Research Article: Open Source Tools and Methods **|** *Novel Tools and Methods*

Rigbox: An Open-Source Toolbox for Probing Neurons and Behavior

https://doi.org/10.1523/ENEURO.0406-19.2020

Cite as: eNeuro 2020; 10.1523/ENEURO.0406-19.2020

Received: 10 April 2020
Revised: 18 May 2020
Accepted: 25 May 2020

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2) Rigbox

3)

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13) We thank Nick Steinmetz, Max Hunter, Peter Zatka-Haas, Kevin Miller, Hamish Forrest, and other members of the lab for troubleshooting, feedback, inspiration, and code contribution. This work was funded by the Medical Research Council (Doctoral Training Award to CPB), the Royal Society (Newton International Fellowship to AJP), EMBO (fellowship to AJP), the Human Frontier Science Program (fellowship to AJP), and by the Wellcome Trust (grant 205093 to MC and KDH). MC holds the GlaxoSmithKline / Fight for Sight Chair in Visual Neuroscience.

14) No.

15)

a) Medical Research Council
b) Wellcome Trust

Rigbox: An Open-Source Toolbox for Probing Neurons and Behavior

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Setting up an experiment in behavioral neuroscience is a complex process that is often managed with ad hoc solutions. To streamline this process we developed Rigbox, a high-performance, open-source software toolbox that facilitates a modular approach to designing experiments (github.com/cortex-lab/Rigbox). Rigbox simplifies hardware I/O, time-aligns datastreams from multiple sources, communicates with remote databases, and implements visual and auditory stimuli presentation. Its main submodule, Signals, allows intuitive programming of behavioral tasks. Here we illustrate its function with two interactive examples: a human psychophysics experiment, and the game of Pong. We give an overview of running experiments in Rigbox, provide benchmarks, and conclude with a discussion on the extensibility of the software and comparisons with similar toolboxes. Rigbox runs in MATLAB, with Java components to handle network communication, and a C library to boost performance.

Significance Statement

Configuring the hardware and software components required to run a behavioral neuroscience experiment and manage experiment-related data is a complex process. In a typical experiment, software is required to design a behavioral task, present stimuli, read hardware input sensors, trigger hardware outputs, record subject behavior and neural activity, and transfer data between local and remote servers. Here we introduce Rigbox, which to the best of our knowledge is the only software toolbox that integrates all the aforementioned software requirements necessary to run an experiment. This MATLAB-based package provides a platform to rapidly prototype experiments. Multiple laboratories have adopted this package to run experiments in cognitive, behavioral, systems, and circuit neuroscience.

Introduction

In behavioral neuroscience, much time is spent setting up hardware and software and ensuring compatibility between them. Experiments often require configuring disparate software to interface with distinct hardware, and integrating these components is no trivial task. Furthermore, there are often separate software components for designing a behavioral task, running the task, and acquiring, processing, and logging the data. This requires learning the fundamentals of different software packages and how to make them communicate appropriately.

Consider a typical experiment focused on decision-making, in which a subject chooses a stimulus amongst a set of possibilities and obtains a reward if the choice was correct (Carandini and Churchland, 2013). The software set-up for this experiment may seem simple: ostensibly, all that is required is software to run the behavioral task, and software to handle experiment data. However, when considering implementation details for these two types of software, the set-up can grow quite complex. Running the behavioral task requires software for starting, stopping, and transitioning between task states, presenting stimuli, reading input devices, and triggering output devices. Handling experiment data requires software for acquiring, processing, and logging stimulus history, response history, and subject physiology, and transferring data between servers and databases.

To address this variety of needs in a single software toolbox, we designed Rigbox (github.com/cortex-lab/Rigbox). Rigbox is modular, high-performance, open-source software for running behavioral neuroscience experiments and acquiring experiment-related data. Rigbox facilitates acquiring, time-aligning, and managing data from a variety of sources. Furthermore, Rigbox allows users to programmatically and intuitively design and parametrize behavioral tasks via a framework called Signals.

We begin by giving a general overview of Signals, the core package of Rigbox. We illustrate two simple interactive examples of its use: an experiment in visual psychophysics, and the game of Pong. Next, we describe how Rigbox runs Signals experiments and manages experiment data. We then discuss Rigbox's design considerations and the various types of experiments that have been implemented using Rigbox. Lastly, we detail Rigbox's requirements and provide benchmarking results.

Code Accessibility

Rigbox is currently under active, test-driven development. All our code is open source, distributed under the Apache 2.0 license at github.com/cortex-lab/Rigbox, and we encourage users to contribute. Please see the contributing section of the README for information on contributing code and reporting issues. When using Rigbox to run behavioral tasks and/or acquire data, please cite this publication.

Signals

Signals is a framework designed for building bespoke behavioral tasks. In Signals, an experiment is built from a reactive network whose nodes (“signals”) represent experiment parameters. This simplifies problems that deal with how experiment parameters change over time by representing relationships between these parameters with straightforward, self-documenting operations. For example, to define a drifting grating, a user could create a signal which changes a grating’s phase as a function of time (Figure 1). This is shown in the code below:

```
theta = 2*pi; % angle of phase in radians
freq = 3; % frequency of phase in Hz
stimulus.phase = theta*freq*t; % phase that cycles at 3 Hz for given stimulus
```

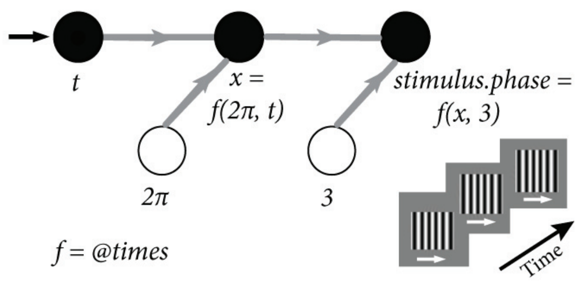

Figure 1: A representation of the time-dependent phase of a visual stimulus in Signals using a clock signal, `t`. `t` represents time in seconds since experiment start (its value therefore constantly increases). An unfilled circle represents a constant value - it becomes a node in the network when combined with another signal in an operation (in this instance, via multiplication, represented by the MATLAB function, `times`). The bottom right shows how the grating’s phase changes over time - the white arrow indicates the phase shift direction.

Whenever the clock signal, `t`, is updated (e.g. by a MATLAB timer callback function), the values of all its dependent signals are then recalculated asynchronously via callbacks. This paradigm is known as functional reactive programming (Lew, 2017).

The operations that can be performed on signals are not just limited to basic arithmetic. Many built-in MATLAB functions (including logical, trigonometric, casting, and array operations) have been overloaded to work on signals as they would on basic numeric or char types. Furthermore, a number of classical functional programming functions (e.g. “map” and “scan”) can be used on signals (Figure 2). These allow signals to gate, trigger, filter, and accumulate other signals in order to define a complete experiment.

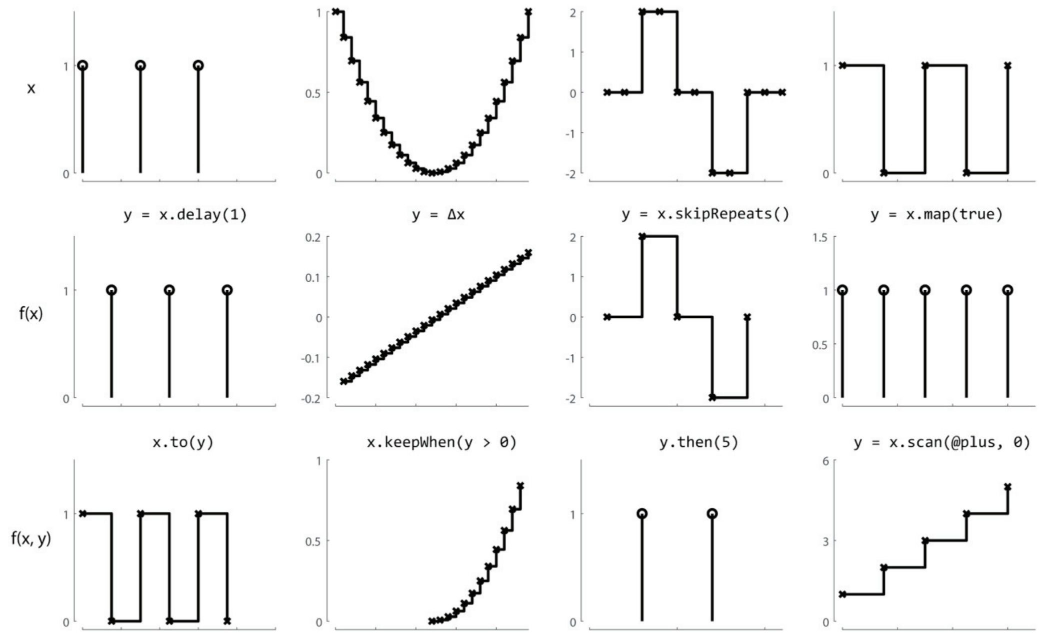

Figure 2: The creation of new signals via example signals methods. Each panel, in which the x-axis represents time and the y-axis represents value, contains a signal. Each column depicts a set of related transformations. The top row contains four arbitrary signals. The second row depicts a signal which results from applying an operation on the signal in the panel above. The third row depicts a signal which results from applying an operation on the signals in the two panels above. Conceptually, each signal can be thought of as both a continuous stream of discrete values, and as a discrete representation whose value changes over time.

Example 1: A Psychophysics Experiment

Our first example of a human-interactive Signals experiment is a script that recreates a psychophysics experiment to study the mechanisms that underlie the discrimination of a visual stimulus (Ringach 1998). In this experiment, the observer looks at visual gratings (Figure 3a) that change rapidly and randomly in orientation and phase. The gratings change so rapidly that they summate in the visual system, and the observer tends to perceive two or three of them as superimposed. The task of the observer is to hit the “ctrl” key whenever the grating’s orientation is vertical. At key press, the probability of detection is plotted as a function of stimulus orientation in the recent past. Typically, this exposes a center-surround type of organization, with orientations near vertical eliciting responses, but orientations further away suppressing responses (Figure 3b). The Signals network representation of this experiment is shown in Figure 4.

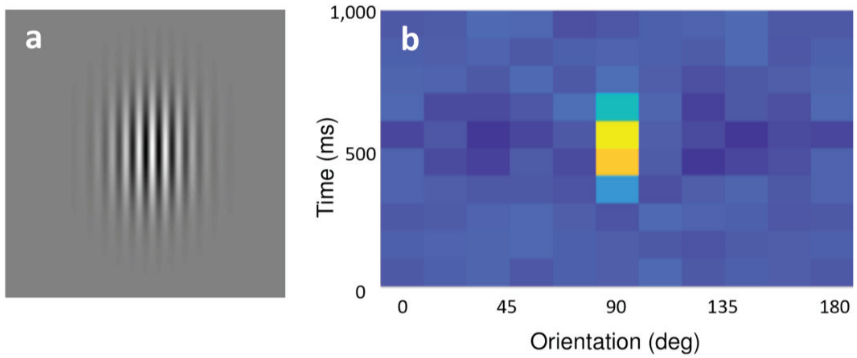

Figure 3: Output shown when running `ringach98.m` **a)** A sample grating which the subject is required to respond to via a "ctrl" key press. **b)** A heatmap showing the grating orientations for the ten frames immediately preceding the key press, summed over all the key presses for the duration of the experiment. After a few minutes, the distribution of orientations that were presented at each key press resembles a 2D Mexican Hat wavelet, centered on the orientation the subject was reporting at the subject's average reaction time. In this example, the subject was reporting a vertical grating orientation (90 degrees) with an average reaction time of roughly 600ms.

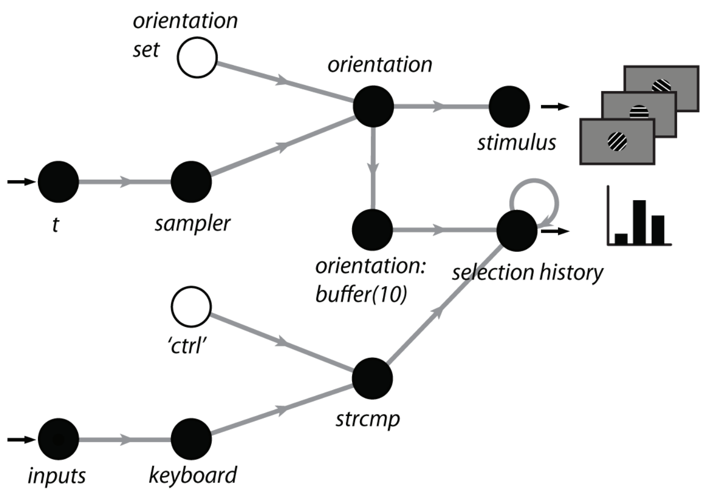

Figure 4: A simplified Signals network diagram of the Ringach experiment. Each circle represents a node in the network that carries out an operation on its direct input. The left-most nodes are inputs to the network, and the values from the right-most layer are used to update the stimulus and the histogram plot. An unfilled circle represents a constant value.

To run this experiment, simply run the `signals/docs/examples/scripts/ringach98.m` file in the Rigbox repository and press the "Play" button. Below is a breakdown of the thirty-odd lines of code:

First, some constants are defined:

```
oris = 0:18:162; % set of orientations, deg
phases = 90:90:360; % set of phases, deg
presentationRate = 10; % Hz
```

```
winlen = 10; % length of histogram window, frames
```

Next, we create a figure:

```
figh = figure('Name', 'Press “ctrl” key on vertical grating',...
  'Position', [680 250 560 700], 'NumberTitle', 'off');
vbox = uix.VBox('Parent', figh); % container for the play/pause button and axes
% Create axes for the histogram plot.
axh = axes('Parent', vbox, 'NextPlot', 'replacechildren', 'XTick', oris);
xlabel(axh, 'Orientation');
ylabel(axh, 'Time (frames)');
ylim([0 winlen] + 0.5);
vbox.Heights = [30 -1]; % 30 px for the button, the rest for the plot
```

Next, we create our Signals network. The function `playgroundPTB` creates a new Signals network and one input signal, `t`. It creates a start button which when pressed starts a MATLAB timer that periodically updates `t` with the time. Finally, it returns an anonymous function, `setElemsFn`, that when called with a visual stimulus object adds the textures to a stimulus renderer:

```
% Create a new Psychtoolbox stimulus window and renderer, returning a timing
% signal, `t`, and function, `setElemsFn`, to load the visual elements.
[t, setElemsFn] = sig.test.playgroundPTB(vbox);
net = t.Node.Net; % handle to the network
```

Now, we derive some new signals from UI key press events and the clock signal:

```
% Create a signal from the keyboard presses.
keyPresses = net.fromUIEvent(figh, 'WindowKeyPressFcn');
% Filter it, keeping only ‘ctrl’ key presses. Turn into logical signal.
reports = strcmp(keyPresses.Key, 'ctrl');
% Sample the current time at `presentationRate`.
sampler = skipRepeats(floor(presentationRate*t));
```

To change the orientation and phase at a given frequency, we derive some indexing signals that will select a value from the orientation and phase sets. The `map` method calls a function with a signal’s value each time it changes. `@(~) foo` is the MATLAB syntax for creating an anonymous function. Each time the `sampler` signal changes, a new random integer is generated.

```
% Randomly sample orientations and phases by generating new indices for selecting
values from `oris` and `phases` each time `sampler` updates.
oriIdx = sampler.map(@(~) randi(numel(oris))); % index for `oris` array
phaseIdx = sampler.map(@(~) randi(numel(phases))); % index for `phases` array
currPhase = phaseIdx.map(@(idx) phases(idx)); % get current phase
currOri = oriIdx.map(@(idx) oris(idx)); % get current ori
```

Next we derive some signals for updating our plot of reaction times. First, a boolean array the size of our orientation set is created, then we derive a matrix from these vectors, storing the last 10 orientations presented.

```
% Create a signal to indicate the current orientation (a boolean column vector)
oriMask = oris' == currOri;
```

```
% Record the last few orientations presented (i.e. `buffer` the last few values that
`oriMask` has taken.) as a MxN matrix where M is the number of orientations (the
length of `oris`) and N is the number of frames (`winlen`)
oriHistory = oriMask.buffer(winlen);
```

Each time the user presses the "ctrl" key (represented by the `reports` signal), the values in the `oriHistory` matrix are added to the histogram via the `scan` method, which initializes the histogram with zeros.

```
% After each keypress, add the `oriHistory` snapshot to an accumulating histogram.
histogram = oriHistory.at(reports).scan(@plus, zeros(numel(oris), winlen));
```

Now, each time the histogram updates, we call `imagesc` with its value, updating the plot axes.

```
% Plot histogram surface each time it changes.
histogram.onValue(@(data) imagesc(oris, 1:winlen, flipud(data'), 'Parent', axh));
```

Finally, we create the visual stimulus signal and send it to the renderer. The `vis.grating` function returns a subscriptable signal, which has parameter fields related to visual grating properties. When the values of these signal fields are updated, the underlying textures are rerendered by `setElemsFn`.

```
% Create a Gabor with changing orientations and phases.
grating = vis.grating(t, 'sinusoid', 'gaussian');
grating.show = true; % set grating to be always visible
grating.orientation = currOri; % assign orientation
grating.phase = currPhase; % assign phase
grating.spatialFreq = 0.2; % cyc/deg
% Add the grating to the renderer.
setElemsFn(struct('grating',                                              grating));
```

With this powerful framework, a user can easily define complex relationships between stimuli, actions, and outcomes in order to create a complete experiment protocol. This protocol takes the form of a user-written MATLAB function, which we refer to as an "experiment definition" ("exp def").

When Rigbox initializes an experiment, a new Signals network is created with input layer signals representing time, experiment epochs (such as new trials), and hardware input devices (such as position sensors). These input signals are passed into the exp def function, and the code in the exp def operates on these signals to create new signals that are added to the network (Figure 5). The exp def is called just once to set up this network.

Figure 5: A Signals representation of an experiment. There are three types of input signals in the network, representing a clock, experiment epochs (such as new trials and experiment start and end conditions), and hardware input devices (such as an optical mouse, keyboard, rotary encoder, lever, etc.) In an exp def, the user defines transformations that create new signals (not shown) from these input signals, which ultimately drive outputs (such as a screen, speaker, and external hardware - such as a reward valve). The exp def is called once in order to create these experimenter-defined signals, which are updated during experiment runtime as the input signals they depend on are updated.

At experiment start, values are posted to the network's input signals. During experiment runtime, these input signals are continuously updated within the experiment's main while loop or through UI and timer callbacks. For example, a position sensor input device may be read from continuously in a while loop in order to update the signal representing this device. These input signal updates asynchronously propagate to the dependent signals that were created in the exp def. The experiment ends when the "experiment stop" signal is updated (e.g. when all trial conditions have occurred or after a specified duration of time).

The following is a brief overview of the structure of an exp def. An exp def takes up to seven input arguments:

```
function expDef(t, events, params, visStim, inputs, outputs, audio)
```

In order, these are 1) the clock signal; 2) an events structure containing signals which define experiment epochs, and signals -- from those created within the exp def -- which the experimenter wishes to log; 3) a signal parameters structure that defines session- or trial-specific signals whose values can be changed directly within a GUI before starting an experiment -- signal parameter defaults are set within the exp def and parameter sets can be saved and loaded across subjects and experiments; 4) the visual stimuli handler which contains as fields all signals which parametrize the display of visual stimuli -- any visual stimulus signal can be assigned various elements, which the viewing model allows to be defined in visual degrees, for being rendered to a screen, and a visual stimulus can be loaded directly from a saved image file; 5) an inputs structure containing signals which map to hardware input devices; 6) an outputs structure containing signals which map to external hardware output devices; 7) the audio stimuli handler which can contain as fields signals which map to available audio devices.

Tutorials on creating an exp def, examples of exp defs and standalone scripts (including those mentioned in this paper), and an in-depth overview of Signals can be found in the `signals/docs` folder within the Rigbox repository.

Example 2: Pong

A second human-interactive Signals experiment contained in the Rigbox repository is an exp def which runs the classic computer game, Pong (Figure 6). The signal which sets the player's paddle position is mapped to the optical mouse. The epoch structure is set so that a trial ends on a score, and the experiment ends when either the player or cpu reaches a target score. The code is divided into three sections: 1) initializing the game, 2) updating the game, 3) creating visual elements and defining exp def signal parameters. To run this exp def, follow the directions in the header of the `docs/examples/expDefs/signalsPong.m` file in the Rigbox repository. Because the file itself (including copious documentation) is over 300 lines, we will share only an overview here; however, readers are encouraged to look through the full file at their leisure.

```
function signalsPong(t, events, p, visStim, inputs, outputs, audio)
```

In this first section, we define constants for the game, arena, ball, and paddles:

```
%% Initialize the game
% how often to update the game in secs
[...]
% initial scores and target score
[...]
% size of arena, ball, and paddle: [w h] in visual degrees
[...]
% ball angle, and ball velocity in visual degrees per second
[...]
% cpu and player paddle X axis positions in visual degrees
[...]
```

The helper function, `getYPos`, returns the y-position of the cursor, which will be used to set the player paddle:

```
  function yPos = getYPos()
    [...]
  end
% get cursor's initial y-position
cursorInitialY = events.expStart.map(@(~) getYPos);
```

In the second section, we define how the ball and paddle interactions update the game:

```
%% Update game
```

```
% create a signal that will update the y-position of the player's paddle using
`getYPos`
playerPaddleYUpdateVal = (cursor.map(@(~)getYPos)-cursorInitialY)*cursorGain
% make sure the y-value of the player's paddle is within the screen bounds,
playerPaddleBounds = cond(...
  playerPaddleYUpdateVal > arenaSz(2)/2, arenaSz(2)/2, ...
  playerPaddleYUpdateVal < -arenaSz(2)/2, -arenaSz(2)/2, ...
  true,playerPaddleYUpdateVal);
% and only updates every `tUpdate` secs
playerPaddleY = playerPaddleBounds.at(tUpdate);
% Create a struct, `gameDataInit`, holding the initial game state
gameDataInit = struct;
…
% Create a subscriptable signal, `gameData`, whose fields represent the current
% game state (total scores, etc.), and which will be updated every `tUpdate` secs
gameData = playerPaddleY.scan(@updateGame, gameDataInit).subscriptable;
```

The helper function, `updateGame`, updates `gameData`. Specifically, it updates the data structure with ball angle, velocity, position, cpu paddle position, and player and cpu scores, based on the current ball position, which is updated at each sampled timestep:

```
  function gameData = updateGame(gameData, playerPaddleY)
    [...]
  end
% define trial end (when a score occurs)
anyScored = playerScore | cpuScore;
events.endTrial = anyScored.then(true);
% define game end (when player or cpu score reaches target score)
endGame = (playerScore == targetScore) | (cpuScore == targetScore);
events.expStop = endGame.then(true);
[...]
```

In the final section, we create the visual elements representing the arena, ball, and paddles, and define the exp def signal parameters:

```
%% Define the visual elements and the experiment signal parameters
% create the arena, ball, and paddles as 'vis.patch' subscriptable signals
arena = vis.patch(t, 'rectangle');
ball = vis.patch(t, 'circle');
ball.colour = p.ballColor;
playerPaddle = vis.patch(t, 'rectangle');
cpuPaddle = vis.patch(t, 'rectangle');
% assign the arena, ball, and paddles to the 'visStim' subscriptable signal handler
```

```
visStim.arena = arena;
visStim.ball = ball;
visStim.playerPaddle = playerPaddle;
visStim.cpuPaddle = cpuPaddle;
% define parameters that will be displayed in the GUI
try
  % `p.ballColor` is a conditional signal parameter: on any given trial, the ball
  % color will be chosen at random among three colors: white, red, blue
  p.ballColor = [1 1 1; 1 0 0; 0 0 1]’; % RGB color vector array
  % `p.targetScore` is a global signal parameter: it can be changed via the GUI used
  % to run this exp def before starting the game
  p.targetScore = 5;
catch
end
```

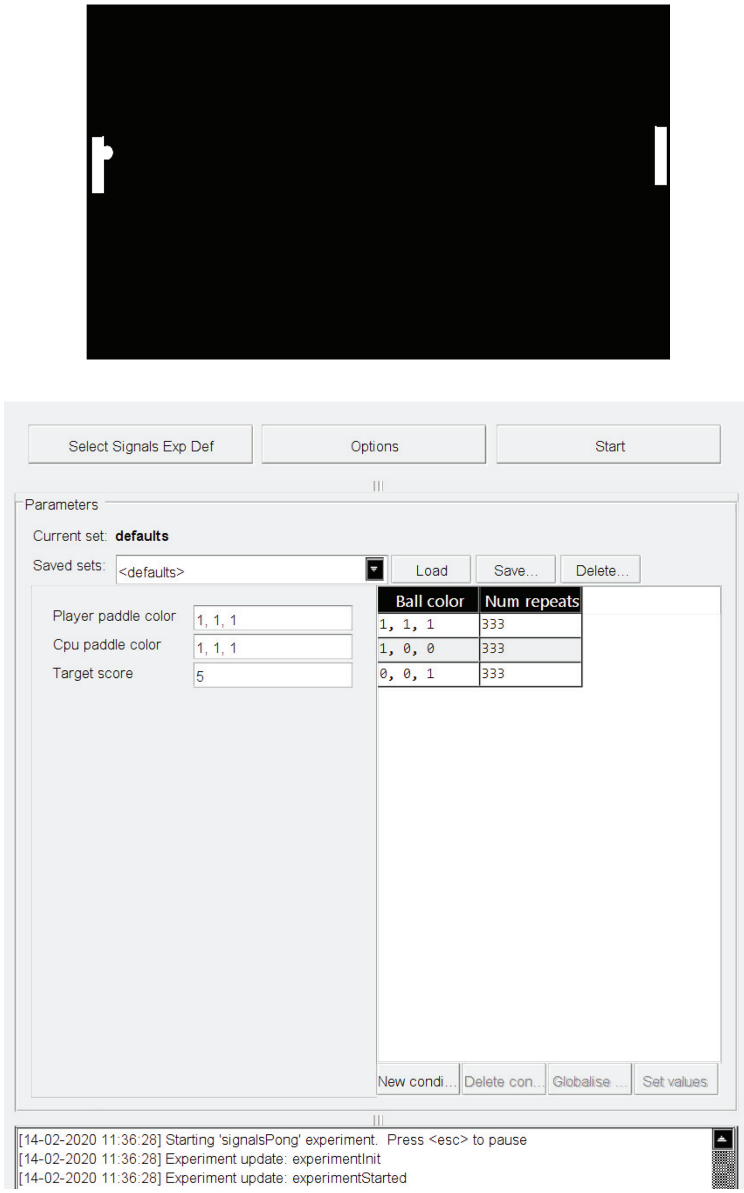

Figure 6: A screenshot of Pong run in Signals. The top shows the paddles and ball during gameplay. The bottom shows the GUI used to launch the game. The paddle colors (represented by an RGB vector) and target score are examples of global signal parameters that can be set once before starting the game. The ball color is an example of a conditional signal parameter that changes randomly after every trial (in this case, after a score) between the arrays indicated in each row (which in this case specify the colors white, red, and blue).

Running Experiments and Managing Data in Rigbox

Rigbox contains a suite of packages for interfacing with hardware, acquiring and managing data, communicating with a remote database, time-aligning events from a variety of sources, and implementing a user interface for managing experiments.

Rigbox simplifies experiments by providing an abstract interface for hardware interactions. All hardware devices, including screens and speakers, are represented by abstract classes that provide a basic set of interface methods. Methods for initializing, configuring and communicating with a particular device are handled by specific subclasses. This design choice avoids the creation of device-specific dependencies within the toolbox and the user's experiment code. In this way, hardware devices can be swapped without modifying code or affecting the experiment workflow, and adding support for new devices is straightforward. For example, to support a new multifunction i/o device (such as an Arduino or other microcontroller), one could simply extend the `+hw/DaqController` class, and to support a new hardware input sensor (such as a lever or joystick), one could simply subclass the `+hw/PositionSensor` class.

Intuitive and robust data management is another essential feature of Rigbox. Simple function wrappers save and locate data via human-readable experiment reference strings that reflect straightforward experiment directory structures: (`subject/date/session`). Data can be saved both locally and remotely, and even distributed across multiple servers. Rigbox uses a single paths config file, making it simple to change the location of data and configuration files. Furthermore, this code can be easily integrated with a user's personal code to generate read and write paths for arbitrary datasets. A `Parameters` class, which sets, validates, and assorts experiment conditions for each experiment, simplifies data analysis across experiments by standardizing parameterization. Rigbox can also communicate with an Alyx database in order to query and post data related to a subject or session. Alyx is a lightweight meta-database that can be hosted on an internal server, or in the cloud (e.g. via Amazon Web Services). Alyx allows users to organize experiment sessions and their associated files, and keep track of subject information, such as diet, breeding, and surgeries (International Brain Laboratory, et al.).

Experiments typically involve recording simultaneously from many devices, and temporal alignment of these recordings can be challenging. Rigbox contains a class called `Timeline` which manages the acquisition and generation of clocking pulses via a National Instruments multifunction i/o data acquisition device (NI-DAQ) (Figure 7). `Timeline`'s main clocking pulse, "chrono", is a digital square wave sent out from the NI-DAQ that can flip each time a new chunk of data is available to the NI-DAQ. A callback function to this flip event collects the NI-DAQ timestamp of the scan where the flip occured. The difference between this timestamp and the system time recorded when the flip command was sent is recorded as an offset time. This offset time can be used to unify all event timestamps across computers: all event timestamps are recorded in time relative to chrono. A `Timeline` object can acquire any number of hardware or software events (e.g. from hardware inputs directly wired to the NI-

DAQ, or UDP messages sent from another computer) and record their values with respect to this offset. For example, a `Timeline` object can record when a reward valve or laser shutter is opened, a sensor is interacted with, a screen displaying visual stimuli is updated, etc. In addition to chrono, a `Timeline` object can also output TTL and clock pulses for triggering external devices (e.g. to acquire frames at a specific rate).

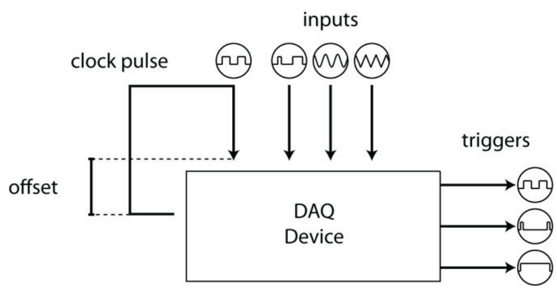

Figure 7: A representation of a Timeline object. The topmost signal is the main timing signal, “chrono”, which is used to unify all timestamps across computers during an experiment. The “inputs” represent different hardware and software input signals read by a NI-DAQ, and the “triggers” represent different hardware output signals, triggered by a NI-DAQ.

Lastly, Rigbox provides an intuitive yet powerful user interface for running experiments. For this, two computers are required. An experiment is started from a GUI on one computer, referred to as the “Master Computer” (MC), which runs the experiment on a recording rig, referred to as the “Stimulus Computer” (SC) (Figure 8). A SC is responsible for stimuli presentation, rig hardware interaction, and data acquisition. The MC GUI is used to select, parameterize, and start experiments (Figure 9). Customizable experiment panels can also be displayed within a different tab in the MC GUI to monitor experiments (Figure 10). MC and SC communicate during runtime via TCP/IP (using WebSockets), and MC can communicate with multiple SCs simultaneously in order to run multiple experiments in parallel.

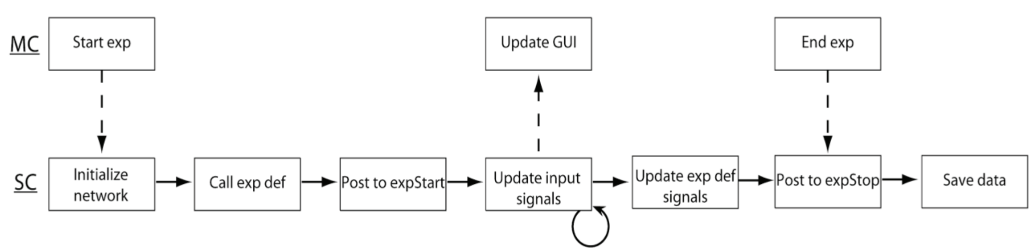

Figure 8: A simplified chronology of events that occur when starting an experiment via the MC GUI. Pushing the “Start” button on the MC GUI sends a message to SC to initialize a Signals network, then call the user’s Signals exp def to create new signals within the network, then post to the `expStart` signal to start the experiment. After starting the experiment, the network’s input signals are continuously updated via callbacks (e.g. via a MATLAB timer callback, or by reading from hardware input devices), which update the rest of the signals in the network (i.e. those signals defined in the user’s exp def). These updates can then be displayed back to the user on the MC GUI. This continues until the experiment is either ended from the MC GUI, or a condition is met within the user’s exp def that updates the `expStop` signal. After the experiment is

ended, experiment data is saved.

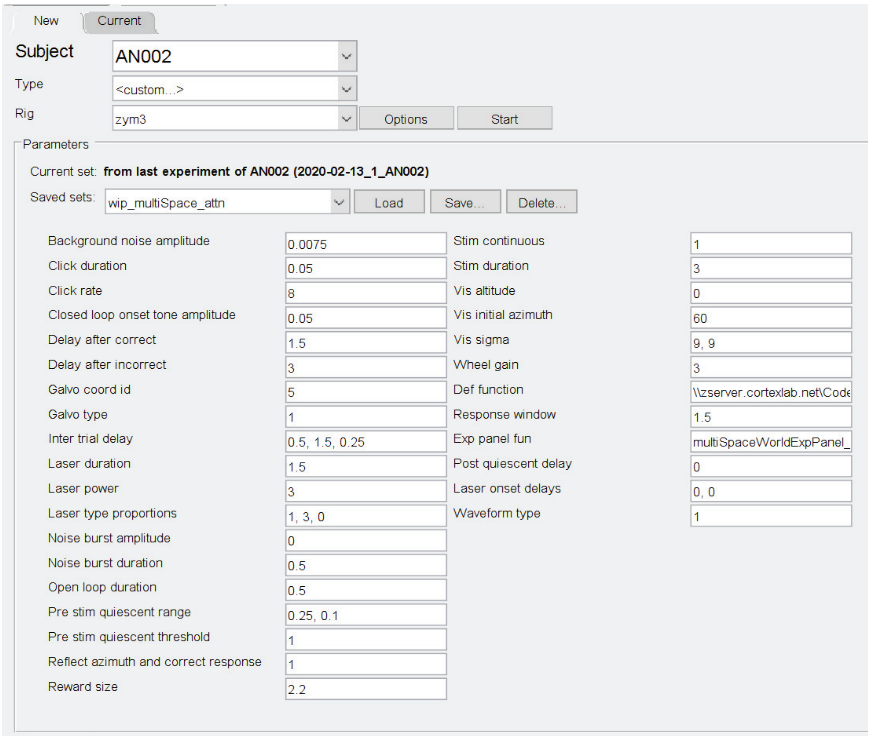

Figure 9: The new experiments tab within the MC GUI. This tab allows a user to select a subject, experiment type, and rig on which to run an experiment. Additionally, rig-specific options can be set via the “Options” button, and signal parameters for the behavioral task can be set via the editable parameter fields.

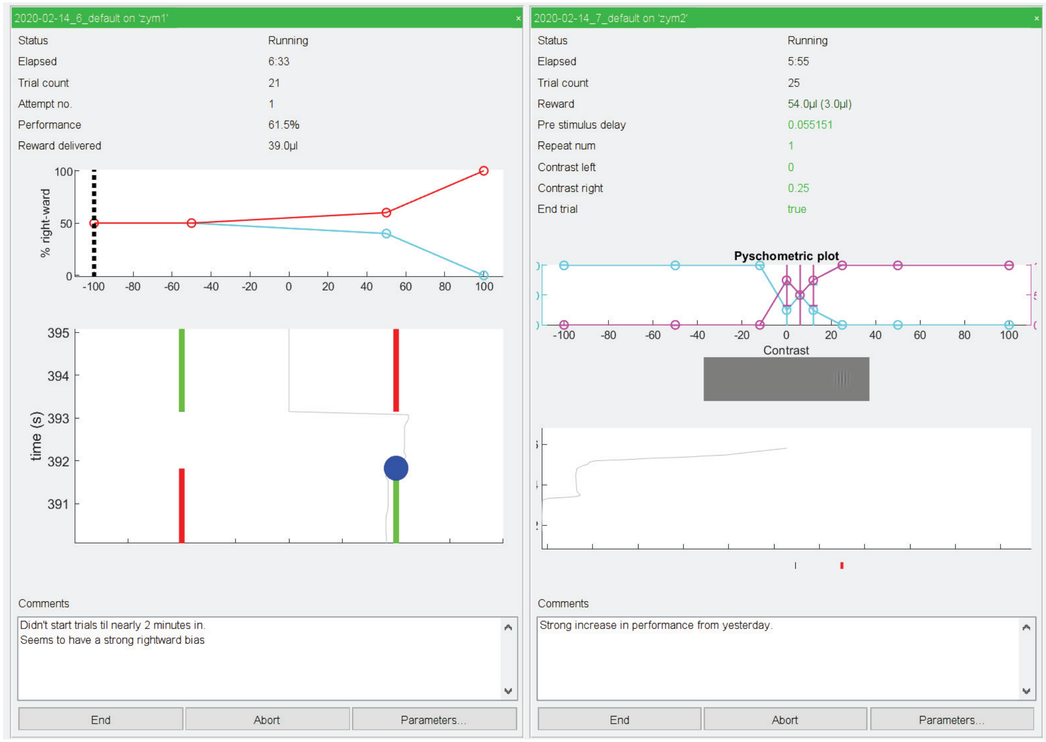

Figure 10: Experiment panels with live updates for two experiments. The top text fields in each panel display experiment information such as elapsed time, trial number, and the current running total of delivered reward. Below the text fields is a psychometric plot showing task performance for specific types of trials, and below this is a plot showing the real-time trace of a hardware input device (the panel on the left shows a two-alternative unforced choice task for which the green bar indicates the direction of the action the subject must make in order to receive a reward). There is also a text field for logging comments which can be immediately posted to an Alyx database. These experiment panels are highly customizable.

Instructions for installation and configuration can be found in the `README` file and the `docs/setup` folder of the GitHub repository. This includes information on required dependencies, setting data repository locations, configuring hardware devices, and enabling communication between the MC and SC computers. Hardware and software requirements can also be found in the repository `README` and this paper's "Requirements and Benchmarking" section.

Discussion

In our laboratory, Rigbox is at the core of our operant, passive, and conditioning experiments. The principal behavioral task we use is a two-alternative forced choice visual stimulus discrimination task (Burgess et al., 2017). Using Rigbox, we have been able to rapidly prototype multiple variants of this task, including unforced choice, multisensory choice, behavior matching, and bandit tasks, using wheels, levers, balls, and lick detectors. The Signals exp defs for each variant act as a concise and intuitive record of the task design. In addition, Rigbox has made it easy to combine these tasks with a variety of recording techniques, including electrode recordings, 2-Photon imaging, and fiber photometry, and neural perturbations, such as scanning laser inactivation and dopaminergic stimulation (Jun et al., 2017; Jacobs et al., 2018; Lak et al., 2018; Steinmetz et al., 2018; Shimaoka et al., 2018; Zatka-Haas et al., 2018). Rigbox has also enabled us to scale our behavioral training: because one MC can control multiple SCs, we run and manage many experiments simultaneously.

Often, experiments are iterative: task parameters are added or modified many times over, and finding an ideal parameter set can be an arduous process. Rigbox allows a user to develop and test an experiment without having to worry about boilerplate code and UI modifications, as these are handled by Rigbox packages in a modular fashion. Much of the code is object-oriented with most aspects of the system represented as configurable objects. Given the modular nature of Rigbox, new features and hardware support may be easily added, provided there is driver support in MATLAB.

To the best of our knowledge, Rigbox is the most complete behavioral control software toolbox currently available in the neuroscience community; however, several other toolboxes implement similar features in different ways (Bcontrol 2014; Sanders 2019; Akam 2019; Aronov and Tank, 2014) (Table 1). Some of these toolboxes also include some features not currently available in Rigbox, for example, microsecond precision triggering of within-trial events, and creating 3D virtual environments. Indeed, the features employed by a particular toolbox have advantages (and disadvantages) depending on the user's desired experiment.

There are pros and cons to following different programming paradigms for software developers who decide how users will design behavioral tasks. Generally, three main paradigms exist: procedural, object-oriented, and functional reactive. Here, in the context of programmatic task design, we briefly discuss the differences between these paradigms and in which scenarios one may be favored over the others. Note: here we only discuss the aspect of a toolbox that deals with behavioral task design, not the overall structure of a toolbox (e.g. Rigbox is built on an object-oriented paradigm, but Signals provides a functional reactive paradigm in which to implement a behavioral task).

	BControl	**pyBpod**	**pyControl**	**VirMEn**	**Rigbox**
Behavioral task design	Procedural	Procedural	Procedural	Object-	Functional

paradigm				Oriented	Reactive
Presents visual stimuli? 3D/VR environments?	no	no	no	yes, yes	yes, no
Interfaces with hardware?	yes	yes	yes	yes	yes
Time-aligns multiple datastreams?	yes	yes	yes	no	yes
Communicates with a remote database?	yes	yes	no	no	yes
Contains unit and integration tests?	?	?	yes	?	yes

Table 1: Comparison of major features across behavioral control system toolboxes. The top row contains the toolbox names, and the first column contains information on a feature's implementation. Note: the toolboxes and features mentioned in this table are not exhaustive.

A procedural approach to task design is probably the most familiar to behavioral neuroscientists. This approach focuses on "how to execute" a task by explicitly defining a control flow that moves a task from one state to the next. The Bcontrol, pyBpod, and pyControl toolboxes follow this paradigm by using real-time finite state machines (RTFSMs) which control a task's state (e.g. initial state, reward, punishment, etc.) during each trial. Some advantages of this approach are that it's simple, intuitive, and guarantees event timing precision down to the minimum cycle of the state machine (e.g. Bcontrol RTFSMs run at a minimum cycle of 6 KHz). Some disadvantages of this approach are that the memory for task parameters are limited by the RTFSM's number of states, and that the discrete implementation of states isn't amenable to experiments which seek to control parameters continuously (e.g. a task which uses continuous hardware input signals).

Like the procedural approach to task design, an object-oriented approach also tends to be intuitive: objects can neatly represent an experiment's state via datafields. Objects representing experimental parameters can easily pass information to each other and trigger experimental states via event callbacks. The VirMEn toolbox implements this approach by treating everything in the virtual environment as an object and having a runtime function update the environment by performing method calls on the objects based on input sensor signals from a subject performing a task. Some disadvantages of this approach are that the speed of experimental parameter updates are limited by the speed at which the programming language performs dynamic binding (which is often much slower than the

RTFSM approach discussed above), and that operation "side effects" (which can alter an experiment's state in unintended ways) are more likely to occur due to the emphasis on mutability, when compared to a pure procedural or functional reactive approach.

By contrast, Signals follows a functional reactive approach to task design. As we have seen, some advantages of this approach include simplifying the process of updating experiment parameters over time, endowing parameters with memory, and facilitating discrete and continuous event updates with equal ease. In general, a task specification in this paradigm is declarative, which can often make it clearer and more concise than in other paradigms, where control flow and event handling code can obscure the semantics of the task. Some disadvantages are that it suffers from similar speed limitations as in an object-oriented approach, and programmatically designing a task in a functional reactive paradigm is probably unfamiliar to most behavioral neuroscientists. When initially thinking about how a functional reactive network runs a behavioral task, it may be helpful to think of experiment parameters as nodes in the network that get updated via callbacks; there are no procedural calls to the network during experiment runtime.

When considering the entire set of behavioral tasks, no single programming paradigm is perfect, and it is therefore important for a user to consider the goals for their task's implementation accordingly.

Requirements and Benchmarking

Hardware Requirements

For most experiments, typical, contemporary, factory-built desktops running Windows 10 with dedicated graphics cards should suffice. Specific requirements of a SC will depend on the complexity of the experiment. For example, running an audio-visual integration task on three screens requires quality graphics and sound cards. SCs may additionally require a multifunction i/o device to communicate with external rig hardware, of which only NI-DAQs (e.g. NI-DAQ USB 6211) are currently supported.

Below are some **minimum** hardware specs required for computers that run Rigbox:

- **CPU:** 4 logical processors @ 3.0 GHz base speed (e.g. Intel Core i5-6500)
- **RAM:** DDR4 16 GB @ 2133 MHz (e.g. Corsair Vengeance 16 GB)

- **GPU:** 2 GB @ 1000 MHz base and memory speed (e.g. NVIDIA Quadro P400)

Software Requirements

Similar to the hardware requirements, software requirements for a SC will depend on the experiment. For example, if acquiring data through a NI-DAQ, the SC will require the MATLAB NI-DAQmx support package in addition to the following **minimum** requirements:

- **OS:** 64 Bit Windows 7 (or later)
- **Libraries:** Visual C++ Redistributable Packages for Visual Studio 2013 & 2015
- **MATLAB:** 2018b or later, including the Data Acquisition Toolbox
- **Community MATLAB toolboxes:**
    - GUI Layout Toolbox (v2 or later)
    - Psychophysics Toolbox (v3 or later)

Benchmarking

Fast execution of experiment runtime code is crucial for performing and accurately analyzing results from a behavioral experiment. Here we provide benchmarking results for the Signals framework. We include results for individual operations on a signal and for operations which propagate through each signal in a network. Single built-in MATLAB operations and Signals-specific methods are consistently executed in the microsecond range (Figure 11). The network used in a typical 2-alternative unforced stimulus discrimination task (`signals/docs/examples/advancedChoiceWorld.m`) contains 338 signals spread over 10 layers; a similar network of 350 signals spread over 20 layers can update all signals in under 5 milliseconds, and a network of 120 signals spread over 20 layers can update all signals with sub-millisecond precision (Figure 12). Lastly, we include results for reading from and triggering hardware devices in the above mentioned stimulus discrimination task.

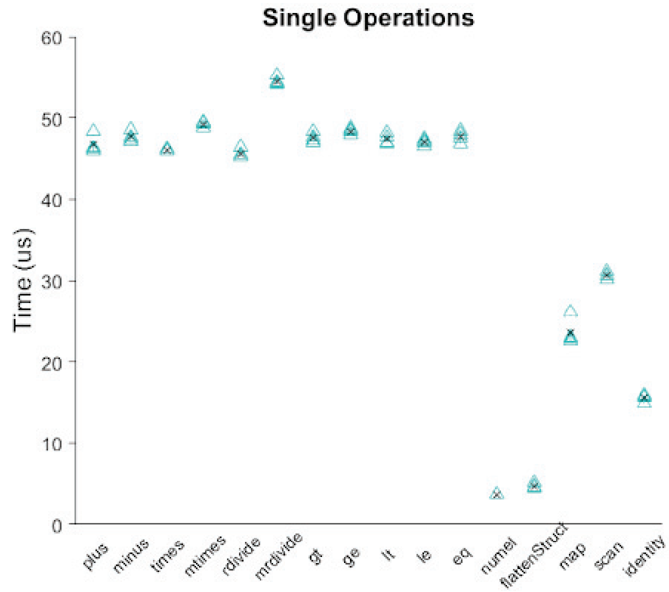

Figure 11: Benchmarking results for operations (specified by the x-axis) on a single signal. The black "x" shows the mean value per group.

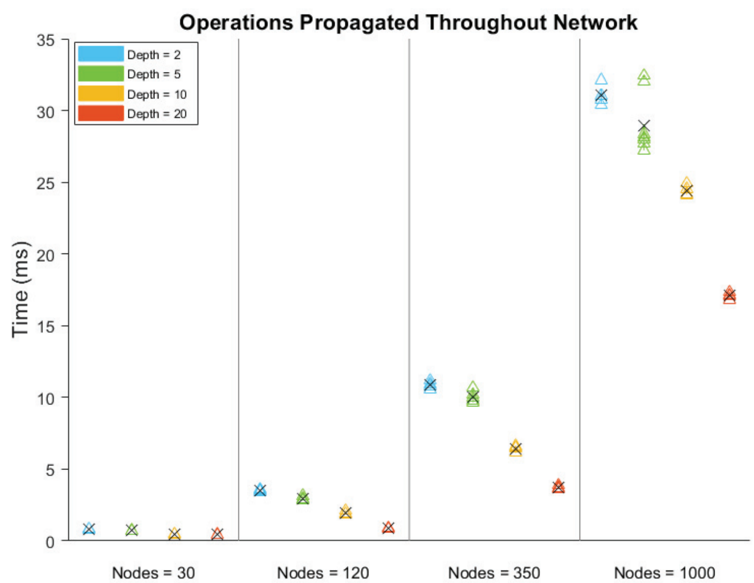

Figure 12: Benchmarking results for updating every signal in a network, for networks of various number of signals (nodes) spread over various number of layers (depth). The black "x" shows the mean value per group.

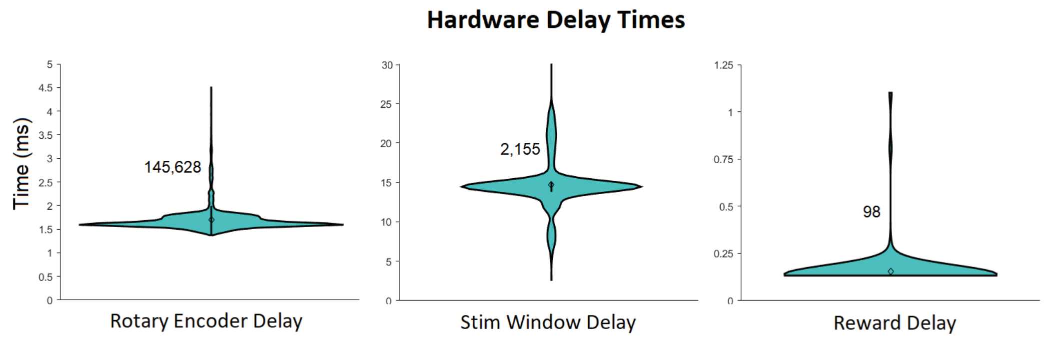

Figure 13: Delay times for specific updates when running a 2AFC visual contrast descrimination task. The number next to each violin plot indicates the number of samples in the group. “Rotary Encoder delay” is the time between polling consecutive position values from a rotary encoder. “Stim Window Delay” is the time between triggering a display to be rendered, and it’s complete render on a screen. “Reward Delay” the time between triggering and opening a reward valve. 99th percentile outliers were not included in the plot for “Rotary Encoder delay”: there were 98 instances in which the delay took between 200-600 ms, due to execution time of the NI-DAQmx MATLAB package when sending analog output (reward delivery) via the USB-6211 DAQ.

Updates of the position of a rotary encoder used to indicate choice typically took less than 2 milliseconds, the time between rendering and displaying the visual stimulus typically took less than 15 milliseconds, and the delay between triggering and delivering a reward was typically under 0.2 milliseconds (Figure 13).

All results in the Benchmarking section were obtained from running MATLAB 2018b on a Windows 10 64-bit OS with an Intel core i7 8700 processor and 16 GB DDR4 dual channel RAM clocking at a double data rate of 2133 MHz. Because single executions of signals operations were too quick for MATLAB to measure precisely, we repeated operations 1,000 times and divided MATLAB’s returned measured time by 1,000. MATLAB 2018b’s Performance Testing Framework was used to obtain these results. `signals/tests/Signals_perftest.m` contains the code used to generate the results shown in Figures 11 and 12, `signals/tests/results/2019-06-14_Signals_perftest.mat` contains a table of this data, and `signals/tests/results/2019-06-04_advancedChoiceWorld_Block.mat` contains the data used to generate the results shown in Figure 13. A National Instruments USB-6211 was used as the data acquisition i/o device.

Extended Data 1: We recommend looking at and downloading the code directly from the github repository, at https://github.com/cortex-lab/Rigbox

Acknowledgments

We thank Andy Peters, Nick Steinmetz, Max Hunter, Peter Zatka-Haas, Kevin Miller, Hamish Forrest, and other members of the lab for troubleshooting, feedback, inspiration, and code contribution. This work was funded by the Medical Research Council (Doctoral Training Award to CPB), and by the Wellcome Trust (grant 205093 to MC and KDH).

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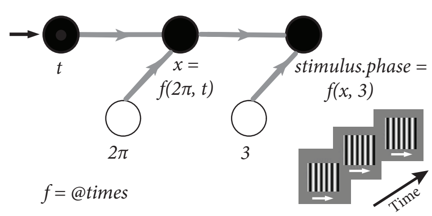
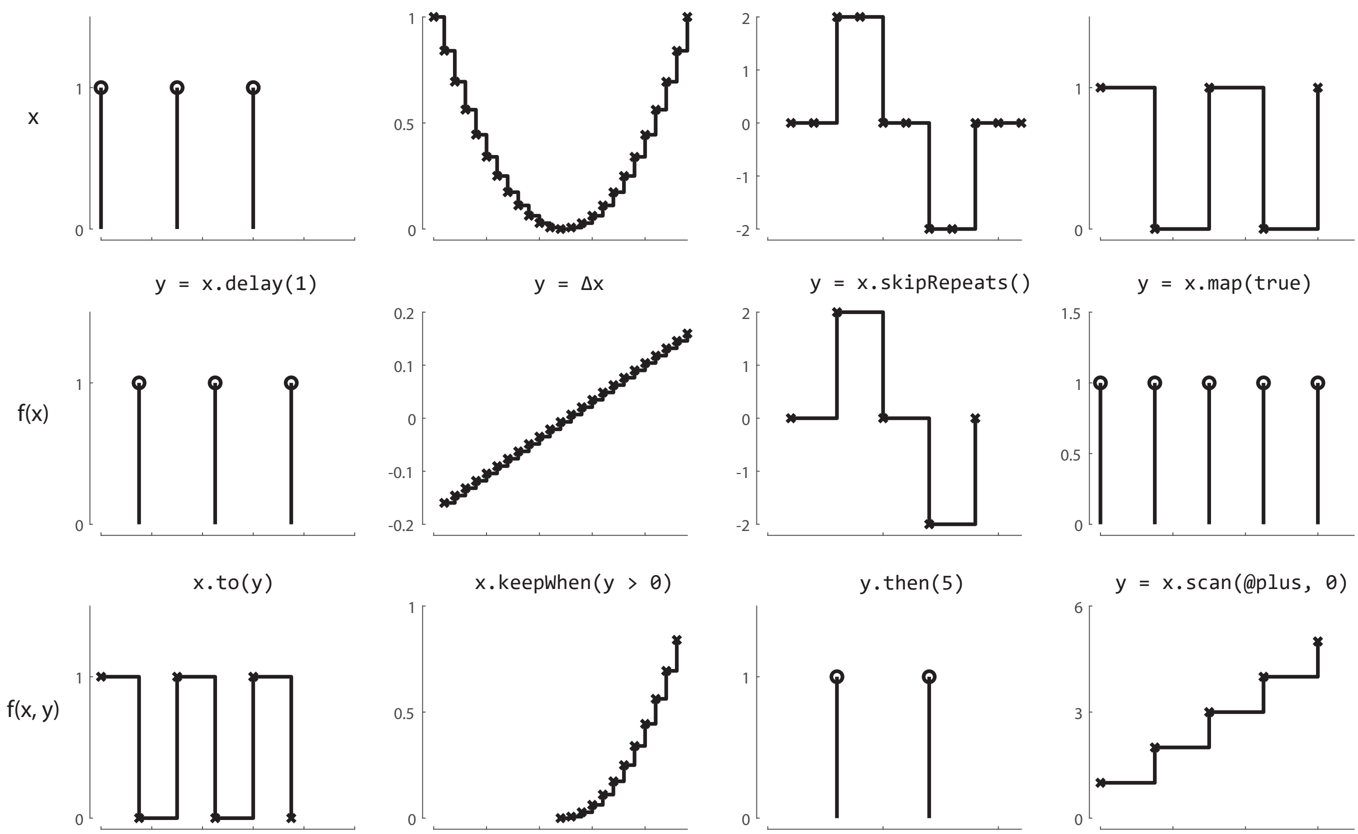
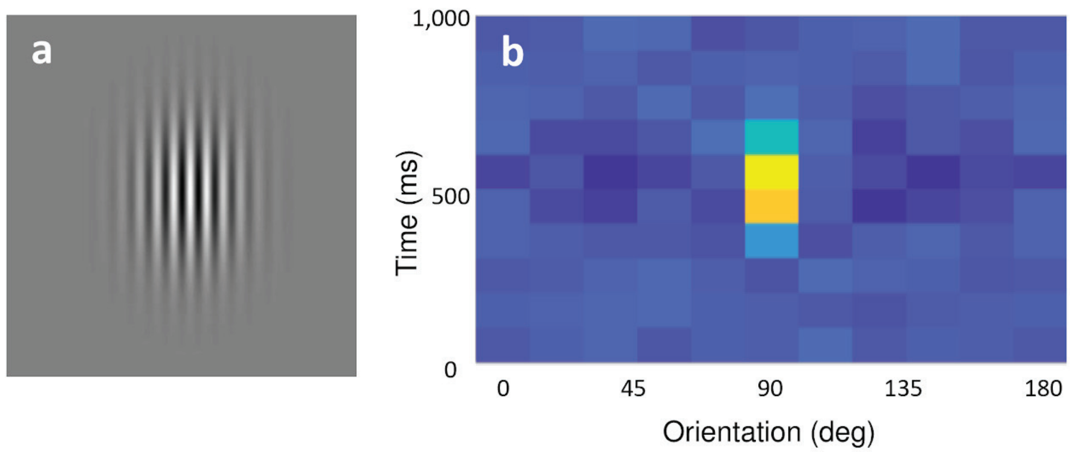
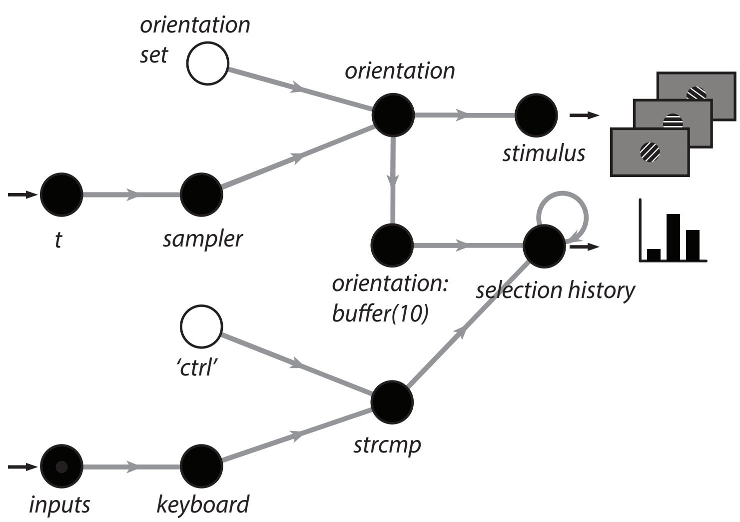
Zatka-Haas, P., Steinmetz, N. A., Carandini, M. Harris, K.D. (2018). Distinct contributions of mouse cortical areas to visual discrimination. *BioRxiv,* 501627.



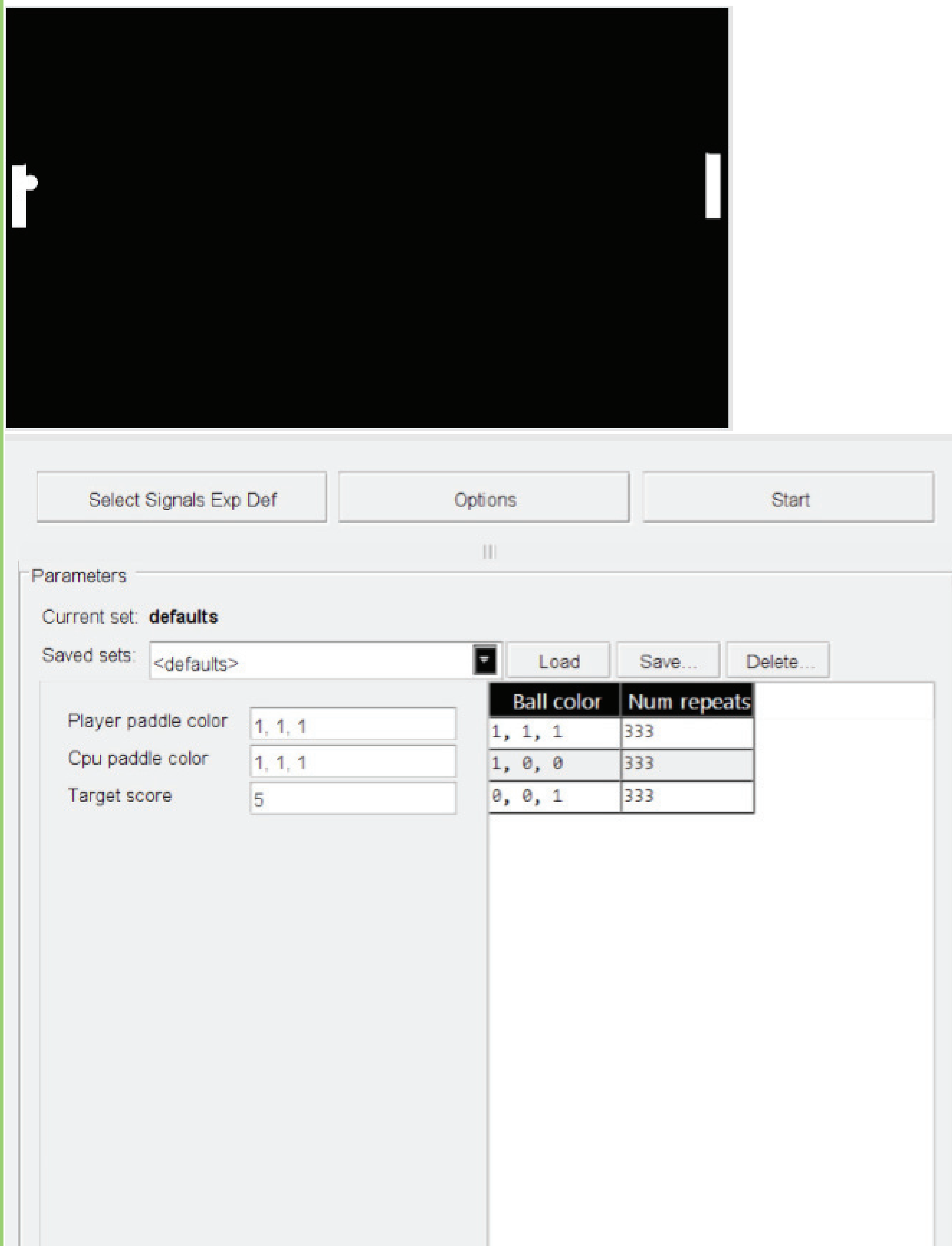
t
x =
f(2π, t)
stimulus.phase =
f(x, 3)
2π
3
f = @times
Time

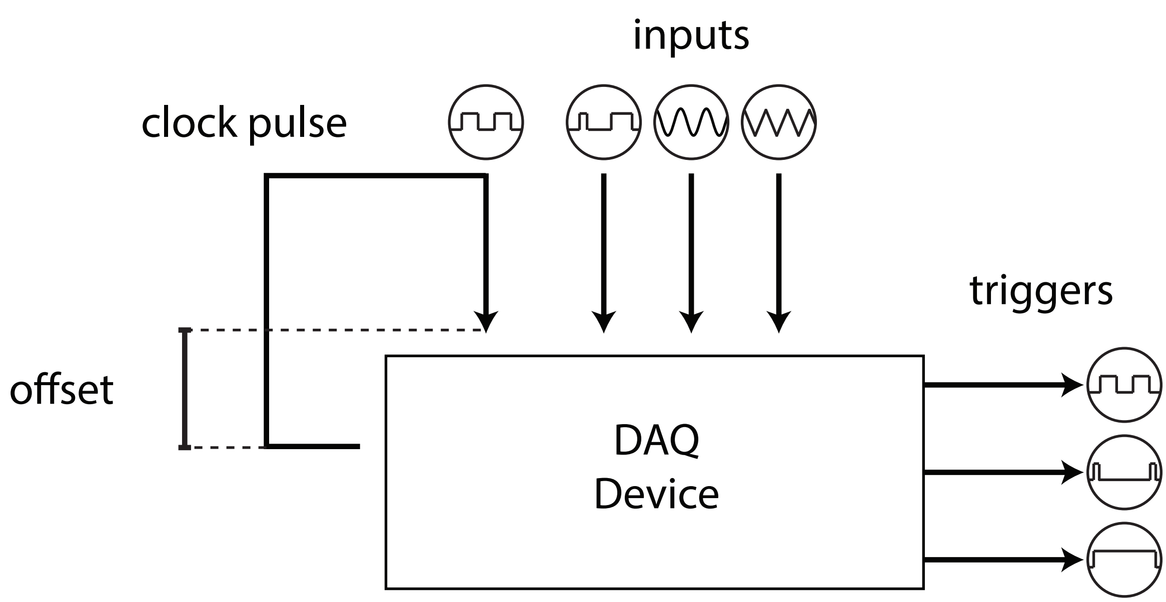

x
y = x.delay(1)
y = Δx
y = x.skipRepeats()
y = x.map(true)
f(x)
x.to(y)
x.keepWhen(y > 0)
y.then(5)
y = x.scan(@plus, 0)
f(x, y)

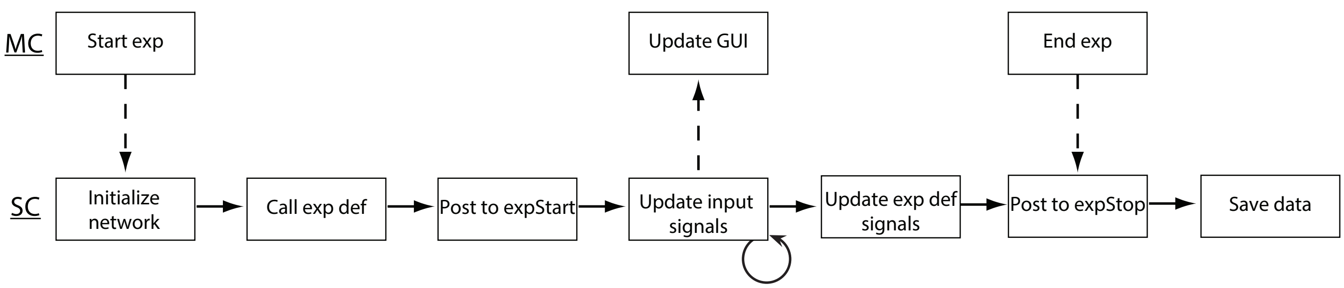

a
b
1,000
500
0
Time (ms)
0
45
90
135
180
Orientation (deg)

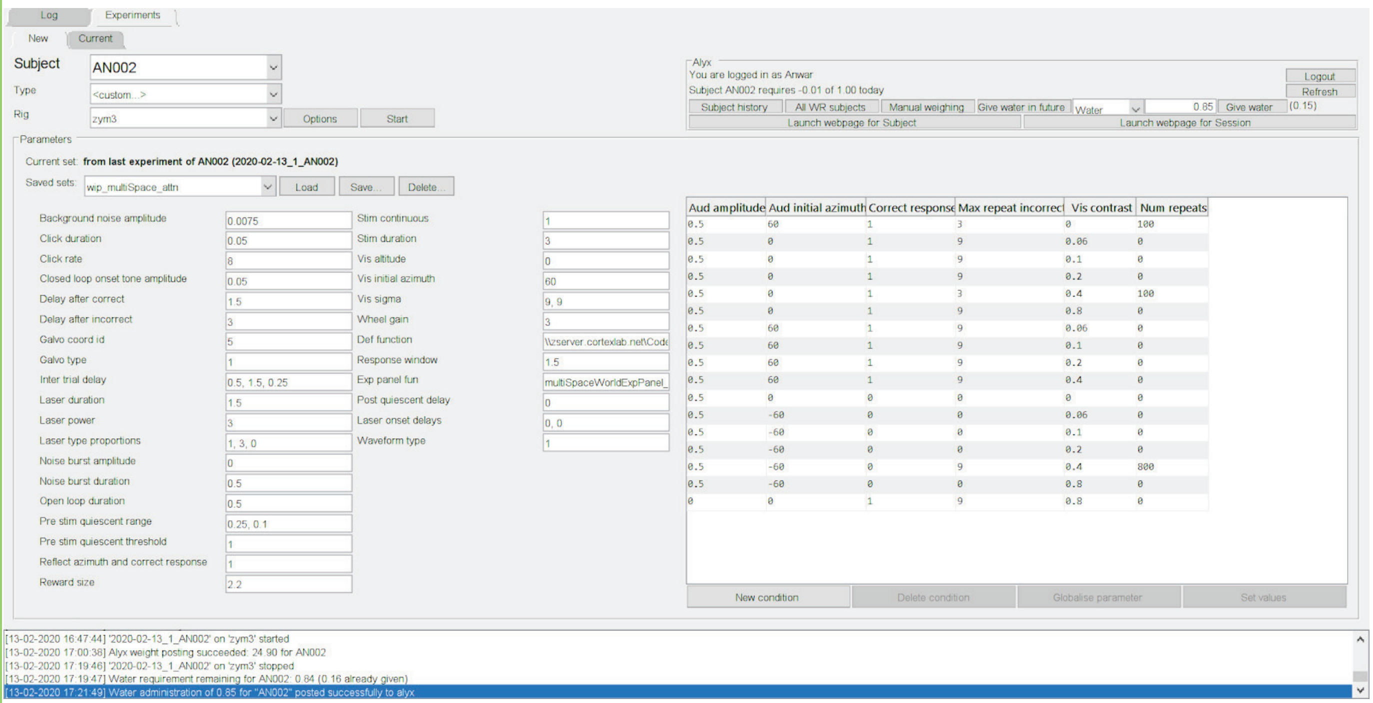

orientation
set
orientation
stimulus
t
sampler
orientation:
buffer(10)
selection history
'ctrl'
strcmp
inputs
keyboard

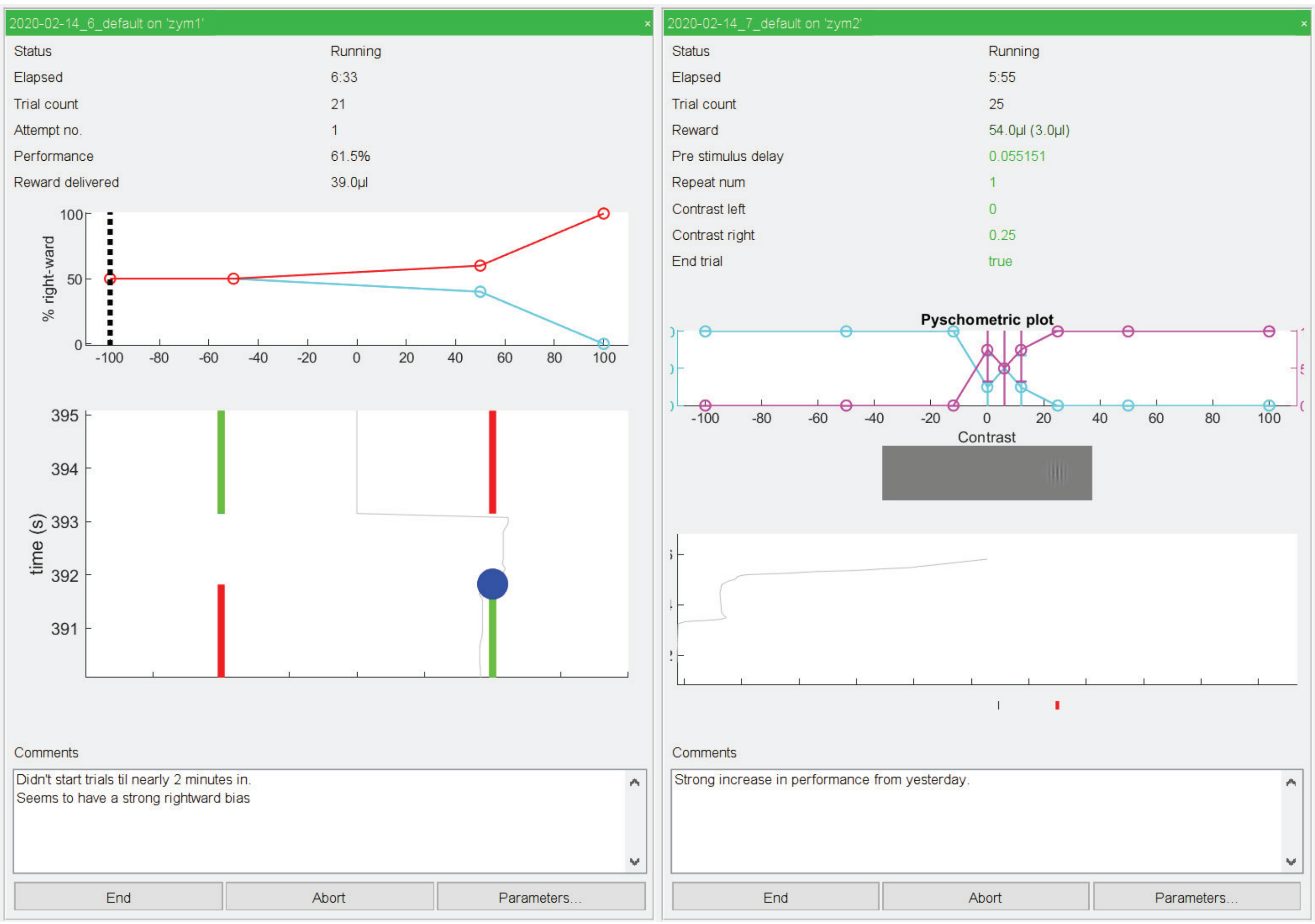

Clock
Experiment epochs
Hardware inputs
Experimenter-defined transformations
Screen
Speaker
External hardware outputs

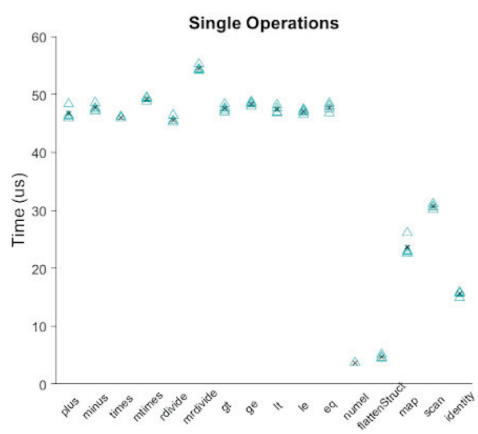

Select Signals Exp Def
Options
Start
Parameters
Current set: defaults
Saved sets:
<defaults>
Load
Save...
Delete...
Player paddle color
1, 1, 1
Cpu paddle color
1, 1, 1
Target score
5
Ball color
Num repeats
1, 1, 1
333
1, 0, 0
333
0, 0, 1
333

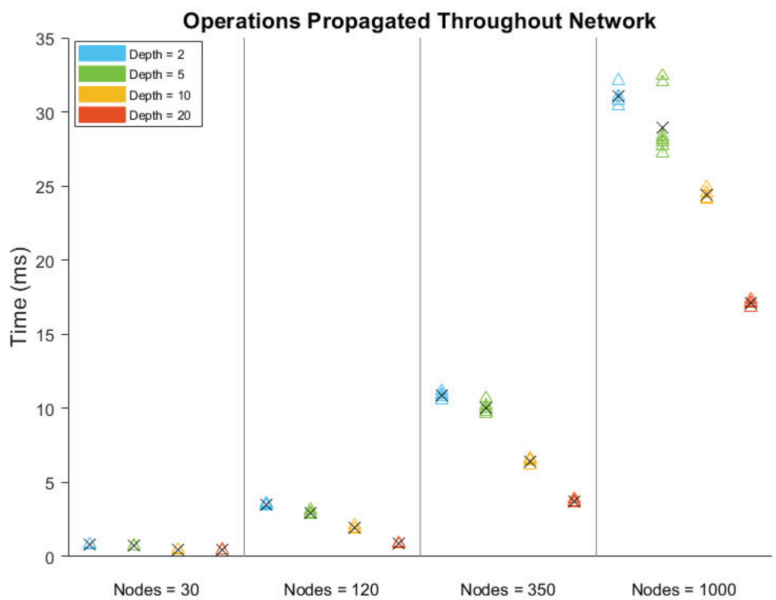

inputs
clock pulse
triggers
offset
DAQ
Device

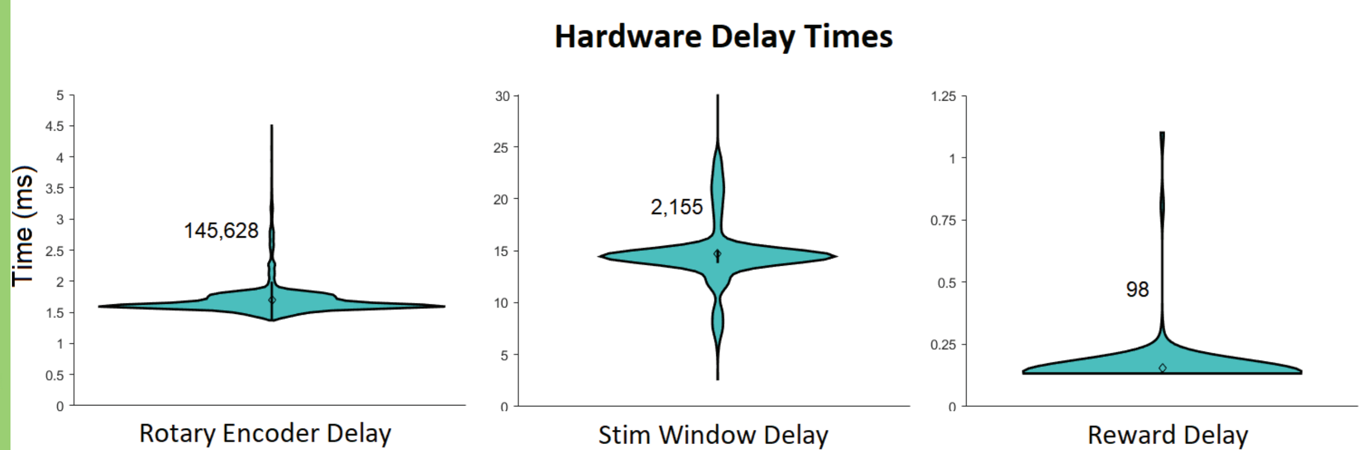

MC
Start exp
Update GUI
End exp
SC
Initialize network
Call exp def
Post to expStart
Update input signals
Update exp def signals
Post to expStop
Save data


Log
Experiments
New
Current
Subject
AN002
Type
<custom...>
Rig
zym3
Options
Start
Alyx
You are logged in as Anwar
Subject AN002 requires -0.01 of 1.00 today
Logout
Refresh
Subject history
All WR subjects
Manual weighing
Give water in future
Water
0.85
Give water
(0.15)
Launch webpage for Subject
Launch webpage for Session
Parameters
Current set: from last experiment of AN002 (2020-02-13_1_AN002)
Saved sets:
wip_multiSpace_attn
Load
Save...
Delete...
Background noise amplitude
0.0075
Click duration
0.05
Click rate
8
Closed loop onset tone amplitude
0.05
Delay after correct
1.5
Delay after incorrect
3
Galvo coord id
5
Galvo type
1
Inter trial delay
0.5, 1.5, 0.25
Laser duration
1.5
Laser power
3
Laser type proportions
1, 3, 0
Noise burst amplitude
0
Noise burst duration
0.5
Open loop duration
0.5
Pre stim quiescent range
0.25, 0.1
Pre stim quiescent threshold
1
Reflect azimuth and correct response
1
Reward size
2.2
Stim continuous
1
Stim duration
3
Vis altitude
0
Vis initial azimuth
60
Vis sigma
9, 9
Wheel gain
3
Def function
\\zserver.cortexlab.net\Code
Response window
1.5
Exp panel fun
multiSpaceWorldExpPanel_
Post quiescent delay
0
Laser onset delays
0, 0
Waveform type
1
Aud amplitude
Aud initial azimuth
Correct response
Max repeat incorrect
Vis contrast
Num repeats
New condition
Delete condition
Globalise parameter
Set values
[13-02-2020 16:47:44] '2020-02-13_1_AN002' on 'zym3' started
[13-02-2020 17:00:38] Alyx weight posting succeeded: 24.90 for AN002
[13-02-2020 17:19:46] '2020-02-13_1_AN002' on 'zym3' stopped
[13-02-2020 17:19:47] Water requirement remaining for AN002: 0.84 (0.16 already given)
[13-02-2020 17:21:49] Water administration of 0.85 for "AN002" posted successfully to alyx


2020-02-14_6_default on 'zym1'
Status
Running
Elapsed
6:33
Trial count
21
Attempt no.
1
Performance
61.5%
Reward delivered
39.0μl
% right-ward
100
50
0
-100
-80
-60
-40
-20
0
20
40
60
80
100
time (s)
395
394
393
392
391
Comments
Didn't start trials til nearly 2 minutes in.
Seems to have a strong rightward bias
End
Abort
Parameters...
2020-02-14_7_default on 'zym2'
Status
Running
Elapsed
5:55
Trial count
25
Reward
54.0μl (3.0μl)
Pre stimulus delay
0.055151
Repeat num
1
Contrast left
0
Contrast right
0.25
End trial
true
Pyschometric plot
Contrast
Comments
Strong increase in performance from yesterday.
End
Abort
Parameters...


Single Operations
Time (us)
60
50
40
30
20
10
0
plus
minus
times
mtimes
rdivide
mrdivide
gt
ge
lt
le
eq
numel
flattenStruct
map
scan
identity


Operations Propagated Throughout Network
Depth = 2
Depth = 5
Depth = 10
Depth = 20
Time (ms)
35
30
25
20
15
10
5
0
Nodes = 30
Nodes = 120
Nodes = 350
Nodes = 1000


Hardware Delay Times
Time (ms)
145,628
Rotary Encoder Delay
2,155
Stim Window Delay
98
Reward Delay
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
0
5
10
15
20
25
30
0
0.25
0.5
0.75
1
1.25