

1 A Customizable Low-Cost System for Massively Parallel Zebrafish 2 Behavior Phenotyping

3 William Joo¹, Michael D. Vivian², Brett J. Graham³, Edward R. Soucy³, Summer B. Thyme^{2*}

4 ¹Biozentrum, University of Basel, CH-4056 Basel, Switzerland

5 ²Department of Neurobiology, University of Alabama at Birmingham, Birmingham, AL 35294, USA

6 ³Center for Brain Science, Harvard University, Cambridge, MA 02138, USA

7 *** Correspondence:**

8 Summer B. Thyme

9 sthyme@gmail.com

10 **Keywords:** zebrafish, high-throughput screens, automated behavior, prepulse inhibition,
11 neuropsychiatric disease, high-speed tracking, DanioVision, ZebraBox.

12 Abstract

13 High-throughput behavioral phenotyping is critical to genetic or chemical screening approaches.
14 Zebrafish larvae are amenable to high-throughput behavioral screening because of their rapid
15 development, small size, and conserved vertebrate brain architecture. Existing commercial behavior
16 phenotyping systems are expensive and not easily modified for new assays. Here, we describe a
17 modular, highly adaptable, and low-cost behavior system. Along with detailed assembly and
18 operation instructions, we provide data acquisition software and a robust, parallel analysis pipeline.
19 We validate our approach by analyzing stimulus response profiles in larval zebrafish, confirming
20 prepulse inhibition phenotypes of two previously isolated mutants, and highlighting best practices for
21 growing larvae prior to behavioral testing. Our new design thus allows rapid construction and
22 streamlined operation of many large-scale behavioral setups with minimal resources and fabrication
23 expertise, with broad applications to other aquatic organisms.

24 1 Introduction

25 High-throughput behavior tracking offers great potential for large-scale mutant phenotyping (Thyme
26 et al., 2019) and drug screening (MacRae and Peterson, 2015). Indeed, drug screens have revealed
27 conserved signaling pathways that regulate complex behaviors in both zebrafish and mammals
28 (Kokel et al., 2010; Rihel et al., 2010; Leung and Mourrain, 2016). Furthermore, larval zebrafish
29 maintained in 96-well plate format execute diverse behaviors including prepulse inhibition, sleep,
30 seizures, prey capture, and responses to visual, acoustic, or thermal stimuli (Burgess and Granato,
31 2007; Chiu et al., 2016; Randlett et al., 2019; Griffin et al., 2020). Many researchers use commercial
32 systems to test these behaviors, but such solutions are limited in their adaptability and prohibitively
33 costly when many parallel systems are required.

34 For example, two of the most commonly used commercial systems are the DanioVision from Noldus
35 and the ZebraBox from ViewPoint. Standard versions of these systems possess limited applications
36 as they provide only baseline movement tracking and LED light control. While add-ons such as high-
37 speed cameras and acoustic stimulation are available, they greatly increase system cost. Furthermore,
38 users are often limited to commercially provided analysis code and data processing formats.

39 To bypass these challenges, we present building plans for a modular behavior setup (Figure 1A),
40 together with software for data acquisition and analysis. Our new design significantly extends
41 systems previously validated in a large-scale mutant screen (Thyme et al., 2019), with more precise
42 control over a broader range of assays and greater ease of construction. This system includes most of
43 the assays of commercially available solutions and easily accommodates additional modules. Our
44 highly efficient analysis software utilizes a high-performance computing cluster for parallel
45 processing of multi-day datasets with hundreds of user-defined events. Additionally, we outline best
46 experimental practices for yielding consistent and reliable behavior data. This fully customizable and
47 modular setup can be easily adapted as new behavior assays are published, significantly lowering
48 barriers to large-scale phenotyping approaches.

49 2 Materials and Methods

50 2.1 Materials

51 All components and costs are described in the Bill of Materials, and all schematics are included in
52 FabricationFiles.zip. While access to a laser cutter and 3D printer substantially decreases cost and
53 time of construction, online manufacturing websites can easily produce equivalent parts (see
54 Supplementary Material).

55 2.2 Box Assembly

56 Supplementary Material describes all assembly steps. The setup housing consists of a light-insulated
57 enclosure, a camera to track fish motion, and a computer/electronics setup to deliver stimuli (Figure
58 1A). The enclosure was laser-cut from high-density polyethylene (HDPE) and fastened with 80/20
59 rails (Figure 1B).

60 The enclosure contains a white LED panel to deliver ambient light or stimuli, an infrared (IR) light to
61 visualize animals, and a 3D-printed fish plate holder with a mounted acoustic transducer (Figure 1B).
62 The white LED panel is mounted on an acrylic shelf and illuminates fish from below, while the IR
63 light rests behind and reflects off the white light panel. Fish were detected with a Grasshopper3
64 camera (FLIR Systems) and a 50 mm fixed focal length lens with an IR filter.

66 2.3 Data Acquisition

67 See Supplementary Material for detailed operation instructions.

68

69 **Computer hardware:** The setup was operated using a standard desktop computer and custom
70 LabVIEW software (Supplementary Software). Minimum hardware requirements for the most
71 computationally demanding assay (acoustic habituation; one-second movies at 285 frames-per-
72 second [fps] acquired every two seconds) were 16.0 GB RAM, an Intel Core i7-9700 processor,
73 Windows 10, and a 1 TB Solid-State Drive.

74

75 **Stimulus Delivery and Data Collection:** Acoustic and visual stimuli were controlled by a circuit
76 board that communicates between LabVIEW software and system devices (Figure 2A). A Teensy 3.6
77 microcontroller and custom Arduino script relays stimulus command strings to LabVIEW (Figure
78 2B). Each “command string” specifies stimulus parameters such as amplitude (a), frequency (f),
79 duration (d), and delay times (D) (full list in Supplementary Material). The microcontroller then
80 sends voltage changes to the surface transducer or LED light panel to produce stimuli. The
81 “command ID” (Figure 2B) specifies the LabVIEW event type, such as high-speed movie acquisition

82 during stimulus presentation.

83
84 To run an experiment, users 1) construct an **events file** with desired command strings, 2) designate
85 regions of interest (ROIs) using a separate LabVIEW script (“Generate ROIs.vi”) (Figure 2C), which
86 generates an **ROI binary data file** (rois) and **ROI string text file** (rois_string). ROIs can match
87 many different multi-well plate formats. 3) Select the events file, the ROI binary data file, and a png
88 image of the plate using the LabVIEW graphical user interface (GUI) (Figure 2D). Users also define
89 data output names and folders. See Supplementary Material for detailed setup instructions. The ROI
90 string text file is used in later stages of the analysis.

91
92 30 fps data is collected for the duration of the experiment in two formats: the change in pixels
93 between each frame within each ROI, and the coordinates of the centroid of each fish in each ROI
94 (**Slow-speed data**, Figure 2E). User-defined LabVIEW events trigger acquisition of one-second
95 movies at 285 fps (**High-speed data**). LabVIEW can also trigger acquisition of 30 fps movies of
96 desired length.

97 2.4 Data Analysis Software

98 Our analysis pipeline (Figure 3) is based in the Python programming language. All analyses were
99 performed on a high-performance computing cluster due to vastly increased parallel processing
100 capacity. LabVIEW generates slow-speed **motion** (delta pixels) and **centroid** (coordinates) data,
101 while our Python scripts extract motion and centroid from high-speed data (Figure 3A). As in
102 LabVIEW, a centroid for each fish is identified in each ROI to determine coordinates. Typical
103 behavior runs often produce close to one thousand high-speed movies, making parallel processing
104 critical to this tracking step.

105
106 Input data from slow- and high-speed tracking is processed to generate numerous measurements and
107 output graphs (Figure 3B) ranging from classic behaviors such as sleep bouts and waking activity
108 (Chen et al., 2017) to recently published observations such as turn angle preference during dark flash
109 response (Horstick et al., 2020). A **Fish object** is created for each animal and contains all associated
110 slow- and high-speed data as well as genotype. Slow-speed data is converted into movement bouts
111 calculated from both motion data and centroid data. Metrics such as frequency, velocity, and fraction
112 of time in well center are calculated for each bout and binned based on time (such as average velocity
113 / 10 minute). High-speed data is processed based on the type of event and the parameters of the event
114 string. Identification of an event response depends on modality (visual, acoustic) and the time delays
115 in the string. Metrics analogous to bout properties are then calculated for the response. High-speed
116 and binned slow-speed data are returned to the Fish object as **ProcessedData objects**, which are then
117 used to generate graphs according to user-defined **event sections**. The event sections are specified in
118 the **sections file**, which segments the behavior run into time windows for different assays. For
119 example, an acoustic habituation assay would be analyzed separately from the prepulse inhibition
120 assay. Event sections may also correspond to different times of the run such as night or day, and need
121 not include high-speed events. Sections without high-speed events are referred to as “time” sections.
122 An example sections file is included in the Supplementary Software. Data and statistics are saved and
123 a graph is generated for every combination of an EventSections object and ProcessedData object. A
124 Kruskal-Wallis one-way ANOVA is calculated for every metric, and a linear mixed model (Thyme et
125 al., 2019) is also calculated for baseline data with a time component. The code is also available on
126 GitHub (<https://github.com/sthyme/ZebrafishBehavior>) and will be updated as improvements are
127 made.

128 **2.5 Assays**

129 The most common multi-well larval zebrafish assays are based on acoustic and visual stimulation,
130 utilizing the surface transducer and the LED light panel. These include responses to increased light or
131 decreased light (dark flash), dark flash habituation, acoustic responses and thresholds, prepulse
132 inhibition, and acoustic habituation. Our setup can test responses to a broad range of acoustic (sound
133 delivered by surface transducer), visual (whole-field luminance changes such as dark or light
134 flashes), and thermal stimuli (cooling or heating with a water circulation system; see Supplementary
135 Material), and can be further modified for additional assays. To test arousal threshold (Figure 5), we
136 delivered acoustic (20 msec, 625 Hz, square wave-form) or dark flash (1 sec) stimuli at 12 different
137 intensities: acoustic = a0.0005, a0.001, a0.003, a0.0075, a0.01, a0.03, a0.06, a0.075, a0.1, a0.3, a0.5,
138 a1, visual = b245, b240, b230, b220, b210, b200, b175, b150, b125, b100, b50, b0, with baseline
139 light = b250. 30-50 total trials of each intensity were administered in randomized order at 2 minute
140 intervals. Other experiments for mutant and wild-type animals correspond to the event strings in the
141 supplemental events file. The design also includes a mini-projector underneath the fish plate, which
142 can present user-defined movies such as moving gratings to induce the optomotor response (Figure 4)
143 (Naumann et al., 2016). Movies are presented through LabVIEW via the VLC media player
144 (LabVIEW utilizes movie filepaths instead of command strings). Supplementary Software includes
145 example grating movies and Python script to generate gratings. Code to track multiple animals was
146 completed with a custom (<http://github.com/docviv/behavior-scripts>) based on an algorithm adapted
147 from (Bolton et al., 2019).

148 **2.6 Zebrafish Husbandry**

149 All zebrafish were housed in the Zebrafish Research Facility of the University of Alabama at
150 Birmingham and experiments were approved under protocol number IACUC-21744 (UAB
151 Institutional Animal Care and Use Committee; Birmingham, Alabama). All crosses were derived
152 from a single parental pair (mainly Ekkwill strain) to minimize genetic background differences.
153 Arousal threshold assays were conducted in a mixed TL/AB background. Larvae were grown in
154 150x15 mm petri dishes with standard methylene blue water, at a density of less than 150 fish per
155 plate. Animals were maintained at 28°C and a 14/10 light/dark cycle. Behavior experiments were
156 conducted on the same light/dark cycle. Dead material and debris were removed twice before 4 dpf
157 (afternoons of day 0 and day 2). All behavior assays were conducted on zebrafish larvae 4-7 days
158 post-fertilization (dpf). Zebrafish of any age can be monitored in this setup with an appropriate
159 holding chamber.

160 **2.7 Zebrafish Sample Processing**

161 Only healthy larvae with normal swim bladder morphology were included in experiments. Larvae
162 were arrayed in 96-well plates (E&K Scientific Cat#2074, 0.7mL/square well volume) in standard
163 methylene blue water. The plate was placed in an ice-water bath until movement abated and sealed
164 with an air-permeable film (Thermo Fisher Scientific Cat#4311971) to eliminate progressive water
165 evaporation during multi-day experiments (Supplementary Figure 13). Sealing is essential to long-
166 term experiments but incompatible with drug delivery. Accordingly, previous drug screens for sleep
167 modulators refilled evaporated water in the evening and morning (Rihel et al., 2010). Sealed plates
168 were placed into the behavior box and secured tightly (screw in one corner) to prevent movement due
169 to the surface transducer. Temperature inside the setup ranged from 29.5-30.5°C (measured with a
170 wireless Temp Stick), while room temperature was maintained at 23°C. For mutant experiments,
171 larvae were genotyped by 1) noting all dead or unhealthy animals, 2) cooling plate on ice until
172 movement ceased, 3) removing water in wells, 4) immersing in sodium hydroxide and transferring to

173 a PCR plate for DNA extraction and amplification.

174 **3 Results**

175 **3.1 Precise Stimulus Control**

176 Previous versions of our setup used two solenoid tappers and a custom white LED array to deliver
177 acoustic and visual stimuli, respectively (Thyme et al., 2019). Stimulus intensity was inconsistent
178 across setups due to variable construction. For example, solenoid tappers delivered limited and
179 inconsistent tap strengths due to variable height alignment and spring properties, and suffered from
180 artifacts such as inadvertent double or triple tapping (data not shown). The single mounted surface
181 transducer now allows consistent and fine control over a broad range of stimulus durations, voltages,
182 waveforms, and frequencies. Likewise, the new white LED panels deliver consistent luminance
183 across a broad range across setups. We include a simple protocol to calibrate and standardize light
184 levels using a photodiode (see Supplementary Material). To validate these modifications, we
185 monitored larval zebrafish responses to acoustic and dark flash stimuli of variable intensities during
186 day and night. By calculating “dose-response” curves for each type of stimulus, we determined
187 arousal threshold, defined as stimulus strength generating half-maximal response probability (Figure
188 5). Larvae exhibited significantly higher arousal threshold during night relative to day (Figure 5A,
189 top; night threshold= 28.30 ± 2.06 , day threshold= 12.57 ± 1). Acoustic stimulus response probabilities
190 did not differ between fish positioned proximally or distally to the transducer, indicating consistent
191 stimulus delivery across the 96-well plate (Figure 5A, bottom). While maximal dark flash responses
192 matched previously reported levels (Figure 5B) (Woods et al., 2014), we observed improved
193 maximal responses to acoustic stimuli relative to previous assays using solenoids (Lee et al., 2017;
194 Singh et al., 2017). Our modifications thus accommodate previously challenging assays and offer
195 improved standardization. Furthermore, our improved analysis code distinguishes clear escape
196 responses (C-bends (Burgess and Granato, 2007) and O-bends (Randlett et al., 2019)) from smaller
197 movements, for more nuanced response quantifications.

198 **3.2 Mutant Prepulse Inhibition Phenotypes**

199 We previously demonstrated (Thyme et al., 2019) that mutants for the schizophrenia risk genes *atxn7*
200 and *akt3* (Schizophrenia Working Group of the Psychiatric Genomics Consortium, 2014; Bergeron et
201 al., 2017) exhibit defects in prepulse inhibition (PPI), a sensory-motor gating phenomenon in which a
202 weak prepulse stimulus suppresses an immediately following strong stimulus response. Because
203 previous experiments relied on solenoid tappers, we tested whether the surface transducer
204 recapitulates the PPI assay and phenotypes. Indeed, *atxn7* and *akt3* mutants both exhibited decreased
205 PPI relative to sibling controls as previously observed (Figure 6A). Frequency of response to the
206 strong stimulus in mutants and controls is substantially reduced when preceded by the weak prepulse
207 (Figure 6B), indicating that the prepulse is effectively inhibiting responsiveness. Mutant PPI
208 responses were increased in both frequency and aspects of the response motion (Figure 6C), whereas
209 control larvae responses were not.

210 **3.3 Wild Type Comparisons**

211 While commonly used wild-type zebrafish strains exhibit substantial genetic diversity (Guryev et al.,
212 2006; Brown et al., 2012), few studies explicitly define optimal growth and husbandry conditions
213 that minimize possibly resultant behavioral variability.

214 As a first step to defining important parameters, we assessed three different conditions on larval

215 zebrafish behavior. 1) To compare separately reared larvae, we divided sibling larvae into two dishes
216 at identical density (Figure 7A). 2) To assess effects of density, we compared sibling larvae reared in
217 two dishes of high or low density. 3) To compare non-siblings, we raised different clutches at
218 identical densities. For each experiment, we also compared within each experimental group as a
219 control and interleaved animals from each condition in the 96-well plate to minimize possible
220 positional effects (Figure 7B).

221 To estimate behavioral differences, we calculated strictly standardized mean difference (SSMD)
222 values across all behavioral parameters (SSMD of 0 indicates no effect). Growing larvae in separate
223 dishes or at different densities did not affect behavior, as demonstrated by largely overlapping SSMD
224 distributions. However, larvae from different clutches exhibited significantly divergent SSMD
225 distributions relative to control within-clutch comparisons (Figure 8A). For example, non-sibling
226 larvae exhibited significantly different spontaneous movement frequency and dark flash response
227 displacement, in contrast to siblings raised at identical or different densities (Figure 8B). Replicates
228 of non-sibling comparisons generated greater numbers of p-values <0.05 and more divergent kernel
229 density estimate peaks relative to other comparisons (Figure 8C). These results highlight the
230 importance of comparing behavioral phenotypes within the same clutch.

231 **4 Discussion**

232 The setup described above can test diverse zebrafish behaviors at high throughput and with minimal
233 specialized expertise, equipment, and cost. In addition to baseline motion parameters, the system can
234 assay prepulse inhibition (Figure 6) and responses to acoustic, visual, and thermal stimuli (Figure 5
235 and data not shown). We also incorporate a mini-projector to test additional visual behaviors such as
236 the optomotor response (Figure 4). Our setup can thus accommodate more sophisticated visual assays
237 including looming stimuli (Temizer et al., 2015), prey capture (Semmelhack et al., 2014), and
238 decision-making based on dot coherence (Bahl and Engert, 2020). Because many components are
239 commercially available, multiple boxes can be completely assembled within two days.

240 Our modular hardware design supports rapid adaptation for additional assays with adult animals or
241 arena shapes beyond 96-well plate format. Modified camera/lens configurations can produce
242 different resolutions or acquisition speeds. The circuit board design includes multiple BNC
243 connectors capable of triggering or sampling from other devices. For example, these connectors can
244 support optogenetic experiments (Oikonomou et al., 2019) as in the DanioVision system, or deliver
245 electric shocks for conditioning assays (Valente et al., 2012), as in the ZebraBox system.

246 The software to execute and analyze experiments is also highly adaptable. Existing experiment
247 events can be modified to yield new event types. For example, users can acquire extended movies
248 (Command ID “2”) of a desired length or frame-rate by customizing the event type. These slow-
249 speed movies provide opportunities for a wide range of new analyses that move beyond
250 centroid/motion data, such as machine learning approaches to uncover phenotypes. This approach
251 would have particular utility when monitoring older animals with more complex behaviors than
252 larvae such as mating (Geng and Peterson, 2019). While our Python-based analyses measure motion
253 parameters more comprehensively than any commercially available zebrafish analysis software,
254 machine learning may distinguish additional classes of movements or responses. For example, we do
255 not explicitly distinguish O-bends and C-bends from other movements, but used parameters such as
256 motion velocity to separate responses. Indeed, our analysis pipeline (Figure 3) is currently based
257 solely on motion quantification, but is also highly flexible. A large set of input options can be
258 modified from default settings without coding (Supplementary Material). Furthermore, the code’s

259 object-oriented and modular style permits independent modification of parameters such as the output
260 graph format.

261 Using this new system, we assessed best practices for raising zebrafish larvae for behavior
262 experiments (Figure 7, Figure 8). First, we found no effect of splitting a clutch across two petri
263 dishes. While we routinely removed all debris from dishes during growth (see Methods), different
264 levels of cleanliness may still influence behavior. Second, we found no effect of growth density up to
265 150 larvae in a 15x150 mm petri dish. Densities higher than 150 were not tested and may negatively
266 impact growth. Third, and most critical, we found that wild-type animals from different clutches
267 exhibited behavioral differences of similar magnitude to mutants with the strongest behavior
268 phenotypes of 165 mutants (Thyme et al., 2019) versus their respective control siblings
269 (Supplementary Figure 14). These results underscore the importance of comparing results within
270 single clutches. We postulate that inter-clutch differences may contribute to variability in other
271 contexts such as calcium imaging, where data is often collected from many parental pairs.

272 The zebrafish model continues to increase in popularity (Teame et al., 2019), while recent advances
273 in genome editing technologies lower experimental barriers for non-traditional models. Our adaptable
274 behavioral setup can monitor any small aquatic organism, particularly in multi-well format, and can
275 thus accelerate discovery along both of these avenues. While neuroscientists likely represent the
276 majority of users, our system can also serve as a powerful diagnostic tool for the development and
277 function of other organs such as muscle (Maves, 2014). Finally, genome sequencing continues to link
278 large numbers of genes to human disease (Schizophrenia Working Group of the Psychiatric
279 Genomics Consortium, 2014; Satterstrom et al., 2020). The high throughput approaches outlined here
280 will be critical to establish connections between disease-associated genes and decipher their
281 neurobiological functions.

282 **Author Contributions**

283 WJ, BJJ, ERS, and SBT contributed to design and construction of the behavior setup. SBT, WJ, and
284 MDV wrote the manuscript. ERS built the majority of the LabVIEW software with contributions
285 from MDV and SBT, and SBT built the majority of the Python software with contributions from
286 MDV. BJJ built the Arduino interface. SBT, WJ, and MDV conducted the experiments to
287 demonstrate box functionality.

288 **5 Funding**

289 This research was supported by R00 MH110603 (SBT) and the UAB VSRC core grant P30
290 EY003039 for use of the supported electronics and machining services.

291 **6 Conflict of Interest**

292 The authors declare that the research was conducted in the absence of any commercial or financial
293 relationships that could be construed as a potential conflict of interest.

294 **7 Acknowledgments**

295 The authors thank Verdion Martina, Gretchen Kioschos, and Emma Jones for assistance in building
296 behavior boxes, Verdion Martina for assisting with data collection, Emma Jones for helpful
297 comments on figures, Ari Ginsparg for assisting with Python environments, the UAB fish facility
298 staff for zebrafish care, the UAB research computing team for providing and maintaining the Cheaha

299 cluster, and the UAB electronics and machine shop.

300 **8 Figure Legends**

301 **Figure 1. Behavior Box Overview.** (A) Schematic of the behavior box setup. A high-speed camera
302 is mounted on top of the box and focused on the fish plate. A microcontroller circuit is connected to a
303 white LED panel at the bottom of a box and a surface transducer attached to the plate holder, which
304 deliver visual and acoustic stimuli, respectively. The microcontroller and camera are connected to a
305 desktop computer, which uses custom LabVIEW software for data acquisition and experiment
306 control. (B) Left: Setup enclosure is affixed to an aluminum frame with clear acrylic shelving for the
307 plate holder and LED panel. Right: The 3D printed fish chamber includes input/output nozzles for
308 water circulation and a screw stud for the surface transducer. See supplemental files for parts list and
309 assembly instructions (Supplementary Figures 1-8).

310 **Figure 2. Data Acquisition Control.** (A) Printed circuit board for electronics control. The LED light
311 panel and surface transducer are manipulated by a Teensy 3.6 microcontroller with a constant current
312 LED driver and an audio amplifier. A custom Arduino script with command options is uploaded to
313 the microcontroller. The board also includes four BNC connectors wired to GPIO pins on the Teensy
314 that support digital input/output, analog input, and other functionality configurable from software.
315 For instance, a photodiode can be connected to calibrate the light panel. (B) Example command
316 string to specify an event such as lights-off or high-speed movie acquisition during stimulus. See
317 Supplementary Software for an example events file. (C) Users define regions of interest
318 corresponding to each well using a LabVIEW graphical interface. Event parameters and ROIs are
319 then transferred to main experiment software. (D) The LabVIEW data acquisition interface can
320 display fish movements in real-time. (E) High-speed data is captured as 1 second 285 fps AVI
321 movies as specified in the events file. Slow-speed data is collected at 30 fps to produce motion (delta
322 pixels) and centroid (coordinates of fish centroid) files for the entirety of the experiment. Slow-speed
323 data is continuously acquired regardless of high-speed events. See Supplementary Figures 9-12 for
324 information regarding data acquisition pipeline.

325 **Figure 3. Data Analysis Pipeline.** (A) The high-speed movies are analyzed by calculating and
326 subtracting a mode image to define frame-by-frame fish contours in each well or ROI, and tracking
327 the centroid of each fish to generate delta pixel and position data. (B) Overview of high- and slow-
328 speed data processing and group comparisons. Fish objects contain all metrics for each fish as well as
329 its genotype (gray = group 1, red = group 2). For slow-speed data, bouts are identified using the delta
330 pixel and positional information. Thresholds are set depending on input data type. Stimulus responses
331 are identified analogously, but are identified with high-speed movie frames. Movement and response
332 features are then calculated, binned if slow-speed data, and plotted based on user defined event
333 sections. For example, slow-speed data is processed in sections based on time, such as “Day 1
334 Evening” or “Day 2 Night”. High-speed data processing considers only the high-speed movie
335 information in a given section, such as the 10 dark flashes in “Dark Flash Block 3”. Sections can be
336 overlapping. Current outputs include both a ribbon plot and a box plot for each metric.

337 **Figure 4. Optomotor Response Assay.** (A) Diagram of the optomotor response assay. Larvae are
338 tracked while a moving grating is projected from below. Blue arrows denote grating movement
339 direction. (B) Fish trajectories (light to dark) during a 25-sec movie (30 fps). Multiple fish were
340 placed in a plate without well dividers. Tracking code is available on GitHub (Methods).

341 **Figure 5. Precise stimulus control.** (A) *Top*: Acoustic stimulus response curves for wild-type larvae

342 during night and day. Night arousal threshold= 28.30 ± 2.06 , Day arousal threshold= 12.57 ± 1 . N=90
343 larvae. *Bottom*: Daytime acoustic stimulus response curves comparing location relative to the
344 transducer. Proximal group includes larvae in the three rows closest to the transducer (N=24). **(B)**
345 Dark flash stimulus response curve for wild-type animals. Responses were filtered to include only O-
346 bend startle responses.

347 **Figure 6. Analysis of Mutants with a Prepulse Inhibition Phenotype. (A)** Responses to acoustic
348 prepulse inhibition (PPI) strong stimulus and a control isolated strong stimulus not preceded by a
349 prepulse, quantified as change in pixels during a 1-second high-speed movie. The weak prepulse (not
350 shown) does not elicit a significant response and any prepulse-responding larvae are not considered
351 in the calculations. Red, mutant; Gray, sibling control (all 5 dpf). Both mutants display increased
352 response frequency to the PPI strong stimulus but similar response to the control isolated stimulus.
353 **(B)** PPI and control response frequencies for each mutant. *atxn7* PPI response frequency: Kruskal-
354 Wallis p-value = 0.0006. *atxn7* strong response frequency: Kruskal-Wallis p-value = 0.79. *akt3* PPI
355 response frequency: Kruskal-Wallis p-value = 0.012. *akt3* strong response frequency: Kruskal-Wallis
356 p-value = 0.64. **(C)** PPI and control response speed for each mutant. *atxn7* PPI response speed:
357 Kruskal-Wallis p-value = 0.0092. *atxn7* strong response speed: Kruskal-Wallis p-value = 0.83. *akt3*
358 PPI response peak speed: Kruskal-Wallis p-value = 0.016. *akt3* strong response peak speed: Kruskal-
359 Wallis p-value = 0.48. *atxn7* N -/- = 27, +/- = 48. *akt3* N -/- = 16, +/- = 16. Single asterisk marks p-
360 value < 0.05, double marks p-value < 0.01.

361 **Figure 7. Experimental Design for Wild Type Comparisons. (A)** *Left*: Comparison of a single
362 clutch split between two petri dishes with a density of 140-150 fish per dish. *Middle*: Comparison of
363 a single clutch split between two petri dishes of different densities: 140-150 fish per dish vs 60-70
364 fish. *Right*: Comparison of two different clutches with equal densities 140-150 fish per dish. **(B)**
365 Format of the 96-well plate organization for each comparison, where gray and black indicate the two
366 experimental groups loaded in alternating columns. *Left*: Comparison between the two experimental
367 groups; *Middle and Right*: control comparisons within each experimental group.

368 **Figure 8. Quantification and Analysis of Wild Type Comparisons. (A)** Probability density
369 function of strictly standardized mean difference (SSMD) values for all behavioral metrics, according
370 to comparisons outlined in Figure 7. *Left*, Split clutch comparison: Experimental N = 45 and 47
371 (Group 1 and Group 2), Control 1 N = 21 and 24, Control 2 N = 24 and 23. *Middle*, Different
372 densities comparison: Experimental N = 47 and 43, Control 1 N = 23 and 23, Control 2 N = 21 and
373 23. *Right*, Different clutches comparison: Experimental N = 47 and 46, Control 1 N = 23 and 24,
374 Control 2 N = 23 and 23. **(B)** Example graphs for two measures included in Figure 7A: movement
375 frequency and dark flash response displacement. Split clutch comparison: Kruskal-Wallis p-value for
376 the Movement Frequency (Active minutes) metric = 0.751. Kruskal-Wallis p-value for the dark flash
377 Stimulus metric (Response Displacement) = 0.196. Different densities comparison: Kruskal-Wallis p-
378 value for the Movement Frequency (Active minutes) metric = 0.415. Kruskal-Wallis p-value for the
379 dark flash Stimulus metric (Response Displacement) = 0.993. Different clutches comparison:
380 Kruskal-Wallis p-value for the Movement Frequency (Active minutes) metric = 9.04×10^{-9} . Kruskal-
381 Wallis p-value for the dark flash Stimulus metric (Response Displacement) = 6.05×10^{-8} . **(D)** Number
382 of p-values < 0.05 and the peak position of the kernel density estimation (KDE) curve for each
383 comparison. 12 sets of comparisons with respective controls (Different clutch comparison: 4
384 independent comparisons and 2 replicates, split clutch comparison: 3 independent comparisons,
385 different density comparison: 3 independent comparisons). The total number of p-values ranged from
386 1,951 to 1,996 depending on the comparison.

387 9 References

388

389 Bahl, A., and Engert, F. (2020). Neural circuits for evidence accumulation and decision making in
390 larval zebrafish. *Nat. Neurosci.* 23, 94–102. doi:10.1038/s41593-019-0534-9.

391 Bergeron, Y., Bureau, G., Laurier-Laurin, M.-É., Asselin, E., Massicotte, G., and Cyr, M. (2017).
392 Genetic deletion of akt3 induces an endophenotype reminiscent of psychiatric manifestations
393 in mice. *Front. Mol. Neurosci.* 10, 102. doi:10.3389/fnmol.2017.00102.

394 Bolton, A. D., Haesemeyer, M., Jordi, J., Schaechtle, U., Saad, F. A., Mansinghka, V. K.,
395 Tenenbaum, J. B., and Engert, F. (2019). Elements of a stochastic 3D prediction engine in
396 larval zebrafish prey capture. *Elife* 8. doi:10.7554/eLife.51975.

397 Brown, K. H., Dobrinski, K. P., Lee, A. S., Gokcumen, O., Mills, R. E., Shi, X., Chong, W. W. S.,
398 Chen, J. Y. H., Yoo, P., David, S., et al. (2012). Extensive genetic diversity and
399 substructuring among zebrafish strains revealed through copy number variant analysis. *Proc.
400 Natl. Acad. Sci. USA* 109, 529–534. doi:10.1073/pnas.1112163109.

401 Burgess, H. A., and Granato, M. (2007). Sensorimotor gating in larval zebrafish. *J. Neurosci.* 27,
402 4984–4994. doi:10.1523/JNEUROSCI.0615-07.2007.

403 Chen, A., Singh, C., Oikonomou, G., and Prober, D. A. (2017). Genetic analysis of histamine
404 signaling in larval zebrafish sleep. *Eneuro* 4. doi:10.1523/ENEURO.0286-16.2017.

405 Chiu, C. N., Rihel, J., Lee, D. A., Singh, C., Mosser, E. A., Chen, S., Sapin, V., Pham, U., Engle, J.,
406 Niles, B. J., et al. (2016). A zebrafish genetic screen identifies neuromedin U as a regulator of
407 sleep/wake states. *Neuron* 89, 842–856. doi:10.1016/j.neuron.2016.01.007.

408 Geng, Y., and Peterson, R. T. (2019). The zebrafish subcortical social brain as a model for studying
409 social behavior disorders. *Dis. Model. Mech.* 12. doi:10.1242/dmm.039446.

410 Griffin, A., Anvar, M., Hamling, K., and Baraban, S. C. (2020). Phenotype-Based Screening of
411 Synthetic Cannabinoids in a Dravet Syndrome Zebrafish Model. *Front. Pharmacol.* 11, 464.
412 doi:10.3389/fphar.2020.00464.

413 Guryev, V., Koudijs, M. J., Berezikov, E., Johnson, S. L., Plasterk, R. H. A., van Eeden, F. J. M., and
414 Cuppen, E. (2006). Genetic variation in the zebrafish. *Genome Res.* 16, 491–497.
415 doi:10.1101/gr.4791006.

416 Horstick, E. J., Bayleyen, Y., and Burgess, H. A. (2020). Molecular and cellular determinants of
417 motor asymmetry in zebrafish. *Nat. Commun.* 11, 1170. doi:10.1038/s41467-020-14965-y.

418 Kokel, D., Bryan, J., Laggner, C., White, R., Cheung, C. Y. J., Mateus, R., Healey, D., Kim, S.,
419 Werdich, A. A., Haggarty, S. J., et al. (2010). Rapid behavior-based identification of
420 neuroactive small molecules in the zebrafish. *Nat. Chem. Biol.* 6, 231–237.
421 doi:10.1038/nchembio.307.

422 Lee, D. A., Andreev, A., Truong, T. V., Chen, A., Hill, A. J., Oikonomou, G., Pham, U., Hong, Y.

423 K., Tran, S., Glass, L., et al. (2017). Genetic and neuronal regulation of sleep by neuropeptide
424 VF. *Elife* 6. doi:10.7554/eLife.25727.

425 Leung, L. C., and Mourrain, P. (2016). Drug discovery: Zebrafish uncover novel antipsychotics. *Nat.*
426 *Chem. Biol.* 12, 468–469. doi:10.1038/nchembio.2114.

427 MacRae, C. A., and Peterson, R. T. (2015). Zebrafish as tools for drug discovery. *Nat. Rev. Drug*
428 *Discov.* 14, 721–731. doi:10.1038/nrd4627.

429 Maves, L. (2014). Recent advances using zebrafish animal models for muscle disease drug discovery.
430 *Expert Opin. Drug Discov.* 9, 1033–1045. doi:10.1517/17460441.2014.927435.

431 Naumann, E. A., Fitzgerald, J. E., Dunn, T. W., Rihel, J., Sompolinsky, H., and Engert, F. (2016).
432 From Whole-Brain Data to Functional Circuit Models: The Zebrafish Optomotor Response.
433 *Cell* 167, 947–960.e20. doi:10.1016/j.cell.2016.10.019.

434 Oikonomou, G., Altermatt, M., Zhang, R.-W., Coughlin, G. M., Montz, C., Gradinaru, V., and
435 Prober, D. A. (2019). The serotonergic raphe promote sleep in zebrafish and mice. *Neuron*
436 103, 686–701.e8. doi:10.1016/j.neuron.2019.05.038.

437 Randlett, O., Haesemeyer, M., Forkin, G., Shoenhard, H., Schier, A. F., Engert, F., and Granato, M.
438 (2019). Distributed plasticity drives visual habituation learning in larval zebrafish. *Curr. Biol.*
439 29, 1337–1345.e4. doi:10.1016/j.cub.2019.02.039.

440 Rihel, J., Prober, D. A., Arvanites, A., Lam, K., Zimmerman, S., Jang, S., Haggarty, S. J., Kokel, D.,
441 Rubin, L. L., Peterson, R. T., et al. (2010). Zebrafish behavioral profiling links drugs to
442 biological targets and rest/wake regulation. *Science* 327, 348–351.
443 doi:10.1126/science.1183090.

444 Satterstrom, F. K., Kosmicki, J. A., Wang, J., Breen, M. S., De Rubeis, S., An, J.-Y., Peng, M.,
445 Collins, R., Grove, J., Klei, L., et al. (2020). Large-Scale Exome Sequencing Study Implicates
446 Both Developmental and Functional Changes in the Neurobiology of Autism. *Cell* 180, 568–
447 584.e23. doi:10.1016/j.cell.2019.12.036.

448 Schizophrenia Working Group of the Psychiatric Genomics Consortium (2014). Biological insights
449 from 108 schizophrenia-associated genetic loci. *Nature* 511, 421–427.
450 doi:10.1038/nature13595.

451 Semmelhack, J. L., Donovan, J. C., Thiele, T. R., Kuehn, E., Laurell, E., and Baier, H. (2014). A
452 dedicated visual pathway for prey detection in larval zebrafish. *Elife* 3.
453 doi:10.7554/eLife.04878.

454 Singh, C., Rihel, J., and Prober, D. A. (2017). Neuropeptide Y regulates sleep by modulating
455 noradrenergic signaling. *Curr. Biol.* 27, 3796–3811.e5. doi:10.1016/j.cub.2017.11.018.

456 Teame, T., Zhang, Z., Ran, C., Zhang, H., Yang, Y., Ding, Q., Xie, M., Gao, C., Ye, Y., Duan, M., et
457 al. (2019). The use of zebrafish (*Danio rerio*) as biomedical models. *Anim. Front.* 9, 68–77.
458 doi:10.1093/af/vfz020.

459 Temizer, I., Donovan, J. C., Baier, H., and Semmelhack, J. L. (2015). A Visual Pathway for

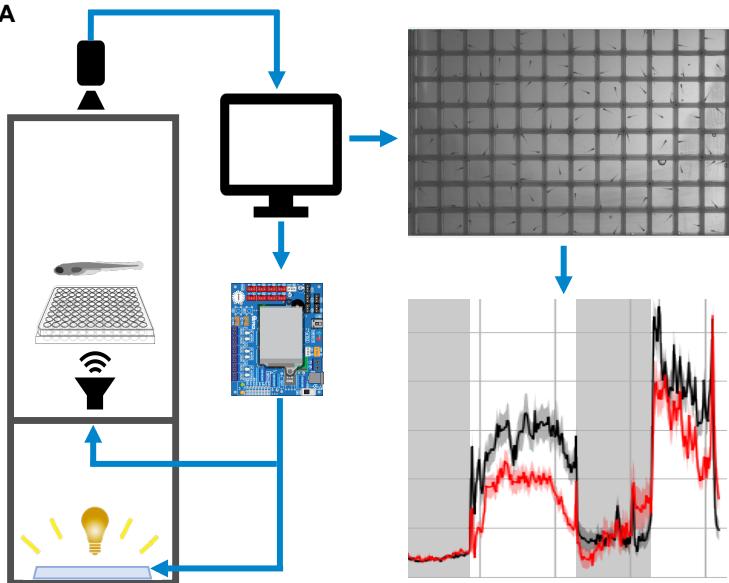
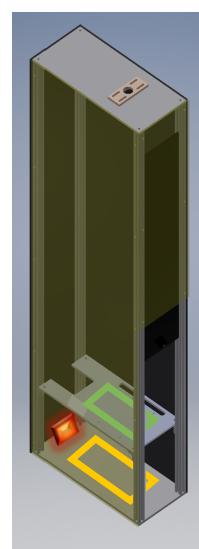
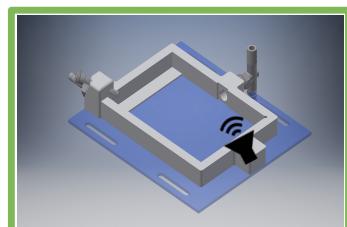
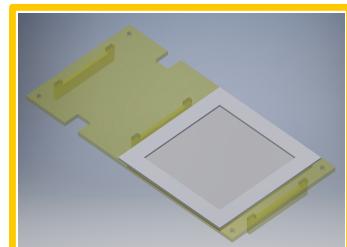
460 Looming-Evoked Escape in Larval Zebrafish. *Curr. Biol.* 25, 1823–1834.
461 doi:10.1016/j.cub.2015.06.002.

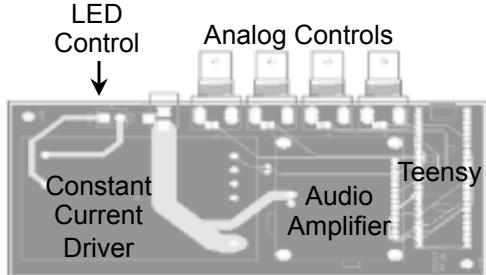
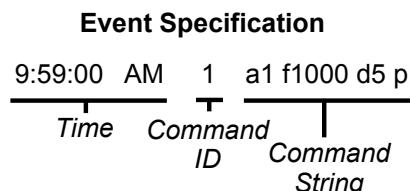
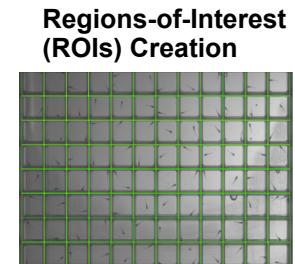
462 Thyme, S. B., Pieper, L. M., Li, E. H., Pandey, S., Wang, Y., Morris, N. S., Sha, C., Choi, J. W.,
463 Herrera, K. J., Soucy, E. R., et al. (2019). Phenotypic Landscape of Schizophrenia-Associated
464 Genes Defines Candidates and Their Shared Functions. *Cell* 177, 478–491.e20.
465 doi:10.1016/j.cell.2019.01.048.

466 Valente, A., Huang, K.-H., Portugues, R., and Engert, F. (2012). Ontogeny of classical and operant
467 learning behaviors in zebrafish. *Learn. Mem.* 19, 170–177. doi:10.1101/lm.025668.112.

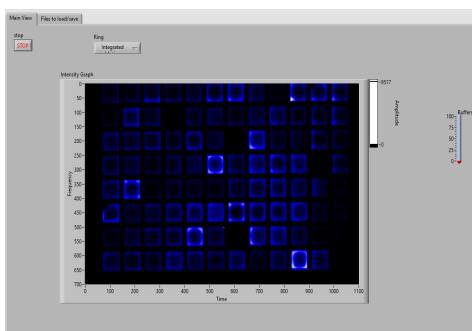
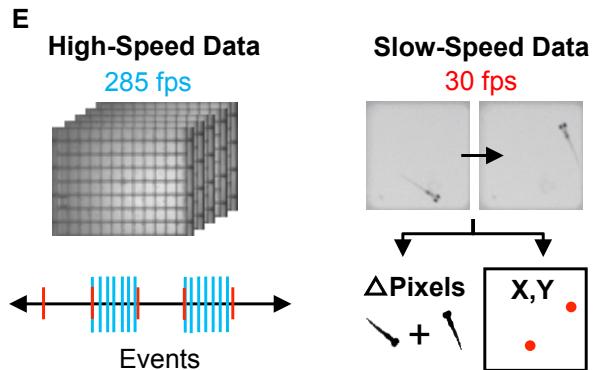
468 Woods, I. G., Schoppik, D., Shi, V. J., Zimmerman, S., Coleman, H. A., Greenwood, J., Soucy, E. R.,
469 and Schier, A. F. (2014). Neuropeptidergic signaling partitions arousal behaviors in zebrafish.
470 *J. Neurosci.* 34, 3142–3160. doi:10.1523/JNEUROSCI.3529-13.2014.

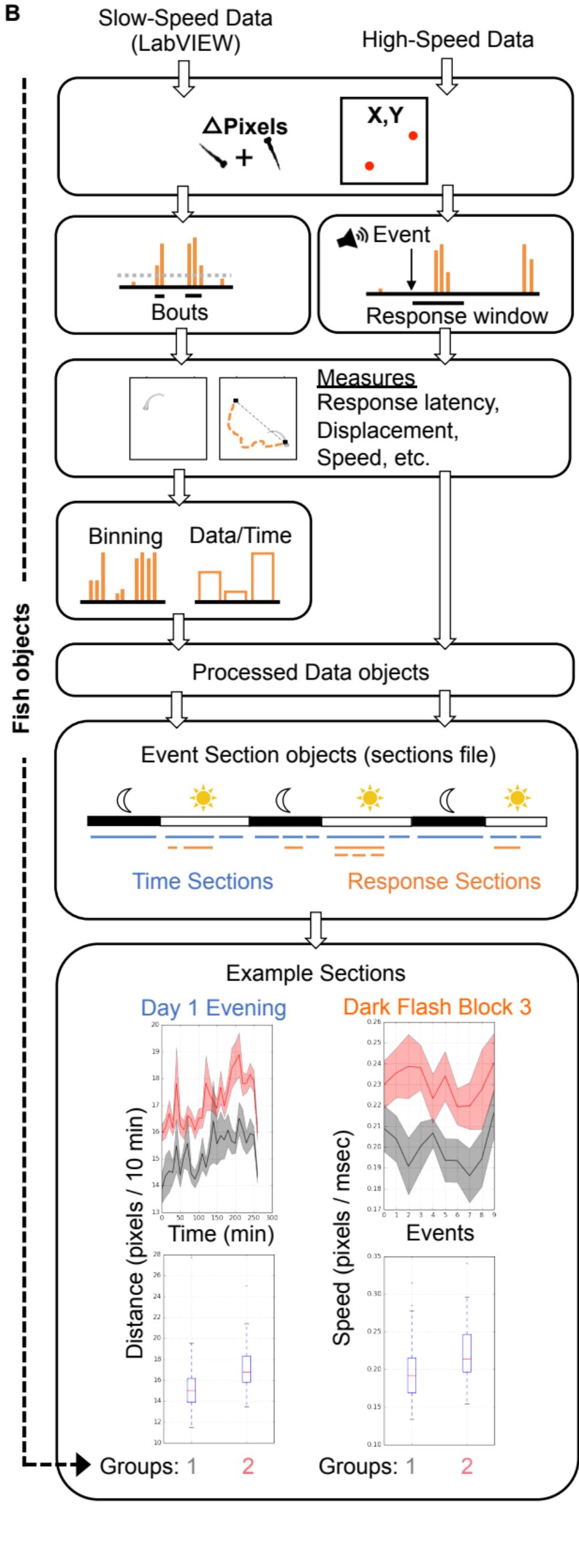
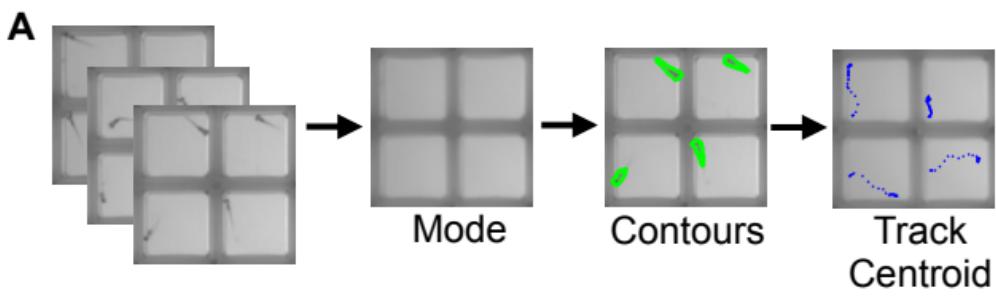
471

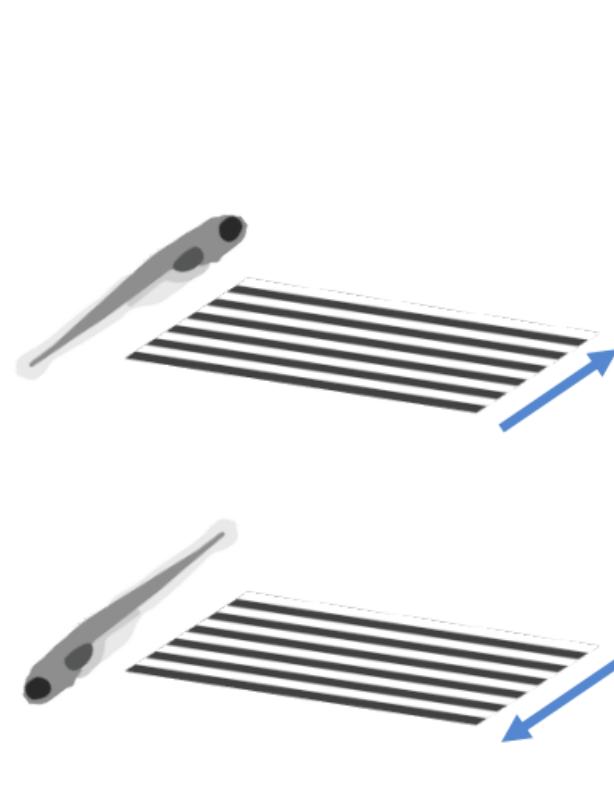
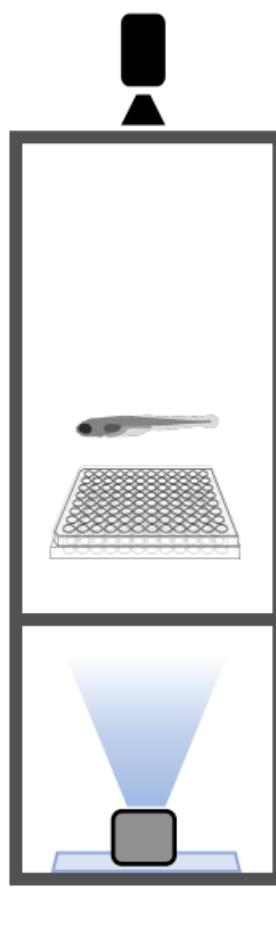
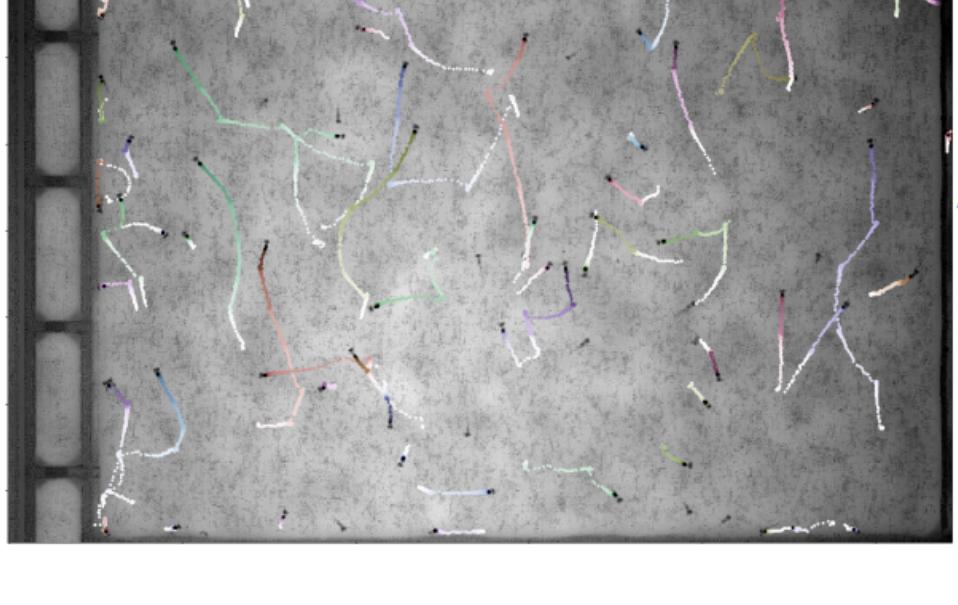
A**B****Plate Chamber****LED Mount**

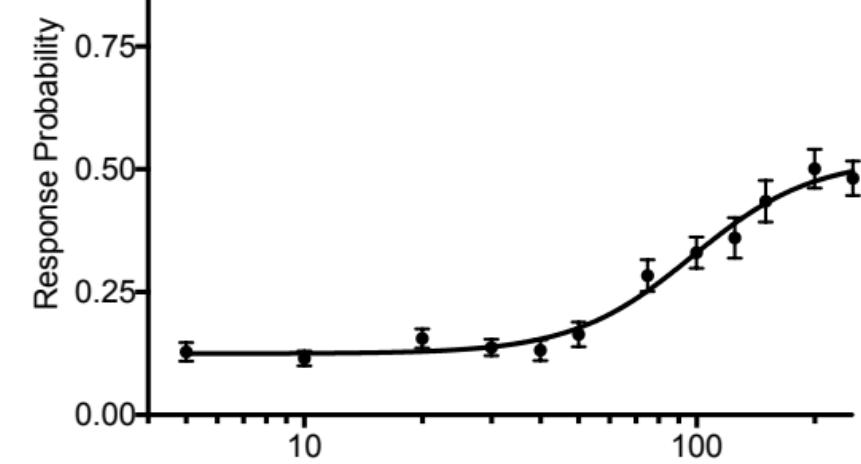
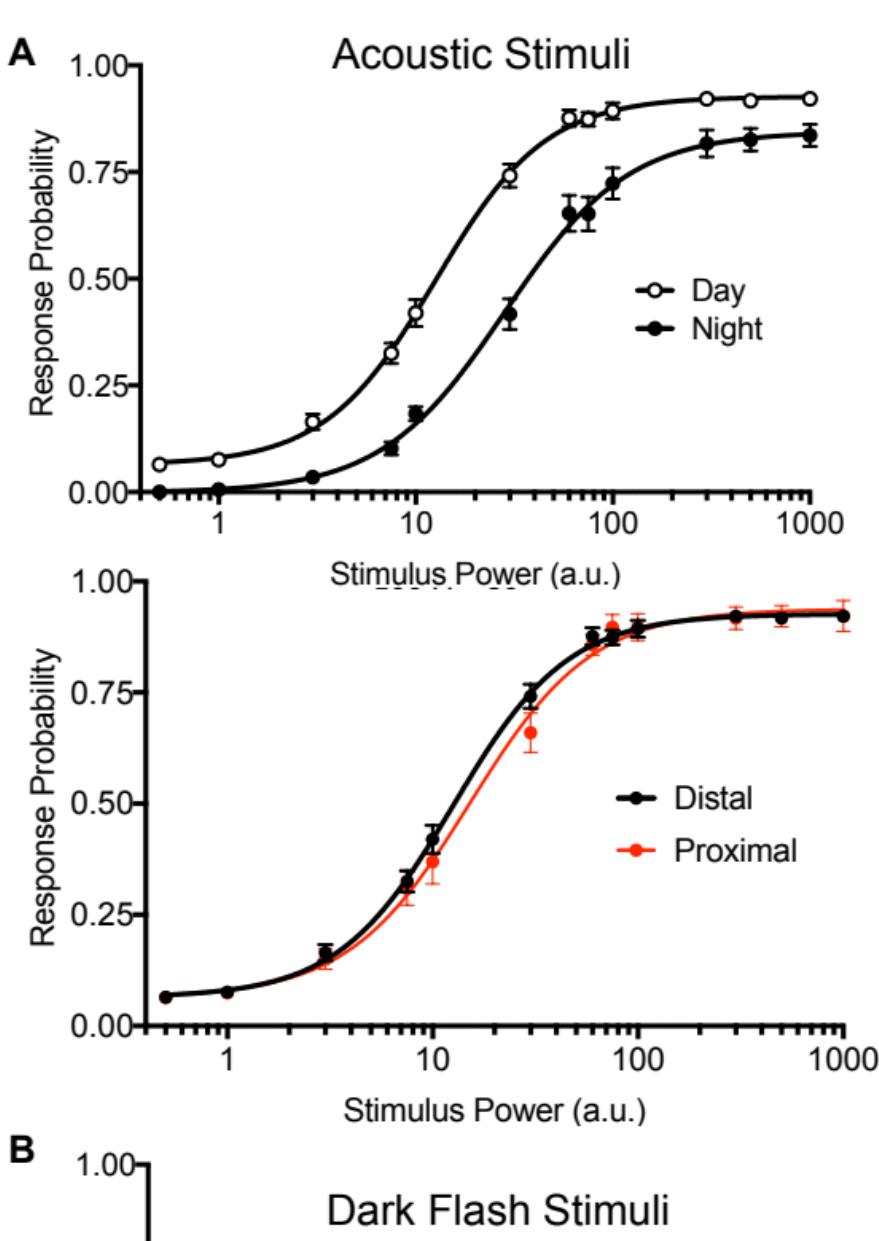
A**B****C****D**

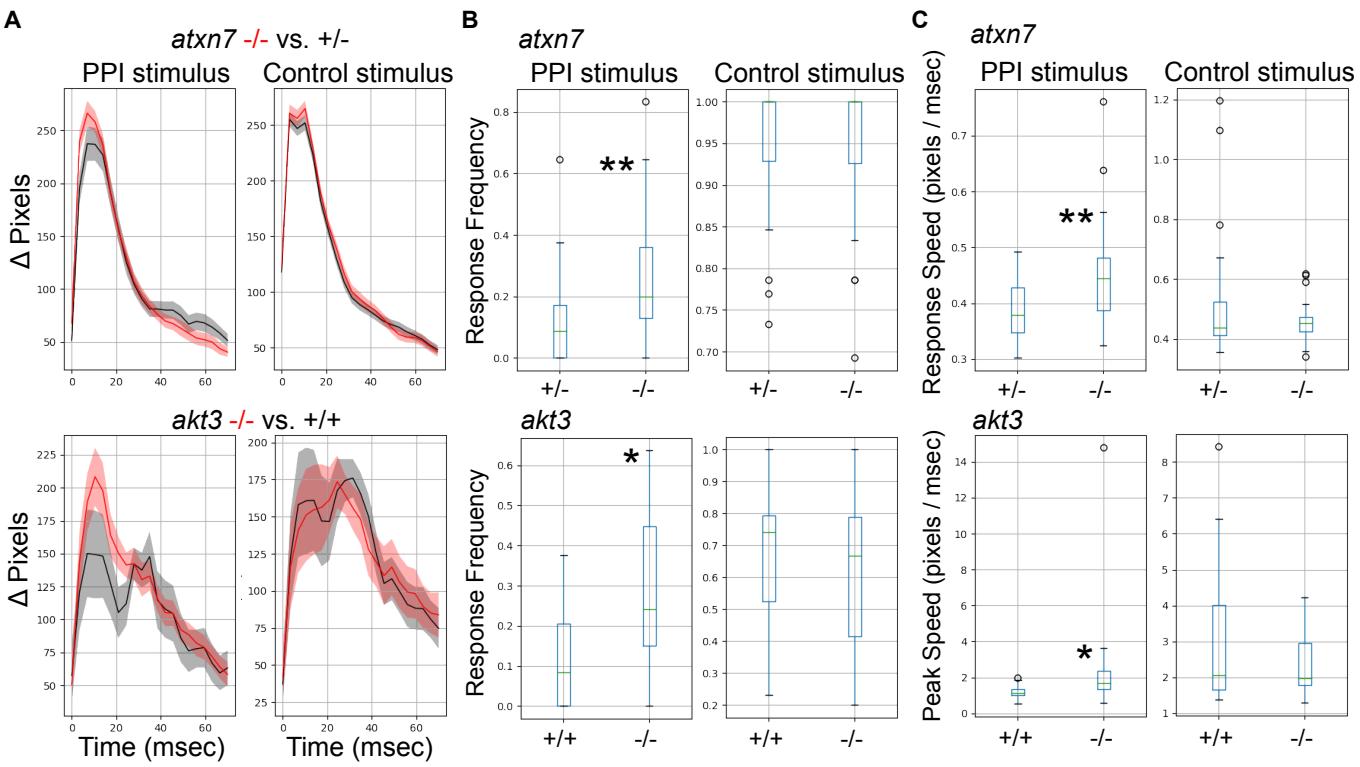
Data Acquisition GUI

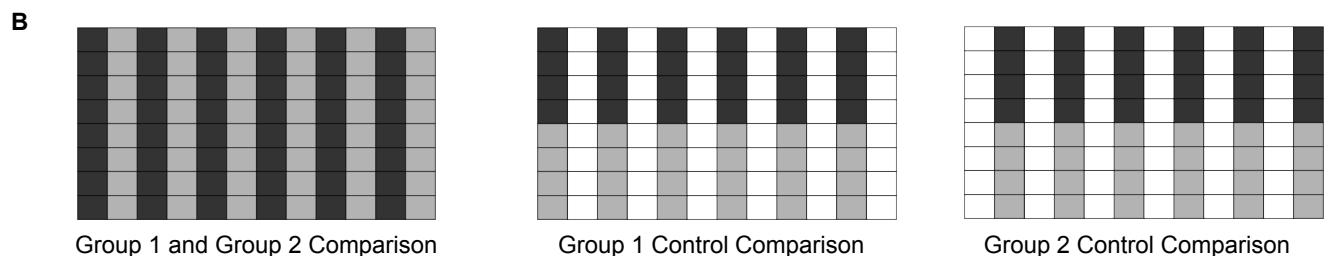
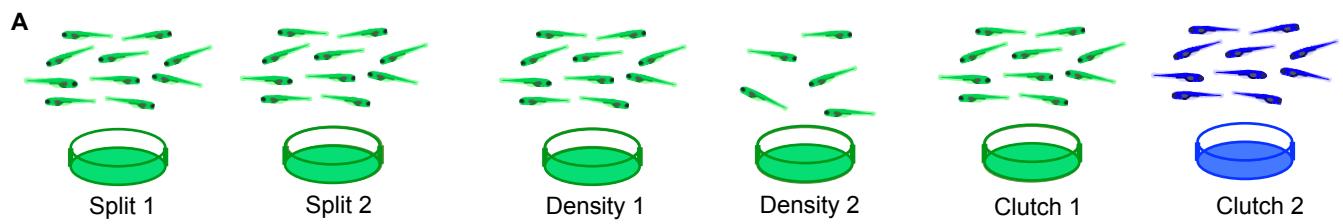
**E**



A**B**



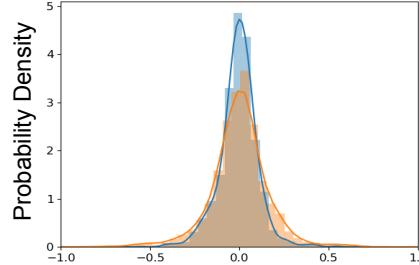




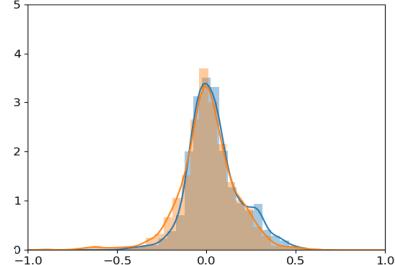
Comparison Control Group 1 Group 2

A

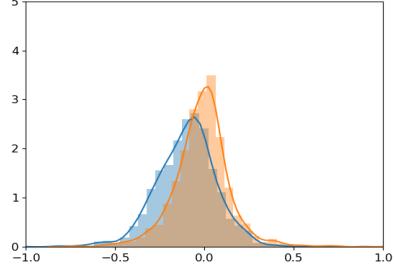
Split Clutch



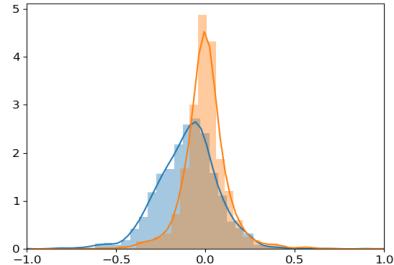
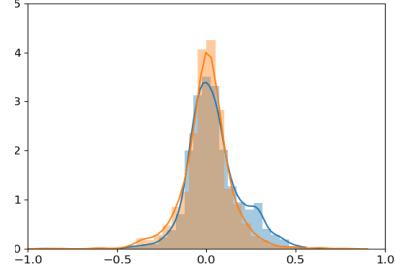
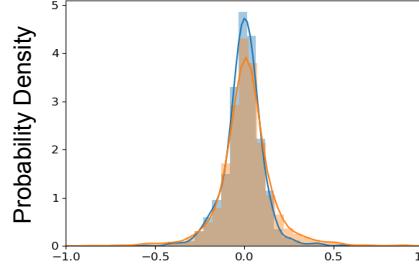
Different Densities



Different Clutches



Control 1



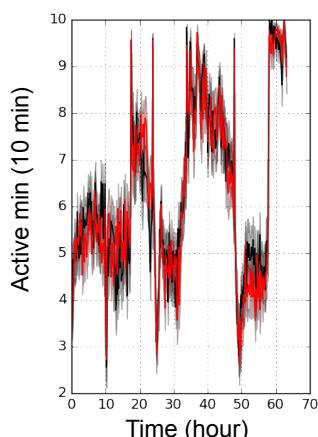
SSMD Values

SSMD Values

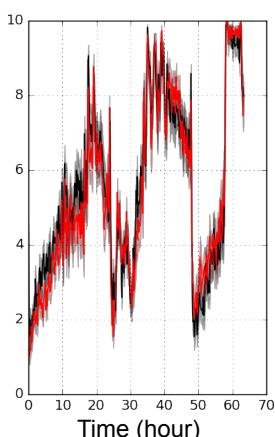
SSMD Values

B

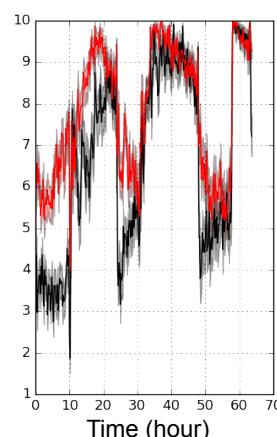
Split Clutch



Different Densities



Different Clutches



C

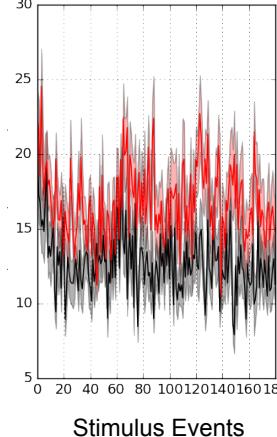
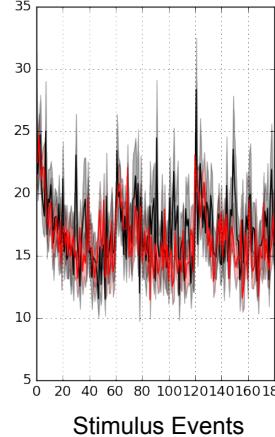
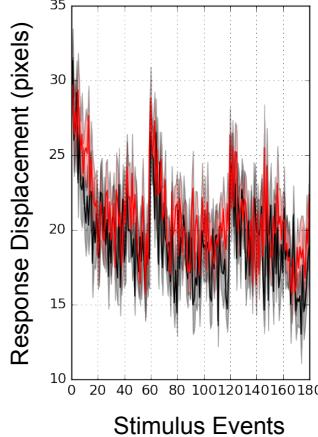
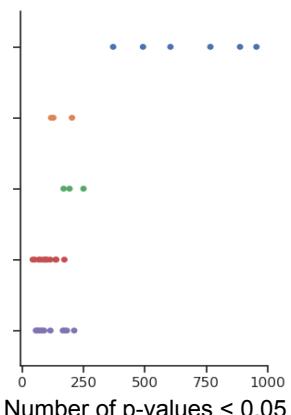
Different Clutches

Split Clutch

Different Densities

Control 1

Control 2



Different Clutches

Split Clutch

Different Densities

Control 1

Control 2

