, `MEArec` uses another Python package (`MEAutility` - `https://meautility.readthedocs.io/`), that allows users to easily import several available probe models and to define custom probe designs. Among others, `MEAutility` include Neuropixels probes [26], Neuronexus commercial probes (`http://neuronexus.com/products/neural-probes/`), and a wide variety of square MEA designs with different contact densities (the list of available probes can be found in Appendix A).

Similarly to the tetrode example, we first have to generate templates for the probes. These are the commands to generate templates and recordings for a Neuropixels design with 128 electrodes (`Neuropixels-128`). The recordings contain 60 neurons, 48 excitatory and 12 inhibitory. With similar commands, we generated templates and recordings for a Neuronexus probe with 32 channels (A1x32-Poly3-5mm-25s-177-CM32 - `Neuronexus-32`) with 20 cells, and a square 10x10 MEA with 15 µm inter-electrode-distance (`SqMEA-10-15`) and 50 cells.

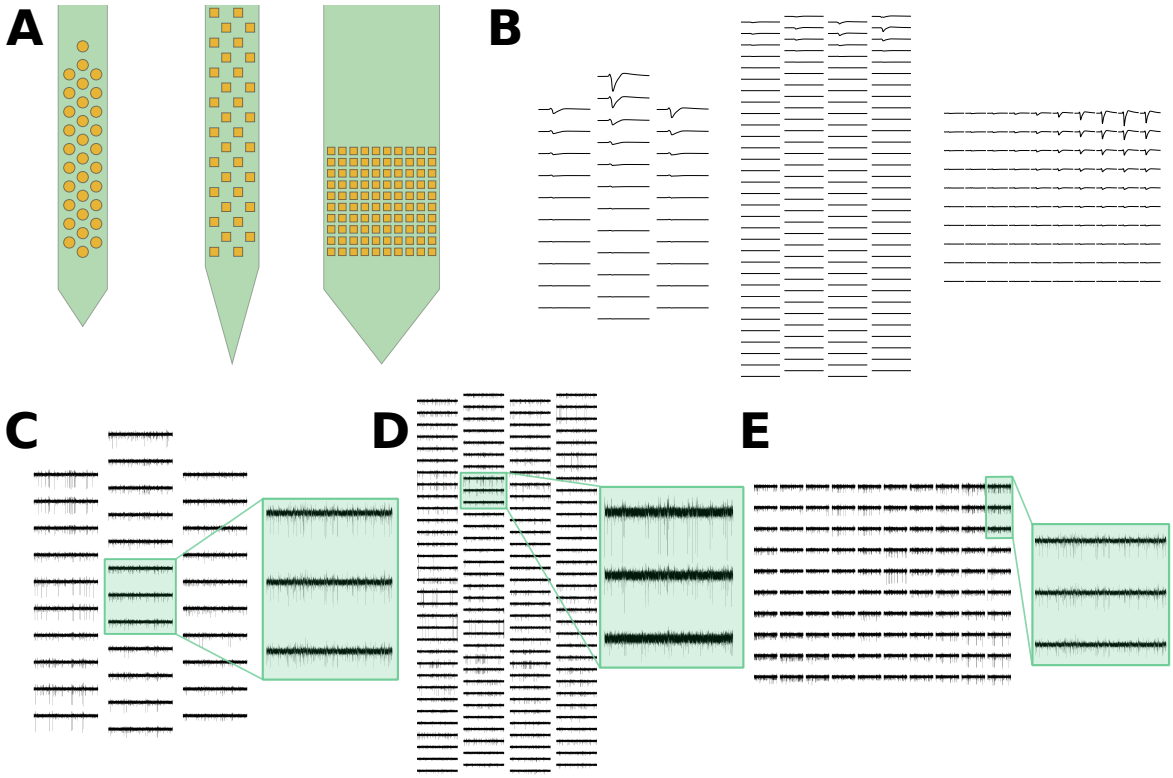

Figure 3: Generation of high-density multi-electrode array recordings. (A) Example of three available probes: a commercial Neuronexus probe (left), the Neuropixels probe (middle), and a high-density square MEA. (B) Sample templates for each probe design. (C-D-E) One-second snippets of recordings from the Neuronexus probe (C), the Neuropixels probe (D), and the square MEA probe (E). The highlighted windows display the activity over three adjacent channels and show how the same spikes are seen on multiple sites.

```
>> mearec gen-templates -prb Neuropixels-128 -n 100 --seed 0
   ...
   Saved templates in path-to-Neuropixels-templates-file.h5

>> mearec gen-recordings -t path-to-Neuropixels-templates-file.h5 -d 30 -ne 48 -ni 12
   --st-seed 0 --temp-seed 1 --noise-seed 2
   ...
   Saved recordings in path-to-Neuropixels-recordings-file.h5
```

Figure 3 shows the three above-mentioned probes (A), a sample template for each probe design (B), and one-second snippets of the three recordings (C-D-E), with zoomed in window to highlight spiking activity.

While all the recordings shown so far have been simulated with default parameters, several aspects of the spiking activity are critical for spike sorting. In the next sections, we will show how these features, including bursting, spatio-temporal overlapping spikes, drifting, and noise assumptions can be explored with `MEArec` simulations.

Bursting modulation of spike amplitude and shape

Bursting activity is one of the most complicated features of spiking activity that can compromise the performance of spike sorting algorithms. When a neuron bursts, i.e. it fires repeated and fast action potentials, the dynamics underlying the generation of the spikes changes over the bursting period [20]. While the bursting mechanism has been largely studied with patch-clamp experiments, combined extracellular-juxtacellular recordings [1] and computational studies [18] suggest that during bursting, extracellular spikes become lower in amplitude and wider in shape.

In order to simulate this property of the extracellular waveforms in a fast and efficient manner, templates are modulated both in amplitude and shape during the convolution operation, depending on the spiking history.

To demonstrate how bursting is replicated, we built a constant spike train with 10 ms inter-spike-interval (Figure 4A). A modulation value is computed for each spike and is used to modulate the convolution operation for that event. The blue dots show the default modulation, in which the modulation values are drawn from a Gaussian distribution with unitary mean. When bursting is enabled, the modulation value is computed as a sublinear power depending of the number of consecutive spikes in a burst and the inter-spike-interval (see Materials and Methods for details). The bursting events can be either controlled by the maximum number of spikes making a burst (orange - 5 spikes; green - 10 spikes) or by setting a maximum bursting duration (red - 75 ms).

The modulation value controls the level of amplitude and shape modulation of the spike event. In Figure 4B, examples of bursting templates are shown. The blue traces display templates only modulated in amplitude, i.e. the amplitude is scaled by the modulation value. The orange and green traces, instead, also present shape modulation, which is achieved by stretching the time axis using a sigmoid transform. The sigmoid transform can be adjusted to have more (green) or less (orange) shape modulation.

Figure 4C shows a one-second snippet of the tetrode recording shown previously after bursting modulation is activated. The top panel shows the spike events, the middle one displays the modulation values, and the bottom panel shows the output of the modulated convolution between one of the templates (on the electrode with the largest amplitude) and the spike train.

Figure 4D and Figure 4E show the waveform projections on the first principal component for the tetrode recording shown previously with and without bursting, respectively. In this case all neurons are bursting units and this causes a stretch in the PCA space, which is a clear complication for spike sorting algorithms.

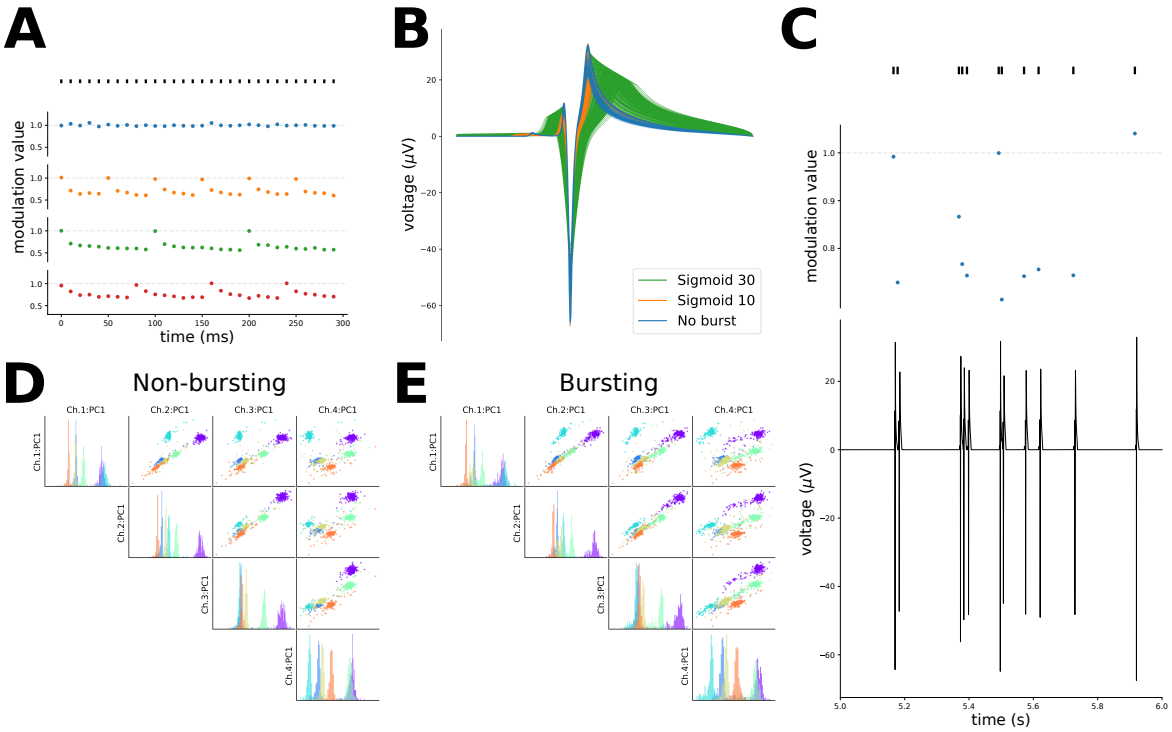

Figure 4: Bursting behavior. (A) Modulation values computation for a sample spike train of 300 ms with constant inter-spike-intervals of 10 ms. The blue dots show the modulation values for each spike when bursting is not activated: each value is drawn from a $\mathcal{N}(1, 0.05^2)$ distribution. When bursting is activated, a bursting event can be limited by the maximum number of spikes (orange - 5 spikes, green - 10 spikes), or by the maximum bursting event duration (red - 75 ms). (B) Modulated templates. The blue lines show templates modulated in amplitude only. The orange and green lines display the same templates with added shape modulation. (C) Modulation in tetrode recordings. The top panel shows spikes in a one-second period. The middle panel displays the modulation values for those spikes. The bottom panel shows the modulated template on the electrode with the largest peak after convolution. (D-E) PCA projections on the first principal component for the tetrode recordings wihout bursting (D) and with bursting (E) enabled. Note that the PCA projections were computed in both cases from the waveforms without bursting. The clusters, with bursting, become more spread and harder to separate than without bursting.

Controlling spatio-temporal overlaps

Another complicated aspect of extracellular spiking activity that can influence spike sorting performance is the occurrence of overlapping spikes. While temporal overlapping of events on spatially separated locations can be solved with feature masking [41], spatio-temporal overlapping can cause a distortion of the detected waveform, due to the superposition of separate spikes. Some spike sorting approaches, based on template-matching, are designed to tackle this problem [37, 43, 10].

In order to evaluate to what extent spatio-temporal overlap affects spike sorting, `MEArec` allows the user to set the number of spatially overlapping templates and to modify the synchrony rate of their spike trains. In Figure 5 we show an example of this on a `Neuronexus-32` probe (see Figure 3A). The recording was constructed with two excitatory and spatially overlapping neurons, whose templates are shown in Figure 5A (see Materials and Methods for details on spatial overlap definition). The spike synchrony rate can be controlled with the `sync_rate` parameter. If this parameter is not set

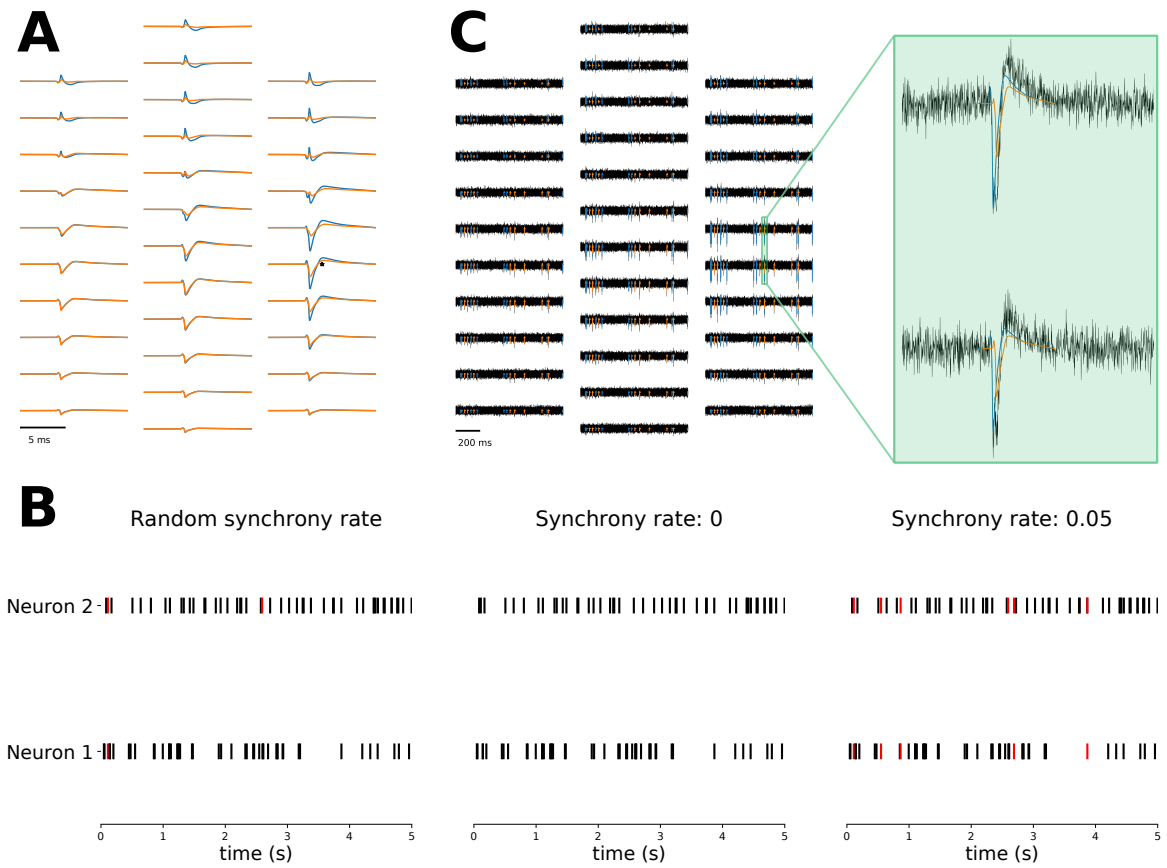

Figure 5: Controlling spatio-temporal overlapping spikes. (A) Example of two spatially overlapping templates. The two templates are spatially overlapping because on the electrode with the largest signal (depicted as an black asterisk) for template A (blue), template B has an amplitude greater than the 90% of its largest amplitude. (B) Without setting the synchrony rate, the random spike trains (left) present a few spatio-temporal collisions (red events). When setting the synchrony rate to 0 (middle), the spatio-temporal overlaps are removed. When the synchony rate is set to 0.05 (right), spatio-temporal overlapping spikes are added to the spike trains. (C) One-second snippet of the recording with 0.05 synchrony. In the magnified window, a spatio-temporal overlapping event is shown: the collision results in a distortion of the waveform.

(Figure 5B - left), some spatio-temporal overlapping spikes are present (red events). If the synchrony rate is set to 0, those spikes are removed from the spike trains (Figure 5B - middle). If set to 0.05, i.e. 5% of the spikes will be spatio-temporal collisions, events are added to the spike trains to reach the specified synchrony rate value of spatio-temporal overlap. As shown in Figure 5C, the occurrence of spatio-temporal overlapping events affects the recorded extracellular waveform: the waveforms of the neurons, in fact, get summed and might be mistaken for a separate unit by spike sorting algorithms when the spikes are overlapping.

The possibility of reproducing and controlling this feature of extracellular recordings within `MEArec` could aid in the development of spike sorters which are robust to spatio-temporal collisions.

Generating drifting recordings

When extracellular probes are inserted in the brain, especially for acute experiments, the neural tissue might slowly move with respect to the electrodes. This phenomenon is known as drift.

Drifting is particularly critical for spike sorting, as the waveform shapes change over time due to the relative movement between the neurons and the probe. New spike sorting algorithms have been developed to specifically tackle the drifting problem (`Kilosort2`[2], `IronClust` [25]).

In order to simulate drift in the recordings, we first need to generate drifting templates:

```
>> mearec gen-templates -prb Neuronexus-32 -n 30 --drifting --seed 0
   ...
   Saved templates in path-to-Neuronexus-drift-templates-file.h5
```

Drifting templates are generated by choosing an initial and final soma position with user-defined rules (see Materials and Methods for details) and by moving the cell along the line connecting the two positions for a defined number of drifting steps (50 by default). An example of a drifting template is depicted in Figure 6A, alongside with the drifting neuron's soma locations.

Once a library of drifting templates is generated, drifting recordings can be simulated. Depending on the drifting velocity, the drifting template is *replayed* so that, for each spike, the correct drifting template is selected for convolution. In Figure 6B, we show an example with four drifting cells, a drifting velocity of 20 µm/s, and a duration of 60 seconds. The colored arrows show the initial and final positions of the four neurons making up the recording. Note that a drifting velocity of 20 µm/s is much larger than normal experimental drifts, and it has been chosen to illustrate the drifting phenomenon. Figure 6C shows the waveforms and the average waveforms for the four neurons on the

[2]e.g. `https://github.com/MouseLand/Kilosort2`

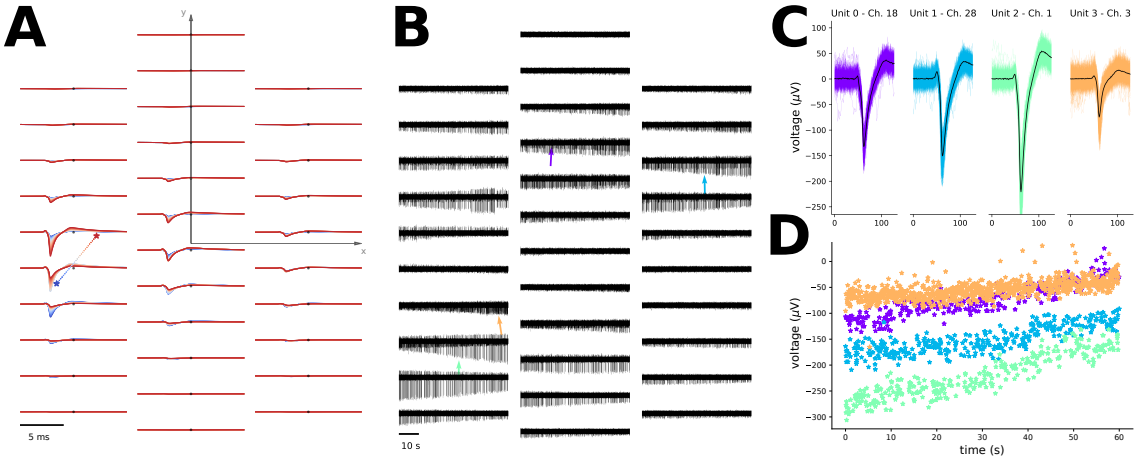

Figure 6: Drifting. (A) Example of a drifting template. The colored asterisks on the left show the trajectory from the initial (blue large asterisk) to the final (red large asterisk) neuron positions. The positions are in the x-y coordinates of the probe plane, and the electrode locations are depicted as black dots. The corresponding templates are displayed at the electrode locations with the same colormap, showing that the template peak is shifted upwards following the soma position. (B) 60-second drifting recording with four neurons moving at a velocity of 20 µm/s. The colored arrows show the initial and final soma positions for each neuron. (C) Waveforms and average waveforms on the electrode with the largest peak for each of the four neurons in the recording. (D) Amplitude of the waveforms over time recorded on the electrode with the largest initial peak. Drifting results in a slow change of amplitude over the course of the recording.

electrode with the largest peak. In this case, the variability is mainly due to the relative movement between the cell and the probe. This can be observed by visualizing the waveform amplitude for each spike over time (Figure 6C - each color is a different neuron).

Modeling experimental noise

Spike sorting performance can be greatly affected by noise in the recordings. Many algorithms first use a spike detection step to identify putative spikes. The threshold for spike detection is usually set depending on the noise standard deviation or mean average deviation [38]. Clearly, recordings with larger noise levels will result in higher spike detection thresholds, hence making it harder to robustly detect lower amplitude spiking activity. In addition to the noise amplitude, other noise features can affect spike sorting performance: some clustering algorithms, for example, assume that clusters have Gaussian shape, due to the assumption of an additive normal noise to the recordings. Moreover, the noise generated by biological sources can produce spatial correlations in the noise profiles among different channels and it can be modulated in frequency [6, 40].

To investigate how the above-mentioned assumptions on noise can affect spike sorting performance, `MEArec` can generate recordings with several noise models. Figure 7 shows 5-second spiking-free recordings of a tetrode probe for five different noise profiles that can be generated (A - recordings, B - spectrum, C - channel covariance, D - amplitude distribution).

The first column shows uncorrelated Gaussian noise, which presents a flat spectrum, a diagonal covariance matrix, and a symmetrical noise amplitude distribution. In the recording in the second column, spatially correlated noise was generated as a multivariate Gaussian noise with a covariance matrix depending on the channel distance. Also in this case, the spectrum (B) presents a flat profile and the amplitude distribution is symmetrical (D), but the covariance matrix shows a correlation depending on the inter-electrode distance. As previous studies showed [6, 40], the frequency content of extracellular noise is not flat, but its spectrum is affected by the spiking activity of distant neurons, which appear in the recordings as below-threshold *biological* noise. To reproduce the spectrum profile that is observed in experimental data, `MEArec` allows coloring the noise spectrum of Gaussian noise with a second order infinite impulse response (IIR) filter (see Materials and Methods for details). Colored noise represents an efficient way of obtaining the desired spectrum, as shown in the third and fourth columns of Figure 7, panel B. Distance correlation is maintained (panel C - fourth column), and the distribution of the noise amplitudes is symmetrical. Finally, a last noise model enables one to generate activity of distant neurons. In this case, noise is built as the convolution between many neurons (300 by default) whose template amplitudes are below an amplitude threshold (10 µV by default). A Gaussian noise floor is then added to the resulting noise, which is scaled to match the user-defined noise level. The *far-neurons* noise profile is shown in the last column of Figure 7. While the spectrum and spatial correlation of this noise profile are similar to the ones generated with a colored, distance-correlated noise (4th column), the shape of the noise distribution is skewed towards negative values (panel D), mainly due to the negative contribution of the action potentials.

The capability of `MEArec` to simulate several noise models enables spike sorter developers to assess how different noise profiles affect their algorithms and to modify their methods to be insensitive to specific noise assumptions.

Testbench for spike sorting development and assessment

In the previous sections, we have shown several examples on how `MEArec` is capable of reproducing several aspects of extracellular recordings which are critical for spike sorting performance, in a fully reproducible way. The proposed design and its integration with a spike sorting evaluation framework called `SpikeInterface`[3] enables developers to actively include customized simulations in the spike sorting development phase.

[3] `https://github.com/SpikeInterface`

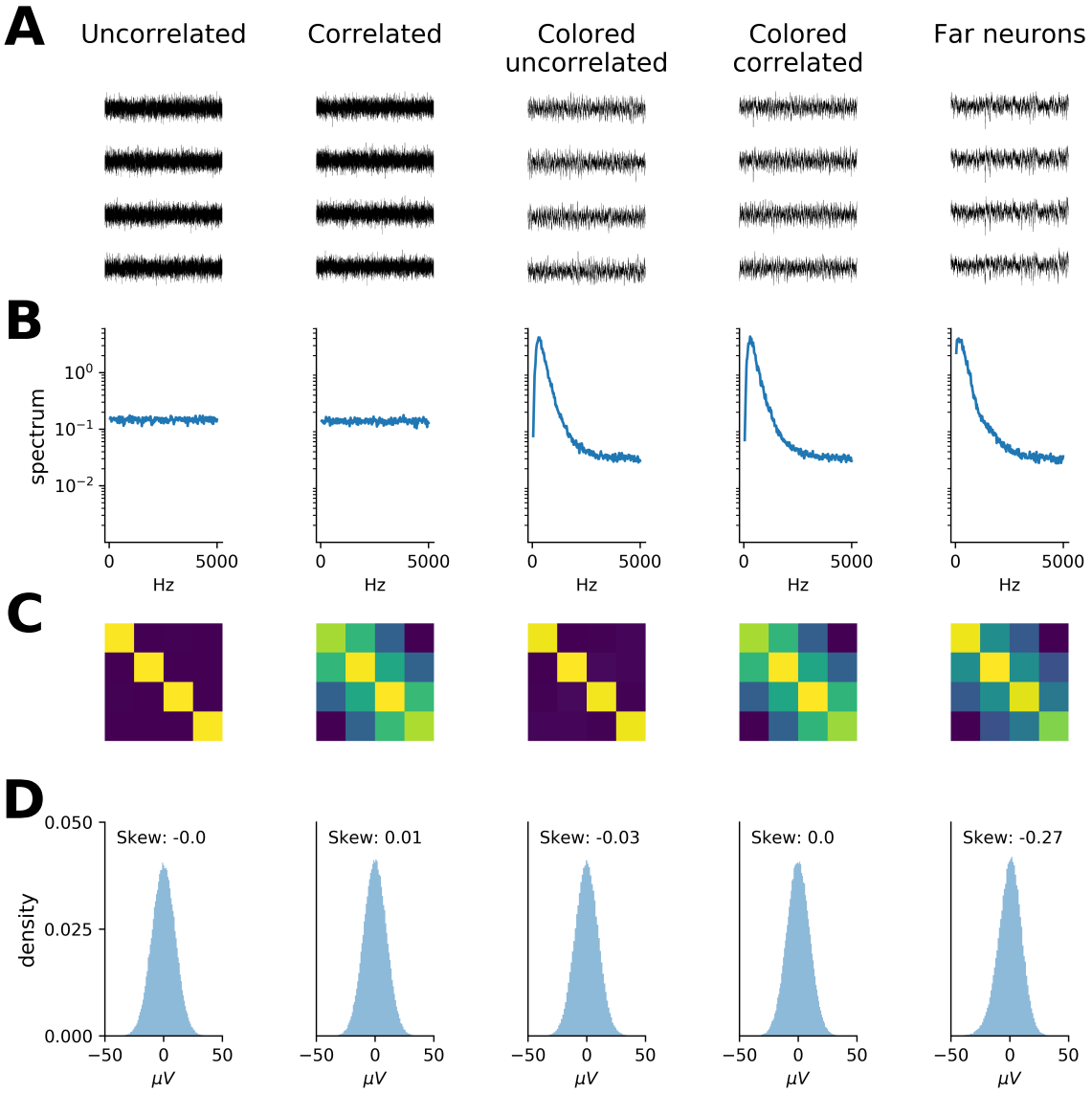

Figure 7: Noise models. The 5 columns refer to different noise models: 1) Uncorrelated Gaussian noise, 2) Distance-correlated Gaussian noise, 3) Colored uncorrelated Gaussian noise, 4) Colored distance-correlated Gaussian noise, and 5) Noise generated by distant neurons. (A) One-second spiking-free recording. (B) Spectrum of the first recording channel between 10 and 5000 Hz. (C) Covariance matrix of the recordings. (D) Distribution of noise amplitudes for the first recording channel. The different noise models vary in the spectrum, channel correlations, and amplitude distributions.

Due to its speed and controllability, we see `MEArec` as a *testbench*, rather than a *benchmark* tool. We provide here a couple of examples. In Figure 8A, we show a one-second section of recordings simulated on a `Neuronexus-32` probe with fixed parameters and random seeds regarding template selection and spike train generation, but with four different levels of additive Gaussian noise, with standard deviations of 5, 10, 20, and 30 µV (Appendix B contains the Python code used to generate and plot these recordings). The traces show the same underlying spiking activity, so the only variability

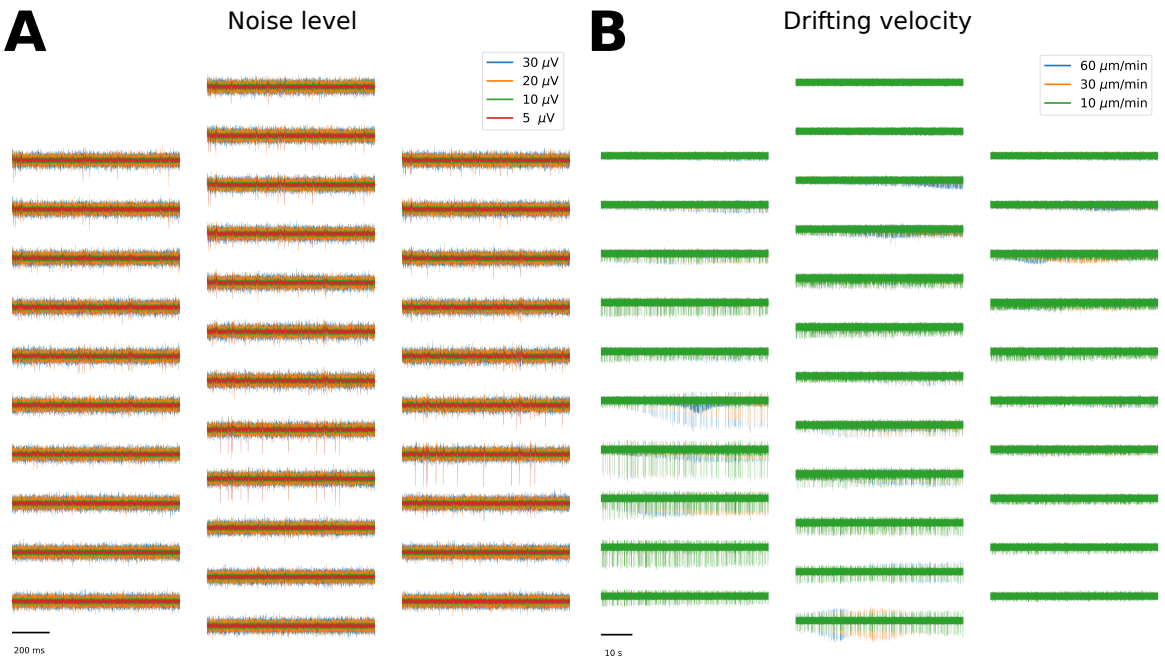

Figure 8: MEArec as testbench platform for spike sorting. (A) Four one-second snippetd of recordings generated with a different noise level parameter (5 - red, 10 - green, 20 - blue, and 30 µV - blue). The underlying spiking activity is exactly the same for all recordings, and the only difference lie in the standard deviation of the underlying uncorrelated Gaussian noise. (B) Three drifting recordings generated with a different drifting velocity parameter (10 - green, 30 - blue, and 60 µm/s - blue). Also in this case, the underlying spiking activity is the same, but it can be observed how the different speeds result in a modification of waveforms over time.

in spike sorting performance will be due to the varying noise levels. Similarly, in Figure 8B, 1-minute drifting recordings were simulated with three different drifting velocities. The recordings show that for low drifting speeds the waveform changes are almost not visible (green traces), while for faster drifts (orange and blue traces), the waveform changes over time become more important.

The capability of MEArec of reproducing such behaviors in a highly controlled manner could aid in the design of specific tests for measuring and quantifying the ability of a spike sorting software to deal with specific complexities in extracellular recordings. Other examples include simulating a recording with increasing levels of bursting in order to measure to what extent bursting units are correctly clustered, or changing the synchrony rate of spatially overlapping units to assess how much spatio-temporal collisions affect performance.

Integration with SpikeInterface We have recently developed SpikeInterface, a Python-based framework for running several spike sorting algorithms, comparing, and validating their results. MEArec can be easily interfaced to SpikeInterface so that simulated recordings can be loaded, spike sorted, and benchmarked with a few lines of code. In the following example, a MEArec recording is loaded, spike sorted with Mountainsort4 [8] and Kilosort2[4] [37], and benchmarked with respect to the ground-truth spike times available from the MEArec simulation:

```
import spikeextractors as se
import spiketoolkit as st
```

[4] https://github.com/MouseLand/Kilosort2

```
# loading MEArec recording
recording = se.MEArecRecordingExtractor('path-to-recording.h5')
# loading ground-truth sorting
sorting_GT = se.MEArecSortingExtractor('path-to-recording.h5')

# run several spike sorters
sorting_MS4 = st.sorters.run_mountainsort4(recording)
sorting_KS2 = st.sorters.run_kilosort2(recording)

# compare with ground-truth and get performance
cmp_GT_MS4 = st.comparison.compare_sorter_to_ground_truth(sorting_GT, sorting_MS4)
cmp_GT_KS2 = st.comparison.compare_sorter_to_ground_truth(sorting_GT, sorting_KS2)

# get and print performance
cmp_GT_MS4.get_performance()
cmp_GT_KS2.get_performance()
```

The combination of `MEArec` and `SpikeInterface` represents a powerful tool for systematically testing and comparing spike sorter performances with respect to several complications of extracellular recordings. `MEArec` simulations, in combination with `SpikeInterface`, are already being used by other groups to benchmark and compare spike sorting algorithms[5].

Performance considerations

As a testbench tool, the speed requirement has been one of the main design principle of `MEArec`. In order to achieve high speed, most parts of the simulation process are fully parallelized. As shown in Figure 2, the simulations are split in templates and recordings generation. The templates generation phase is the most time consuming, but the same template library can be used to generate several recordings. This phase is further split in two sub-phases: the intracellular and extracellular simulations. The former only needs to be run once, as it generates a set of cell model-specific spikes that are stored and then used for extracellular simulations, which is instead probe specific.

We present here run times for the different phases of the templates generation and for the recordings generation. All simulations were run on an Ubuntu 18.04 Intel(R) Core(TM) i7-6600U CPU @ 2.60GHz, with 16 GB of RAM.

The intracellular simulation run time for the 13 cell models shipped with the software was ~ 130 seconds (~ 10 seconds per cell model).

Run times for extracellular simulations for several probe types, number of templates in the library, and drifting templates are shown in the *Templates generation* section of Table 1. The run times for this phase mainly depend on the number of templates to be generated (N templates column), on the minimum amplitude of accepted templates (Min. amplitude column), and especially on drifting (Drifting column). When simulating drifting templates, in fact, the number of actual extracellular spikes for each cell model is N templates times N drift steps. Note that in order to generate the *far-neurons* noise model, the minimum amplitude should be set to 0, so that low-amplitude templates are not discarded. The number of templates available in the template library will be the specified number of templates (N templates) times the number of cell models (13 by default).

Recordings are then generated using the simulated template libraries. In Table 1, the *Recordings generation* section shows run times for several recordings with different probes, durations, number of cells, bursting, and drifting options. The main parameter that affects simulation times is the number of cells, as it increases the number of modulated convolutions. Bursting and drifting behavior also increase the run time of the simulations, because of the extra processing required in the convolution

[5] `https://spikeforest.flatironinstitute.org`

Templates generation						
Probe	N templates	N channels	Min. amplitude	Drifting	N drift steps	Run time (s)
tetrode-mea-l	30	4	30	No	-	169
tetrode-mea-l	100	4	30	No	-	588
tetrode-mea-l	100	4	0	No	-	236
Neuronexus-32	100	32	30	No	-	567
Neuropixels-128	100	128	30	No	-	809
SqMEA-10-15	30	100	30	No	-	1027
Neuronexus-32	30	32	30	Yes	50	2000
Recordings generation						
Probe	N cells	N channels	Duration	Bursting	Drifting	Run time (s)
tetrode-mea-l	6	4	10	No	No	2
tetrode-mea-l	6	4	600	No	No	27
Neuronexus-32	20	32	30	No	No	12
Neuronexus-32	20	32	30	Yes	No	45
Neuropixels-128	60	128	30	No	No	62
SqMEA-10-15	50	100	30	No	No	48
Neuronexus-32	4	32	60	No	Yes	20
Neuronexus-32	20	32	60	No	Yes	53

Table 1: Templates and recordings generation run times depending on several simulation parameters.

step. The simulation run times, however, range from a few seconds to a few minutes. Therefore, the speed of `MEArec` enables users to generate numerous recordings with different parameters for testing spike sorter performances.

Discussion

In this paper we have presented `MEArec`, a Python package for simulating extracellular recordings for spike sorting development and validation. We first showed the ease of use of the software, whose command line interface and simple Python API enable users to simulate extracellular recordings with a couple of commands or a few lines of code. We then introduced an overview of the software function, consisting in separating the *templates* and the *recordings* generation to improve efficiency and simulation speed. We explored the capability of reproducing and controlling several aspects of extracellular recordings which can be critical for spike sorting algorithms, including spikes in a burst with varying spike shapes, spatio-temporal overlaps, drifting units, and noise assumptions. We illustrated two examples of using `MEArec`, in combination with `SpikeInterface`[6], as a testbench platform for developing spike sorting algorithms. Finally, we benchmarked the speed performance of `MEArec` (Table 1).

Investigating the validation section of several recently developed spike sorting algorithms [41, 37, 26, 22, 25, 27, 43], it is clear that the neuroscientific community needs a standardized validation framework for spike sorting performance. Some spike sorters are validated using a so called hybrid approach, in which well-identified units from previous experimental recordings are artificially injected in the recordings and used to compute performance metrics [41, 37]. The use of templates extracted from previously sorted datasets poses some questions regarding the accuracy of the initial sorting, as well as the complexity of the well-identified units. Alternatively, other spike sorters are validated on experimental paired ground-truth recordings [8, 43]. While these valuable datasets [19, 21, 35, 31] can certainly provide useful information, the low count of ground-truth units makes the validation incomplete and could result in biases (for example algorithm-specific parameters could be tuned to reach a higher performance for the recorded ground-truth units). A third validation method consist of using simulated ground-truth recordings [11]. While this approach is promising, in combination with experimental paired recordings, the current available simulators [6, 18, 33] present some limitations in terms of biological realism, controllability, speed, and/or ease of use (see Introduction). We therefore introduced `MEArec`, a software package which is computationally efficient, easy to use, highly controllable, and capable of reproducing critical characteristics of extracellular recordings relevant to

[6] `https://github.com/SpikeInterface`

spike sorting, including bursting modulation, spatio-temporal overlaps, drifting of units over time, and various noise profiles.

The capability of `MEArec` to replicate complexities in extracellular recordings which are usually either ignored or not controlled in other simulators, permits the user to include tailored simulations in the spike sorting implementation process, using the simulator as a testbench platform for algorithm development. `MEArec` simulations could not only be used to test the final product, but specific simulations could be used to help implementing algorithms that are able to cope with drifting, bursting, and spatio-temporal overlap, which are regarded as the most complex aspects for spike sorting performance [40, 43].

In `MEArec`, in order to generate extracellular templates, we used a well-established modeling framework for solving the single neuron dynamics [7], and for calculating extracellular fields generated by transmembrane currents [29, 18]. These models have some assumptions that, if warranted, could be addressed with more sophisticated methods, such as finite element methods (FEM). In a recent work [5], we used FEM simulations and showed that the extracellular probes, especially MEAs, affect the amplitude of the recorded signals. While this finding is definitely interesting for accurately modeling and understanding how the extracellular potential is generated and recorded, it is unclear how it would affect the spike sorting performance. Moreover, when modeling signals on MEAs, we used the method of images [34, 5], which models the probe as a infinite insulating plane and better describes the recorded potentials for large MEA probes [5].

Secondly, during templates generation, the neuron models were randomly moved around and rotated with physiologically acceptable values [4]. In this phase, some dendritic trees might unnaturally cross the probes. We decided to not modify the cell models and allow for this behavior for sake of efficiency of the simulator. The modification of the dendritic trees for each extracellular spike generation would in fact be too computationally intense. However, since the templates generation phase is only run once for each probes, in the future we plan to both to include the probe effect in the simulations and to carefully modify the dendritic positions so that they do not cross the probes' plane.

Another limitation of the proposed modelling approach is in the replication of bursting behavior. We implemented a simplified bursting modulation that attempts at capturing the features recorded from extracellular electrodes by modifying the template amplitude and shape depending on the spiking history. However, more advanced aspects of waveform modulation caused by bursting, including morphology-dependent variation of spike shapes, cannot be modelled with the proposed approach, and their replication requires a full multi-compartment simulation [18]. Nevertheless, the suggested simplified model of bursting could be a valuable tool for testing the capability of spike sorters to deal with this phenomenon.

Finally, the current version of `MEArec` only supports cell models from the Neocortical Microcircuit Portal [30, 39], which includes models from juvenile rat somatosensory cortex. The same cell model format is also being used to build a full hippocampus model [32] and other brain regions, and therefore the integration of new models should be straightforward. Moreover, we are in the process of extending the supported cell models for the Allen Brain Institute database [16][7], which contains models from mice and human cells. Further, by design, the templates and recordings generation phases are split. Therefore, the recordings generation mechanism could also be used, in principle, for user-defined template libraries, either from other unsupported cell models or from units extracted from experimental recordings.

In conclusion, we introduced `MEArec`, which is a Python-based simulation framework for extracellular recordings. Thanks to its speed and controllability, we see `MEArec` to aid both the development and validation spike sorting algorithms and to help understanding the limitation of current methods, to improve their performance, and to generate new software tools for the hard and still partially unsolved spike sorting problem.

[7] `https://celltypes.brain-map.org/`

Materials and Methods

Templates generation

This section explains the templates generation phase of the simulator (Figure 2A). Table 2 shows the list of parameters involved in this phase, their default values, types, and an explanation of their function.

`MEArec` is compatible with realistic multi-compartment neuronal models from the Neocortex Microcircuit Portal (NMC - [39, 30]). Upon installation, 13 cell models from layer 5 are copied in the package folder. Moreover, the user can manually download other cell models from the portal and use them for the simulation.

Intacellular simulation

The neuronal model dynamics is solved using the `NEURON` simulator [7]. The neuron's soma is stimulated with a constant current for a user-defined simulation time (1 secondecond by default - `sim_time` parameter) and the stimulation weight is adjusted (using the `weights` parameter) so that the number of spikes in the simulation period is within a target interval (between 3 and 50 by default - `target_spikes` parameter). The stimulation starts after `delay` ms from the start of the simulation to avoid initialization artifacts. The simuation time step is defined by the parameter `dt` (default is 0.03125 ms, corresponding to 32 kHz). Single spikes are then detected by threshold crossing, aligned, and cropped (using the `cut_out` parameter). The transmembrane currents of all segments are saved to disk, so that the intracellular simulation only needs to be run once for each cell model.

Extracellular simulation

Transmembrane currents generated by the *intracellular simulation* are used to compute extracellular potentials at the electrode locations using `LFPy` [17]. Transmembrane currents are distributed over a line source with the length of its corresponding neural segment. Using the quasi-static approximation [36] and with the assunmption of a homogeneous, isotropic, and infinite neural tissue with conductivity $\sigma = 0.3\,\mathrm{S/m}$ [15], the contribution of each compartment i at position $\boldsymbol{r}_i$ with transmembrane current $I_i(t)$ to the electric potential on an electrode at position $\boldsymbol{r}_j$ reads [23, 17, 4]:

$$\phi_i(\boldsymbol{r}_j, t) = \frac{1}{4\pi\sigma} I_i(t) \int \frac{\mathrm{d}r_i}{\|\boldsymbol{r}_j - \boldsymbol{r}_i\|}. \tag{1}$$

While the assumption of an infinite milieu holds for small probes, such as microwires and tetrodes, when using larger silicon probes, the use of the method of images (MoI) [34] can yield a better estimate of the extracellular potential [5]. Using MoI, the contribution of a transmembrane current to an electrode at position $\boldsymbol{r}_j$ reads:

$$\phi_i(\boldsymbol{r}_j, t) = \frac{1}{2\pi\sigma} I_i(t) \int \frac{\mathrm{d}r_i}{\|\boldsymbol{r}_j - \boldsymbol{r}_i\|}. \tag{2}$$

The simulated extracellular spike is obtained by summing up the contributions of all compartments. For each recording site, the electric potential can be computed on several points within the electrode area (`ncontacts` parameter - 10 points by default), that are then averaged to model the spatial filtering properties of the electrodes (disk-electrode approximation [29]).

Each cell model, during the *templates generation* phase, is used to generate several spikes (`n` parameter - 50 by default). For each extracellular action potential, the neuron is randomly moved to a position within user-defined boundaries (`xlim`, `ylim`, `zlim` parameters). If the boundary for a specific axis is set to `null`, the limits are computed as the boundary of the probe in that axis plus the `overhang` value (default 30 µm). Moreover, a random rotation of the model can be optionally added (`rot` parameter). The models can be only shifted (norot), rotated along a single axis (xrot, yrot, zrot), rotated with a physiological rotation (physrot), or rotated randomly along all axes (3drot). For

further details we refer to [4]. Extracellular spikes are included in the dataset only if their maximum amplitude is greater than a user-defined minimum amplitude (`min_amp` parameter - 30 µV by default). In order to use the *far-neurons* noise model (Figure 7), the minimum amplitude parameter should be set to 0, so that low amplitude templates are not discarded.

Probe models

Probe models are handled using the `MEAutility` Python package (`https://meautility.readthedocs.io/`), which is automatically installed upon `MEArec` installation. The probe type can be chosen using the `probe` parameter (if not set, a random probe will be selected). `MEAutility` contains a large variety of available probe designs, e.g. commercial Neuronexus probes, Neuropixels [26], and high-density square MEA (Figure 3), and it also allow users to define new probes using a `yaml` file or a Python dictionary. The probe definition contains information about the number and arrangement of the electrodes, the electrode shape and size (used for spatial filtering), the plane in which electrodes are located, and the probe type (`wire` or `mea`), which tells the simulator whether to use the infinite assumption (Equation 1) or MoI (Equation 2) for the extracellular potential calculation. In order to list the available probes and their information, one can use the `mearec available-probes --info` command.

Drifting templates

When inserting recording probes in the brain, over time there might be relative movement between the probe and the tissue, which causes a so-called drift in the recorded action potentials. In order to incorporate this phenomenon in the simulation of the recordings, drifting templates has to be generated (when the `drifting` parameter is set to true). From an initial random position of the cell model which satisfies the requirements in terms of location (within boundaries) and amplitude (above the detection threshold) a final drifting position is found so that the same conditions are satisfied. Moreover, the user can choose preferred drifting direction by setting the `drift_xlim`, `drift_ylim`, and `drift_zlim` parameters. When the final position is selected, the cell model is moved along a straight line connecting the initial and final position and the extracellular spike is simulated for `drift_steps` equidistant points (30 points by default) along this line (Figure 6A).

The templates generation phase can be reproduced by setting the `seed` parameter, which is randomly selected if it is set no `null`.

Recordings generation

When a template library is generated, it can be used to generate many recordings, as shown in Figure 2B. Tables 3 and 4 show the list of parameters involved in the recordings generation phase, their default values, types, and an explanation of their function.

Spike trains generations

In order to obtain the spiking activity, spike trains have to be generated. All the spike train generation parameters can be found in the `spiketrains` section of the recordings parameters.

Spike trains can be generated either as Poisson or Gamma processes (`process` parameter). If the Gamma process is selected, its shape is controlled by the `gamma_shape` parameter (default is 2). The user can decide the number of excitatory (`n_exc`) and inhibitory neurons (`n_inh`) in the recordings. The average and standard deviation of the firing rates of excitatory and inhibitory neurons can be chosen (with the `f_exc`, `f_inh`, `st_exc`, and `st_inh` parameters), as well as the minimum accepted firing rate (`min_rate` - default 0.5 Hz). Alternatively, the user can define the type (E-I) and mean firing rate of all neurons in the recordings. As Poisson and Gamma processes do not have a minimum inter-spike-interval, spikes violating a refractory period (`ref_per` - 2 ms by default) are removed from the spike trains. Finally, the duration of the spike trains sets the duration of the recordings (`duration`

Parameter	Value	Type	Explanation
Intracellular simulation settings			
sim_time	1	float	intracellular simulation time in seconds
target_spikes	[3, 50]	list (int)	min-max number of spikes in sim_time
cut_out	[2, 5]	list (float)	pre-post peak cut_out in ms
dt	0.03125	float	time step in ms (default is 32 kHz)
delay	10	float	stimulation delay in ms
weights	[0.25, 1.75]	list (float)	weights to multiply stimulus amplitude if number of spikes is above (0.25) or below (1.25) target spikes
Extracellular simulation settings			
rot	physrot	string	rotation to apply to cell models (norot, xrot, yrot, zrot, physrot, 3drot)
probe	Neuronexus-32	string	extracellular probe (if null an available probe is randomly chosen)
ncontacts	10	int	number of contacts per recording site
overhang	30	float	extension in µm beyond MEA boundaries for neuron locations (if corresponding lim is null)
xlim	[10,80]	list (float)	limits (low, high) for neuron locations in the x-axis in µm
ylim	null	list (float)	limits (low, high) for neuron locations in the y-axis in µm
zlim	null	list (float)	limits (low, high) for neuron locations in the z-axis in µm
min_amp	30	float	minimum template amplitude
n	50	int	number of spikes per cell model
n_overlap_pairs	null	int	number of spatially overlapping templates
drifting	False	bool	if True, drifting templates are simulated
max_drift	100	float	maximum distance from the initial and final cell position
min_drift	30	float	minimum distance from the initial and final cell position
drift_steps	30	int	number of drift steps
drift_xlim	[-10, 10]	list (float)	limits (low, high) for neuron drift locations in the x-axis (depth)
drift_ylim	[-10, 10]	list (float)	limits (low, high) for neuron drift locations in the y-axis (depth)
drift_zlim	[20, 80]	list (float)	limits (low, high) for neuron drift locations in the z-axis (depth)
seed	null	int	random seed for positions and rotations

Table 2: Templates generation parameter list, values, types, and explanations.

parameter), and the user can set the random seed for spike train generation (`seed` parameter in the `spiketrains` section). Spike trains are represented as `neo.SpikeTrain` objects [14].

Excitatory and inhibitory cell types

The `cell_types` section of the recordings parameters tells the simulator which cell types are excitatory and which are inhibitory. For all cell models in the Neocortical Microcircuit Portal [39], excitatory cells can be pyramidal cells (PC), star pyramidal cells (SP), and stellate cells (SS). The population of inhibitory cells is more diverse and it includes: axon cells (AC), bipolar cells (BP), bitufted cells (BTC), basket cells (BC), Chandelier cells (ChC), double bouquet cells (DBC), Martinotti cells (MC), and neurogliaform cells (NGC) [30]. This substrings are used to identify the cell models belonging to the excitatory and inhibitory group for the template selection process.

Template selection and pre-processing

After spike trains are generated, templates are selected from the template library and associated with each spike train. The parameters involved in the template selection and pre-processing are in the `templates` section of the recordings parameters.

Templates are chosen based on amplitude, distance, spatial overlap, and cell type. The selection algorithm discards templates with a peak amplitude below and above user-defined threshold (`min_amp` and `max_amp` parameters) and with a distance from already selected neurons below a minimum distance

(`min_dist` parameter). Moreover, the user can select specific boundaries in the x-, y-, and z-direction (`xlim`, `ylim`, and `zlim` parameter). If the boundaries are set to `null` (by default), there is no restriction on the neurons' location. Templates are chosen so that the number of excitatory and inhibitory types matches the spike trains' ones. Finally, the user can select the number of spatially overlapping template pairs in the recordings (`n_overlap_pairs` parameter). Two templates A and B are identified as spatially overlapping if the amplitude of template B on the electrode with largest amplitude for template A is above 90% (`overlap_threshold` parameter) of its maximum amplitude, and viceversa. The template selection seed can be set with the `seed` parameter in the `templates` section of the recordings parameters.

When templates are selected, they are pre-processed before the convolution operation. First, the templates are padded on both sides (by default extending the templates of 3 ms on each side - `pad_len` parameter) in order to ensure a smooth convolution operation. The template baseline is first removed, then the templates are extended in both directions by linearly interpolating their initial and final values to 0. Finally, this linearly extended template is re-interpolated with a cubic spline.

Next, to model the time variation occurring during sampling, for each template `n_jitter` versions are created (10 by default). Jittering is performed by upsampling the templates (8x by default - `upsample` parameter) and shifting them randomly in time within a sampling period, before downsampling them back to the original sampling frequency.

Recordings construction

In the `recordings` section of the recordings parameters, the user can set several parameters for the recordings generation. If not specified, the sampling frequency of the recordings (`fs` parameter) is the same as the generated templates (32 kHz by default), but the user can choose a different sampling rate. In this case the templates are resampled using a polyphase filter. If the `overlap` parameter is set to true, each spike is annotated as `NO` (no overlap), `TO` (temporal overlap), or `STO` (spatio-temporal overlap). If the `extract_waveforms` parameter is set to true, after the recordings generation the waveforms are extracted from the recordings and loaded to the spike train objects.

Overlapping spikes and spatio-temporal synchrony Spatio-temporal overlapping of spikes can make spike sorting very challenging [37, 43]. In order to control how spike sorting is affected by the rate of overlapping spikes, `MEArec` enables users to modify the spike trains in order to introduce a controlled amount of spatio-temporal overlapping synchrony (Figure 5).

If the synchrony rate is set (`sync_rate` parameter), the spike trains of spatially overlapping templates are modified to reach the desired synchrony rate. If the chosen synchrony rate is lower than the initial rate, spatio-temporal overlapping spikes are randomly removed from the spike trains. Conversely, when the chosen synchrony rate is greater than the initial rate, additional spikes that do not violate the refractory period are randomly added to the corresponding spike trains until the desired rate is reached. The additive spikes are jittered randomly within a user-defined interval (`sync_jitt` - default $\pm 1\ ms$).

Modulated convolution Pre-processed templates and spike trains are combined with a customized (modulated) convolution. The convolution step can be performed in parallel on chunks (20 seconds by default - `chunk_conv_duration` parameter). In order the replicate the variability of spikes in experimental data and computational models [1, 18], the convolution between spike trains and templates is modulated, i.e. the template corresponding to each spike can be modified both in amplitude and in shape (Figure 4).

There are three types of amplitude `modulation` available: 1) *none* (no modulation), 2) *template*, 3) *electrode* modulation (default). On top of amplitude modulation, when `modulation` is not *none*, shape modulation can be used by setting the `shape_mod` parameter to true.

Amplitude modulation. The amplitude modulation consists of scaling the amplitude of each spike event with a modulation value. When the *template* modulation is selected, the modulation

value is the same for all the electrodes. When the *electrode* modulation is used, each electrode has a slightly different modulation value. For the *template* and *electrode* modulation types, if the `bursting` parameter is set to false, the modulation value is a random value drawn from a normal distribution $\mathcal{N}(1, \texttt{sdrand}^2)$, (where `sdrand` is 0.05 by default). As the distribution has mean equal 1, the average amplitude of the resulting modulated spikes is the same as the original template. When the `bursting` parameter is set to true, the modulation values are computed to reproduce the amplitude scaling due to bursting behavior (see Figure 4A). The user can choose how many units will be affected by bursting (`n_bursting` parameter). Consecutive spikes occurring within a user-defined bursting period (`max_burst_duration` parameter - default 100 ms) are scaled with a sub-linear function (up to a maximum number of consecutive spikes `n_burst_spikes` - 10 by default). The amplitude scaling for the i-th consecutive spike within a bursting event is computed as:

$$mod_i = (\frac{avg_isi_{0-i}}{c \cdot max_burst_duration})^{exp_decay}$$

where avg_isi_{0-i} is the average inter-spike-interval (ISI) from the first bursting spike to the current spike in the bursting event, c is the number of consecutive spikes encountered up to spike i, `max_burst_duration` is the maximum bursting period (default 100 ms), and `exp_decay` is the exponent (0.1 by default). Additionally, the ISI-dependent modulation value is scaled a by a random value drawn from a normal distribution at the template level (*template* modulation) or electrode level (*electrode* modulation).

Shape modulation. When `shape_mod` is set to true, spikes are also modulated in shape. Shape modulation consists of strecthing the template depending on its modulation value. The stretch is achieved in the following way: first, the template time axis is centered to the template peak and scaled so that its length is equal to 1 – we will refer to this centered and normalized time axis as x_c; second, x_c is multiplied by the `bursting_sigmoid` parameter, which controls the amount of stretch – we will refer to this transformed time axis as x_t; then, a stretch factor s is computed for the entire template (the same factor is computed for all electrodes) as the average modulation value of all electrodes (if *electrode* modulation is used); if the stretch factor is less than 1, x_t is projected on a sigmoid function:

$$x_s = \frac{1}{(1 + \exp^{-(1-s)\cdot x_t})} - 0.5$$

x_s is now a non-linear stretched time axis. The template is interpolated on x_s with a cubic spline and transformed back to the original time axis x_c. The shape modulation with two different `bursting_sigmoid` values is shown in Figure 4B. The amplitude of the shape-modulated template is finally scaled with the modulation value to include the amplitude modulation.

Noise models and post-processing Additive noise is superimposed to the signals after the modulated convolution is finished. There are three types of noise models that can be set using the `noise_mode` parameter: *uncorrelated*, *distance-correlated*, and *far-neurons*. The uncorrelated noise model is an additive Gaussian noise with a user-defined standard deviation (`noise_level` parameter - 10 µV by default). The distance-correlated mode generates a multivariate normal noise with a covariance matrix dependent on the distance between electrodes. The covariance between electrode i and j is defined as $c_{ij} = {}^{d_h}/_{2 \cdot d_{ij}}$, where d_{ij} is the distance between the electrodes and d_h is the distance at which the covariance is 0.5 (`noise_half_distance` parameter - 30 µm by default). Finally, the *far-neurons* model generates noise as the activity of many neurons (`far_neurons_n` parameter - 300 by default) with small amplitudes (below `far_neurons_max_amp` - 10 µV by default). The population of distant neurons has an excitatory/inhibitory ratio of `far_neurons_exc_inh_ratio` (default 0.8). A random noise floor with a standard deviation of `far_neurons_noise_floor` (default 0.5) times the standard deviation of the distant neurons' spiking activity is added, in agreement with experimental data [6].

Uncorrelated and distance-correlated noise types can also be modulated in frequency to match the spectrum observed in experimental data [6, 17]. Extracellular spiking activity exhibit a peak in

Parameter	Value	Type	Explanation
Spike trains			
n_exc	7	int	number of excitatory cells
n_inh	3	int	number of inhibitory cells
f_exc	5	float	average firing rate of excitatory cells in Hz
f_inh	15	float	average firing rate of inhibitory cells in Hz
st_exc	1	float	firing rate standard deviation of excitatory cells in Hz
st_inh	3	float	firing rate standard deviation of inhibitory cells in Hz
min_rate	0.5	float	minimum firing rate in Hz
ref_per	2	float	refractory period in ms
process	poisson	string	process for spike train simulation (poisson-gamma)
gamma_shape	2	float	gamma shape (for gamma process)
duration	10	float	duration in seconds
seed	null	int	random seed for spiketrain generation
Cell types			
excitatory	['PC', 'SS', 'SP']	list (string)	Excitatory cell types
inhibitory	['AC', 'BP', 'BC', 'BTC', 'ChC', 'DBC', 'MC', 'NGC']	list (string)	Inhibitory cell types
Templates			
min_dist	25	float	minimum distance between neurons
min_amp	50	float	minimum spike amplitude in µV
max_amp	500	float	maximum spike amplitude in µV
xlim	null	list (float)	limits for neuron x in µm (min, max)
ylim	null	list (float)	limits for neuron y in µm (min, max)
zlim	null	list (float)	limits for neuron z in µm (min, max)
overlap_threshold	0.9	float	threshold to consider two templates spatially overlapping
n_jitters	10	int	number of temporal jittered copies for each template
upsample	8	int	upsampling factor to extract jittered copies
pad_len	[3, 3]	list (float)	padding of templates in ms
seed	null	int	random seed to select templates

Table 3: Recordings generation parameter list, values, types, and explanations.

frequency at around 300 Hz, a $1/f$ spectrum, and a random noise floor. Noise can be *colored* (when the `noise_color` parameter is true) with a second order infinite impulse response (IIR) peak filter and an additional gaussian noise floor. The frequency peak, quality factor, and weight of the random noise floor can be set with the `color_peak`, `color_q`, and `color_noise_floor` parameters. Note that with distance-correlated noise the correlation is slightly reduced by the color filter, as a random noise floor is added.

Optionally, the signals can be filtered (by setting the `filter` to true) with an high-pass or band-pass Butterworth filter of order `filter_order` (3 by default) and cutoff frequencies of `filter_cutoff` ([300, 6000] Hz by default).

Drifting recordings When the `drifting` parameter is set to true, drifting recordings are generated. The template library must have been generated with the `drifting` mode as well. The user can decide the number of drifting units (`n_drifting` parameter). If `n_drifting` is `null`, all units will be drifting.

The generation of drifting recordings is only different in the template selection and modulated convolution steps. In the template selection, in addition to the selection rules based on template amplitude, inter-neuron distance, and spatial overlap, templates are selected if the angle between the drifting direction (computed as the vector connecting the final and initial position) and a user-defined preferred direction (`preferred_dir` parameter - [0, 0, 1] by default) is within an angle tolerance (`angle_tol` parameter - 15° by default).

In the modulated convolution, the correct template among the drifting templates for each spike occurrence is selected based on the current drifting position computed as the initial position plus drifting velocity times simulation time. The drifting velocity can be modified by the user (`drift_velocity` parameter - 5 µm/min by default) and the user can decide to start the drift after `t_start_drift` seconds.

Parameter	Value	Type	Explanation
Recordings			
fs	null	int	sampling frequency in Hz (if null it is computed form the templates)
overlap	False	bool	if True, temporal and spatial overlap are computed for each spike (it may be time consuming)
extract_waveforms	False	bool	if True, waveforms are extracted from recordings
sync_rate	null	float	synchrony rate ([0-1]) for spike trains of spatially overlapping templates
sync_jitt	1	float	jitter in ms for added synchronous spikes
modulation	electrode	string	type of modulation [none | template | electrode] none - no modulation template - each spike instance is modulated with the same value on each electrode electrode - each electrode is modulated separately
sdrand	0.05	float	standard deviation of Gaussian modulation
bursting	False	bool	if True, spikes are modulated in amplitude depending on the ISI
exp_decay	0.1	float	(bursting) experimental decay in amplitude between consecutive spikes
n_burst_spikes	10	int	(bursting) max number of 'bursting' consecutive spikes
max_burst_duration	100	float	(bursting) duration in ms of maximum burst modulation
shape_mod	False	bool	if True waveforms are stretched in shape with a sigmoid transform depending on their modulation value
bursting_sigmoid	30	float	sigmoid range used to stretch the template
n_bursting	null	int	number of bursting units. If null all units are bursting
chunk_conv_duration	20	float	chunk duration for convolution (if running into MemoryError)
noise_level	10	float	noise standard deviation in uV
noise_mode	uncorrelated	string	[uncorrelated | distance-correlated | far-neurons]
noise_color	False	bool	if True noise is colored resembling experimental noise
noise_half_distance	30	float	(distance-correlated) distance between electrodes in µm for which correlation is 0.5
far_neurons_n	300	int	(far-neurons) number of far neurons to be simulated
far_neurons_max_amp	10	float	(far-neurons) maximum amplitude of far neurons
far_neurons_noise_floor	0.5	float	(far-neurons) percent of additive random noise
far_neurons_exc_inh_ratio	0.8	float	(far-neurons) excitatory / inhibitory noisy neurons ratio [0-1]
color_peak	300	float	(color) peak / cutoff frequency of resonating filter in Hz
color_q	2	int	(color) quality factor of resonating filter
color_noise_floor	0.5	float	(color) percent of additive random noise
chunk_noise_duration	0	float	chunk duration for noise addition
seed	null	int	random seed for noise generation
filter	True	bool	if True recordings are filtered
filter_cutoff	[300, 6000]	float/list	filter cutoff frequencies in Hz
filter_order	3	int	filter order
chunk_filter_duration	0	float	chunk duration for filtering
drifting	False	bool	if True drifitng recordings are simulated
n_drifting	null	int	number of drifting units. If null all units are drifing
preferred_dir	[0, 0, 1]	list	preferred drifting direction ([0, 0, 1] is positive z, direction)
angle_tol	15	float	tolerance for direction in degrees
drift_velocity	5	float	drift velocity in µm/min
t_start_drift	0	float	time in seconds after which drifting starts

Table 4: (Continued) Recordings generation parameter list, values, types, and explanations.

Statistical analysis

No statistical analysis is used in this contribution.

Code availability

The presented software package is available at `https://github.com/alejoe91/MEArec` and `https://github.com/alejoe91/MEAutility` (used for probe handling). The packages are also available on `pypi`: `https://pypi.org/project/MEArec/` - `https://pypi.org/project/MEAutility/`.

Data availability

All the datsets generated for the paper and used to make figures are available on Zenodo at `https://doi.org/10.5281/zenodo.3247736`.

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Appendix A - command line interface (CLI)

MEArec implements a command line interface (CLI) to make templates and recordings generation easy to use and to allow for scripting. In order to discover the available commands, the user can use the --help option:

```
>> mearec --help

Usage: mearec [OPTIONS] COMMAND [ARGS]...

  MEArec: Fast and customizable simulation of extracellular recordings on
  Multi-Electrode-Arrays

Options:
  --help  Show this message and exit.

Commands:
  available-probes        Print available probes.
  default-config          Print default configurations.
  gen-recordings          Generates RECORDINGS from TEMPLATES.
  gen-templates           Generates TEMPLATES with biophysical simulation.
  set-cell-models-folder  Set default cell_models folder.
  set-recordings-folder   Set default recordings output folder.
  set-recordings-params   Set default recordings parameter file.
  set-templates-folder    Set default templates output folder.
  set-templates-params    Set default templates parameter file.
```

Each available command can be inspected using the --help option:

```
>> mearec command --help
```

At installation, MEArec creates a configuration folder (.config/mearec) in which global settings are stored. The default paths to cell models folder, templates and recordings output folders and parameters can be set using the set-cell-models-folder, set- commands. By default, these files and folders are located in the configuration folder.

```
>> mearec default-config

{'cell_models_folder': path-to-cell_models,
 'recordings_folder': path-to-recordings-folder,
 'recordings_params': path-to-recordings-params.yaml,
 'templates_folder': path-to-templates-folder,
 'templates_params': path-to-templates-params.yaml}
```

A list of available probes can be found by running the available-probes command:

```
>> mearec available-probes

Neuronexus-32 ---------- Neuronexus A1x32-Poly3-5mm-25s-177-CM32 probe.
                         32 circular contacts in 3 staggered columns.

Neuropixels-128 ---------- Neuropixels probe.
                           128 square contacts in 4 staggered columns.
```

```
Neuropixels-24 ---------- Neuropixels probe.
                          24 square contacts in 4 staggered columns.

Neuropixels-384 ---------- Neuropixels probe.
                           384 square contacts in 4 staggered columns.

Neuropixels-64 ---------- Neuropixels probe.
                          64 square contacts in 4 staggered columns.

Neuroseeker-128 ---------- Neuroseeker probe.
                           128 square contacts in 4 columns.

SqMEA-10-15 ---------- Square MEA. 100 square contacts in 10x10 matrix configuration
                       with 15um pitch.

SqMEA-15-10 ---------- Square MEA. 225 square contacts in 15x15 matrix configuration
                       with 10um pitch.

SqMEA-5-30 ---------- Square MEA. 25 square contacts in 5x5 matrix configuration
                      with 30um pitch.

SqMEA-6-25 ---------- Square MEA. 36 square contacts in 6x6 matrix configuration
                      with 25um pitch.

SqMEA-7-20 ---------- Square MEA. 49 square contacts in 7x7 matrix configuration
                      with 20um pitch.

four-tetrodes ---------- 4 tetrodes on a shank with 100um inter-tetrode distance.

tetrode ---------- Microwire tetrode with 4 circular contacts.

tetrode-mea-d ---------- Silicon tetrode with 4 square contacts
                         in diamond configuration.

tetrode-mea-l ---------- Silicon tetrode with 4 square contacts
                         in linear configuration.

tetrode-mea-s ---------- Silicon tetrode with 4 square contacts
                         in square configuration.
```

Finally, examples of templates and recordings generation commands can be found in the Results section.

Appendix B - Python API example

`MEArec` implements a Python API for simulating both templates and recordings. The Python API is recommended for generating recordings for testbench purposes. For example, the following script is used to generate four recordings with varying noise level, shown in Figure 8A:

```
import MEArec as mr
import matplotlib.pylab as plt
import numpy as np
```

```python
# load template file as a TemplateGenerator object
template_file = 'path-to-template-file.h5'
tempgen = mr.load_templates(template_file)

# load default recording parameters
params = mr.get_default_recordings_params()

# set seeds for spike trains and template selection
params['spiketrains']['seed'] = 0
params['templates']['seed'] = 1

# list of noise levels
noise_levels = [30, 20, 10, 5]

# generate recordings
recordings_noise = []
for n in noise_levels:
    print('Noise level:', n)
    params['recordings']['noise_level'] = n
    params['recordings']['seed'] = np.random.randint(1000)
    recgen = mr.gen_recordings(tempgen=tempgen, params=params)
    recordings_noise.append(recgen)

# plot recordings on the same axis
colors = plt.rcParams['axes.prop_cycle'].by_key()['color']
fig = plt.figure()
ax = fig.add_subplot(111)
for i, rec in enumerate(recordings_noise):
    ax = mr.plot_recordings(rec, colors=colors[i], ax=ax)
```

For additional examples, please refer to the Github page `https://github.com/alejoe91/MEArec`.