



# Cross-species real-time detection of trends in pupil size fluctuation

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## Abstract

Pupillometry is a popular method because pupil size is easily measured and sensitive to central neural activity linked to behavior, cognition, emotion, and perception. Currently, there is no method for online monitoring phases of pupil size fluctuation. We introduce *rtPupilPhase*—an open-source software that automatically detects trends in pupil size in real time. This tool enables novel applications of real-time pupillometry for achieving numerous research and translational goals. We validated the performance of *rtPupilPhase* on human, rodent, and monkey pupil data, and we propose future implementations of real-time pupillometry.

**Keywords** Pupil · Pupillometry · Cross-species · Cognitive neuroscience

Pupillometry—the measure of pupil size—has grown in popularity with evidence that pupil size is an easily measured marker of neurophysiological activity. For instance, neuromodulatory networks, including the locus coeruleus-noradrenergic and basal forebrain-cholinergic systems, are linked to changes in pupil size (Fig. 1A) (Joshi et al., 2016; Reimer et al., 2016). These brain networks are also involved in widespread regulation of cortical and subcortical regions (Pfeffer et al., 2022; Slater et al., 2022). Therefore, pupillary dynamics can reflect both large-scale brain activity and behavioral, cognitive, emotive, and perceptual states that emerge by central neural mechanisms. For example, pupil size predicts states of locomotion, arousal, and conscious awareness (Bradley et al., 2008; Kronemer et al., 2022; Reimer et al., 2014).

The central neural underpinnings of pupil size explain *pupillary unrest*: fluctuations in pupil size under constant environmental luminance (Fig. 1B) (Bouma & Baghuis, 1971; Yoss et al., 1970). Pupillary unrest has a dominant frequency near 0.5 Hz, although stimulus evoked pupillary fluctuations (e.g., a flickering light) can induce pupil size changes up to ~3.5 Hz (Naber et al., 2013; Schwiedrzik & Sudmann, 2020; Turnbull et al., 2017). While pupil size fluctuations do not conform to a perfect sine wave (e.g., Rosenberg & Kroll, 1999), pupil size trends are summarized in four main phases: (1) *dilation*, (2) *peak* (i.e., local maximum), (3) *constriction*, and (4) *trough* (i.e., local minimum; Fig. 1B). Previous research finds that these pupil phases are a lagging (~0.1 seconds) indicator of central neural activity (Fig. 1B) (Breton-Provencher & Sur, 2019; Joshi et al., 2016; Montefusco-Siegmund et al., 2022; Pfeffer et al., 2022; Reimer et al., 2014).

The sensitivity of pupil phase to brain activity has encouraged the widespread recording of pupil size in myriad experimental contexts and across species. Pupillometry is commonly recorded passively and analyzed post hoc (e.g., correlating pupil size with behavioral performance and neuroimaging signals). Retrospective pupillometry analyses restrict experimental design and the interpretation of results. Alternatively, online or real-time pupillometry—detecting trends in pupil size at or near the moment of their occurrence—would enable new task types (e.g., closed-loop paradigms) and novel applications (e.g., self-regulation of

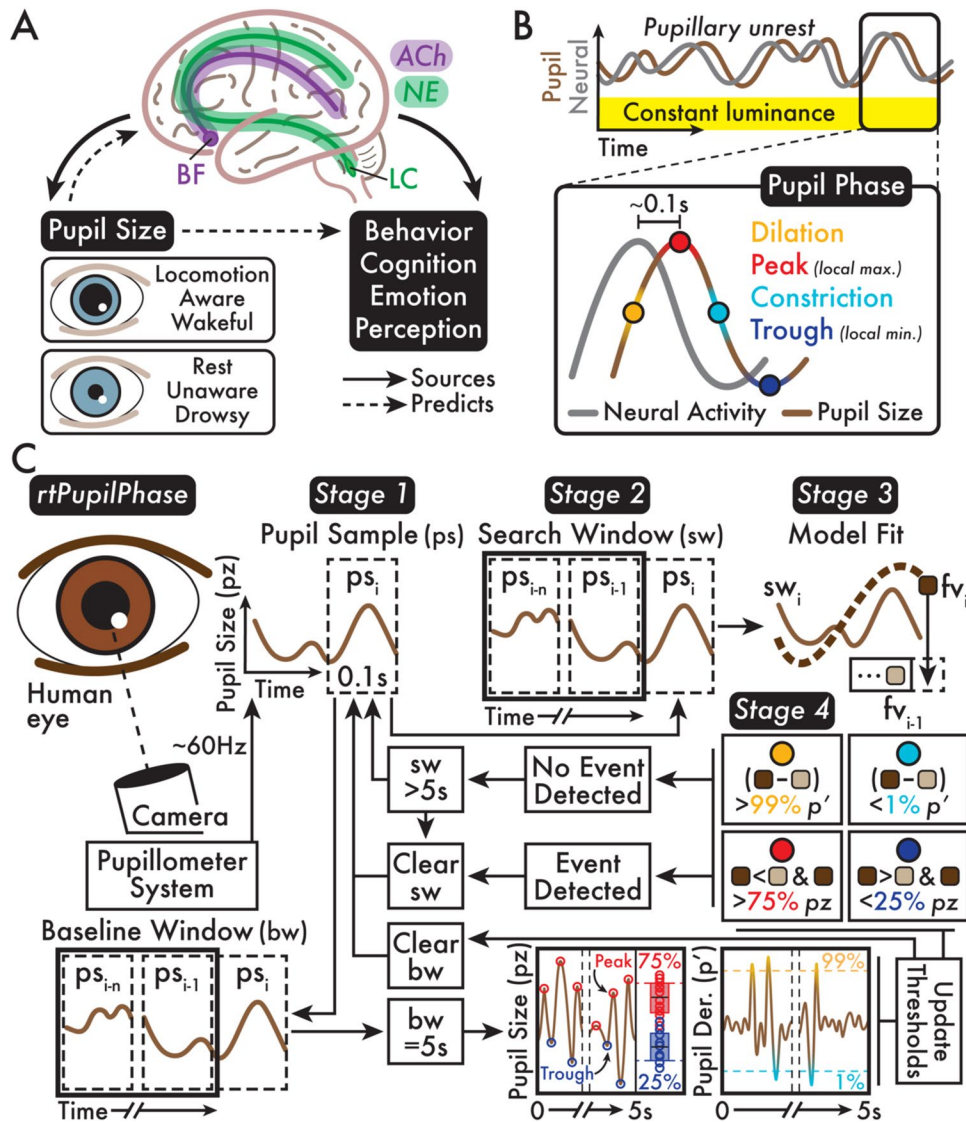
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**Fig. 1** Neural sources and phases of pupil size fluctuation and the rtPupilPhase method schematic summary. **A** Major neuromodulatory networks, including the basal forebrain (BF) cholinergic system (ACh), and the locus coeruleus (LC) noradrenergic system (NE), broadly modulate subcortical and cortical activity. In addition, spontaneous and evoked ACh and NE neural activity are linked with pupil size. Therefore, pupil size can predict both large-scale brain activity and behavioral, cognitive, emotive, and perceptual states. For example, in humans, dilated pupils indicate locomotion, awareness, and wakefulness, while constricted pupils indicate rest, unawareness, and drowsiness. **B** *Pupillary unrest* is the spontaneous fluctuation of pupil size independent of environmental luminance. These trends in pupil size or *pupil phase* are a lagging (~0.1 seconds [s]) indicator of neural activity. Although depicted as a sine wave, the light-independent trend of pupillary unrest is a heterogeneous, chaotic signal. Pupil size fluctuations are summarized in four main phases: (1) *dilation*, (2) *peak* or local maximum (max), (3) *constriction*, and (4) *trough* or local minimum (min). **C** The *rtPupilPhase* method is summarized

in four stages. *Stage 1*: Live-streamed pupil data (~60 Hz sampling rate; see *Human pupillometry acquisition*, [Methods](#) section) is gathered into *pupil samples* (ps) of 0.1-second intervals. *Stage 2*: The ps is added to a *search window* (sw) and *baseline window* (bw). *Stage 3*: The sw data is modeled with a quadratic fit. The final pupil size value (fv) from the fitted sw model is recorded. *Stage 4*: A pupil phase event is determined by comparing the fv from the current and previous sw and pupil size and pupil size derivative thresholds that are updated approximately every 5 s according to analysis of the bw. *Dilation*:  $fv_i - fv_{i-1}$  is greater than the dilation pupil derivative threshold ( $p'$ ); *peak*:  $fv_i$  is less than  $fv_{i-1}$  and  $fv_i$  is greater than the peak pupil size (pz) threshold; *constriction*:  $fv_{i-1} - fv_i$  is less than the constriction pupil derivative threshold ( $p'$ ); *trough*:  $fv_i$  is greater than  $fv_{i-1}$  and  $fv_i$  is less than the trough pupil size threshold. The sw is reset whenever an event was detected or the sw exceeds 5 s. See the *Real-time detection of pupil phase events*, [Methods](#) section for full details

arousal state via pupil size feedback) (Meissner et al., 2023). Despite the potential advantages, there is currently no published procedure for the real-time detection of pupil phase.

To address this deficit, we introduce *rtPupilPhase*—an open-source software that automatically detects dilation, peak, constriction, and trough pupil phase events in real time. *rtPupilPhase* also identifies pupil phase-independent or *random* events that we used to evaluate the performance of *rtPupilPhase*. In future applications, random events could also serve as a phase-independent control condition. Monitoring pupil phase in real time is challenging, in part, because pupil size change is sluggish, undergoes baseline shifts, and the regular occurrence of behaviors that occlude the pupil (e.g., blinking and whisking in rodents). *rtPupilPhase* mounts these challenges and achieves the real-time detection of pupil phase events in four main stages (Fig. 1C; see *Real-time detection of pupil phase events*, Methods section). In summary, *rtPupilPhase* aggregates intervals of live-streamed pupil size data, models these data intervals, and records detected pupil phase events determined by recurrently updated, individual-specific pupil size and pupil size derivative (i.e., pupil size samples  $x_1-x_2$ ,  $x_2-x_3$ , etc.) thresholds.

We evaluated *rtPupilPhase* using data from healthy, adult human participants ( $N = 8$ ; see *Participants*, Methods section) who completed a passive fixation task integrated with *rtPupilPhase* under constant luminance and simultaneous head-fixed, pupillometry recording (see *Fixation task* and

*human pupillometry acquisition*, Methods section). *rtPupilPhase* detected hundreds of pupil phase events in real time per participant (Supplementary Fig. 1). The median pupil phase inter-event duration was 0.067 seconds or a ~15 Hz detection rate (Fig. 3B; Supplementary Fig. 2A; see *Pupil phase event detection temporal performance*, Methods section). In fact, the majority (67.91%) of pupil phase inter-event durations were less than 0.1 seconds (Fig. 3B). Therefore, the temporal performance of *rtPupilPhase* tested with the current parameters (Table 1) supports its use to monitor both spontaneous and evoked pupillary dynamics that are estimated to fluctuate at frequencies between ~0.5 and 3.5 Hz (Naber et al., 2013; Turnbull et al., 2017).

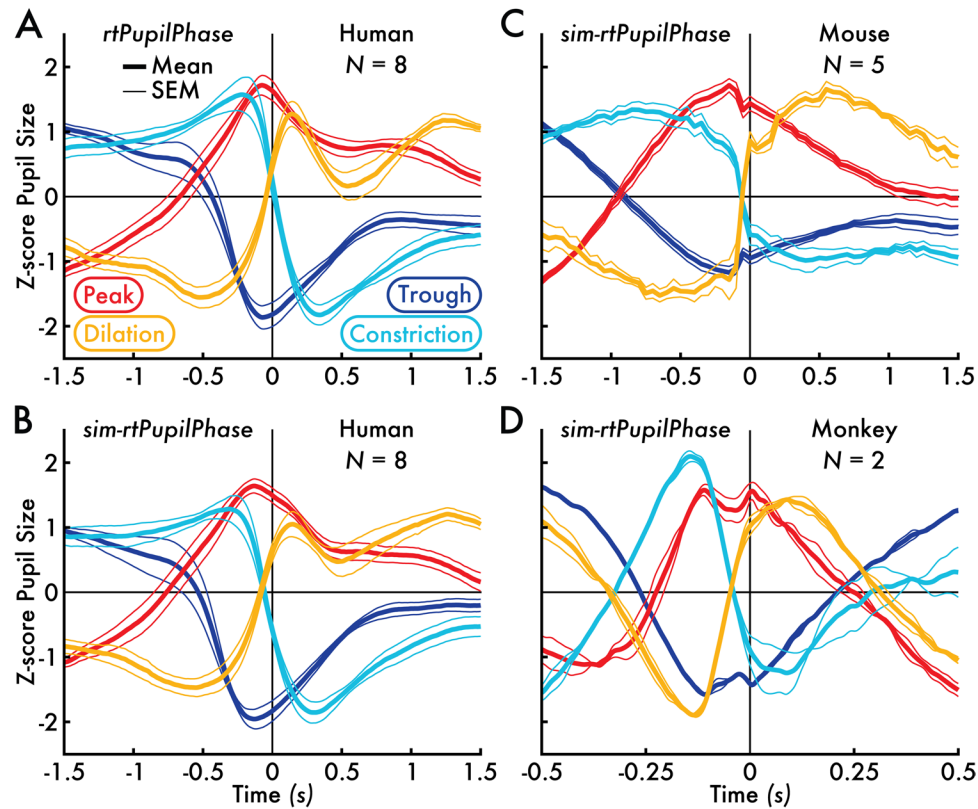
We extracted epochs of pupil size data centered on these pupil phase events (see *Human pupil size, blink, and saccade fraction epoch extraction*, Methods section). The resulting pupil size epoch time courses demonstrated that *rtPupilPhase* reliably located pupil phases with high-temporal precision at the event (Supplementary Fig. 2), participant (Supplementary Fig. 3A), and group levels (Fig. 2A; Supplementary Fig. 4A). In addition, the pupil size time courses significantly differed (cluster-based permutation testing,  $p < 0.05$ ; see *Cluster-based permutation testing*, Methods section) between pupil phase and random events, particularly in the interval immediately preceding the pupil phase event (Supplementary Fig. 4A).

To assess the accuracy of *rtPupilPhase*, we compared the real-time detected pupil phase events against the *true*

**Table 1** *rtPupilPhase* and *sim-rtPupilPhase* parameters. For the monkey dataset, the *sim-rtPupilPhase* baseline window duration and inter-event interval were adjusted to 0.5 and 1.5 seconds, respectively. The percentile (%) thresholds are applied on pupil size and pupil derivative data from the baseline window and used to detect pupil phase events. \*Human *sim-rtPupilPhase* data were down-sampled from 1000 to 60 Hz to match the approximate online sampling rate while

testing *rtPupilPhase* on humans. The variable online sampling rate of the human pupillometry recordings (see *Human pupillometry acquisition*, Methods section) meant there was variability in the duration of the pupil sample, max search window, and baseline window. See the *Real-time detection of pupil phase events* and *Human, mouse, and monkey simulated real-time detection of pupil phase events*, Methods section, for details

	Sampling rate (Hz)	Pupil sample duration (s)	Max search window duration (s)	Baseline window duration (s)	Inter-event interval (s)	Pupil phase percentile thresholds (%)
Human ( $N = 8$ ) <i>rtPupilPhase</i>	~60	0.1	5	5	3	Peak: 75 Trough: 25 Dilation: 99 Constriction: 1
Human ( $N = 8$ ) <i>sim-rtPupilPhase</i>	1000*	0.1	5	5	3	Peak: 75 Trough: 25 Dilation: 99 Constriction: 1
Mouse ( $N = 5$ ) <i>sim-rtPupilPhase</i>	~20	0.1	5	5	1	Peak: 75 Trough: 25 Dilation: 99 Constriction: 1
Monkey ( $N = 2$ ) <i>sim-rtPupilPhase</i>	1000	0.1	5	0.5	1.5	Peak: 75 Trough: 25 Dilation: 99 Constriction: 1



**Fig. 2** Human, mouse, and monkey mean  $z$ -score pupil size time courses centered on pupil phase events detected with `rtPupilPhase` and `sim-rtPupilPhase`. **A** The `rtPupilPhase` human ( $N = 8$ ) mean  $z$ -score pupil size time courses. **B** The `sim-rtPupilPhase` human ( $N = 8$ ) mean  $z$ -score pupil size time courses. **C** The `sim-rtPupilPhase` mouse ( $N = 5$ ) mean  $z$ -score pupil size time courses. **D** The `sim-rtPupilPhase`

monkey ( $N = 2$ ) mean  $z$ -score pupil size time courses. The pupil phase event time is 0 seconds (s). The group mean pupil phase event pupil size time course is shown in the thicker trace, bounded by thinner traces that depict the standard error of the mean (SEM). The trace color corresponds with the pupil phase event type

pupil phase events, as determined by post hoc evaluation of the pupil data (see *Pupil phase event detection accuracy and sensitivity performance*, [Methods](#) section). `rtPupilPhase` achieved an average pupil phase event-level accuracy of 88.16% (dilation), 79.26% (peak), 86.90% (constriction), and 73.37% (trough), all statistically greater than the random event accuracy of approximately 50% ( $p < 0.0005$ ; [Fig. 3A](#)). In addition, `rtPupilPhase` achieved high sensitivity. The on-target accuracy (i.e., comparing *detected* pupil phase events with the corresponding *true* pupil phase events; e.g., detected dilation versus true dilation; [Fig. 3A](#)) was significantly greater ( $p < 0.002$ ) than the off-target sensitivity (i.e., comparing *detected* pupil phase events with *true off-target* pupil phase events; e.g., detected dilation versus true peak) across all pupil phases ([Supplementary Fig. 5](#)). In addition, the off-target sensitivity decreased with distance from the on-target pupil phase according to the pupil phase order. For example, the on-target detected dilation accuracy was 88.16%, followed by the off-target sensitivities of 61.27%, 11.84%, and 34.30% for peak, constriction, and trough events, respectively

([Supplementary Fig. 5A](#)). Altogether, these results support that `rtPupilPhase` correctly identifies pupil phases near the moment of their true occurrence in real time.

We also explored the rate of blinks and saccades preceding the real-time detected pupil phase events, as eye movements are known to affect pupil size (Yoo et al., 2021). Blink and saccade occurrence epochs centered on the pupil phase events detected with `rtPupilPhase` were extracted. The resulting epoch time courses averaged within event type and across participants revealed increases in blink and saccade fraction preceding the event time, each event type with different periods of peak change ([Supplementary Fig. 6C, E](#)). To determine if the performance of `rtPupilPhase` was explained by blinks and saccades, we removed all pupil size epochs with blinks or saccades in the 0.5 seconds preceding the real-time detected pupil phase events. Nonetheless, the pupil size time course trends among the remaining event epochs were unchanged across pupil phases ([Supplementary Fig. 6A](#)). This result supports that `rtPupilPhase` detects pupil size trends independent of blinks and eye movements.

Next, we aimed to evaluate if *rtPupilPhase* could be used on pupillometry from nonhuman animals. As a proof of concept, we developed *sim-rtPupilPhase*—a software that *simulates* *rtPupilPhase* offline using previously collected pupil data (see *Human simulated real-time detection of pupil phase events*, [Methods](#) section). We verified that *sim-rtPupilPhase* replicates the performance of *rtPupilPhase* using the previously described human pupil data. Although, achieving an exact duplication of the *rtPupilPhase* result with *sim-rtPupilPhase* was not possible due to the variable online sampling rate of the human pupillometry recordings (see *Human pupillometry acquisition*, [Methods](#) section). Still, a similar number of pupil phase events were detected with *sim-rtPupilPhase* as with *rtPupilPhase* (Supplementary Fig. 1B). Crucially, the extracted epochs centered on the pupil phase events detected with *sim-rtPupilPhase* reproduced the trends and statistics across pupil size, blink, and saccade fraction time courses from events detected with *rtPupilPhase* (Fig. 2A versus B; Supplementary Fig. 3A versus B; Supplementary Fig. 4A versus B; Supplementary Fig. 6A versus B, C versus D, and E versus F).

After validating on humans, we implemented *sim-rtPupilPhase* to estimate the performance of *rtPupilPhase* on previously acquired pupil data from mice ( $N = 5$ ; Shahsavarani et al., 2023) and rhesus macaques ( $N = 2$ ; data newly published here). As with the human dataset, *sim-rtPupilPhase* detected hundreds of pupil phase events for each nonhuman animal (Supplementary Fig. 1C, D). Likewise, the trend of the pupil size epoch time courses centered on these events was consistent with the human event pupil size time courses detected with *rtPupilPhase* on the individual animal (Supplementary Fig. 3C, D) and group levels (Fig. 2C, D; Supplementary Fig. 4C, D). These nonhuman animal results were achieved with minimal adjustment to *sim-rtPupilPhase* and *rtPupilPhase* parameters despite major differences among the datasets, including pupil physiology, experimental setup, task demands, and recording system (Table 1; see *Mouse and monkey simulated real-time detection of pupil phase events*, [Methods](#) section).

In summary, event-, participant-, and group-level analyses support that *rtPupilPhase* was accurate and sensitive for predicting pupil phase in real time and across species. Future users of *rtPupilPhase* are encouraged to adapt and expand this method to improve performance and achieve unique applications. Assisting in future optimization, the fixation task (see *Fixation task*, [Methods](#) section) can be called from the command line interface with options to change the *rtPupilPhase* parameters (Table 1). Likewise, *sim-rtPupilPhase* can be used as a tool for testing the *rtPupilPhase* parameters without collecting additional data.

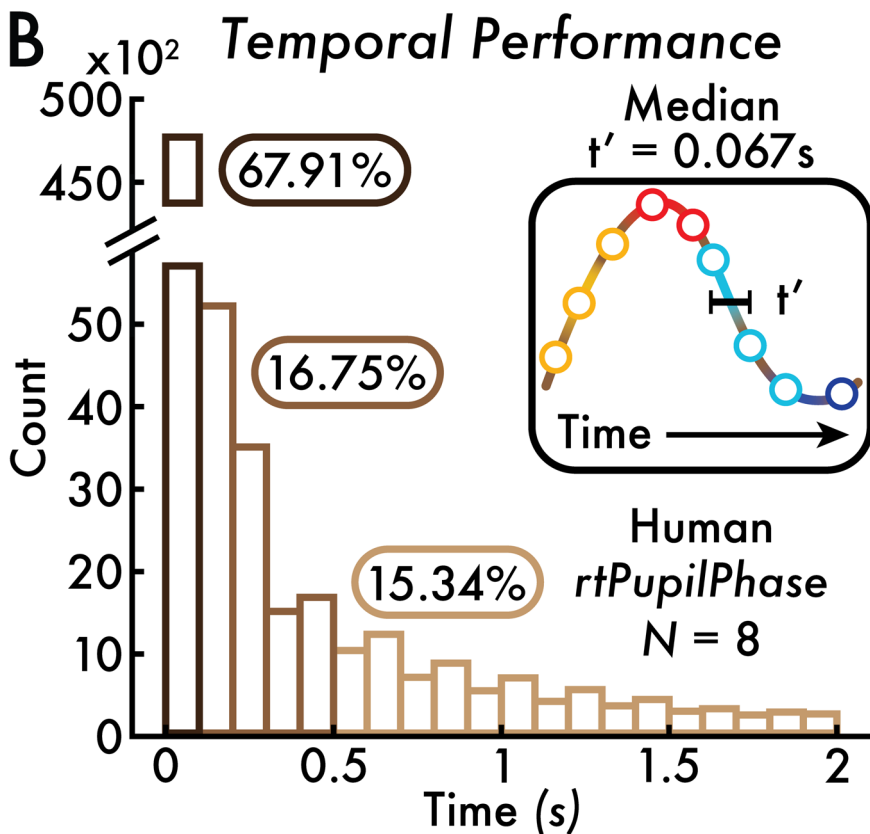
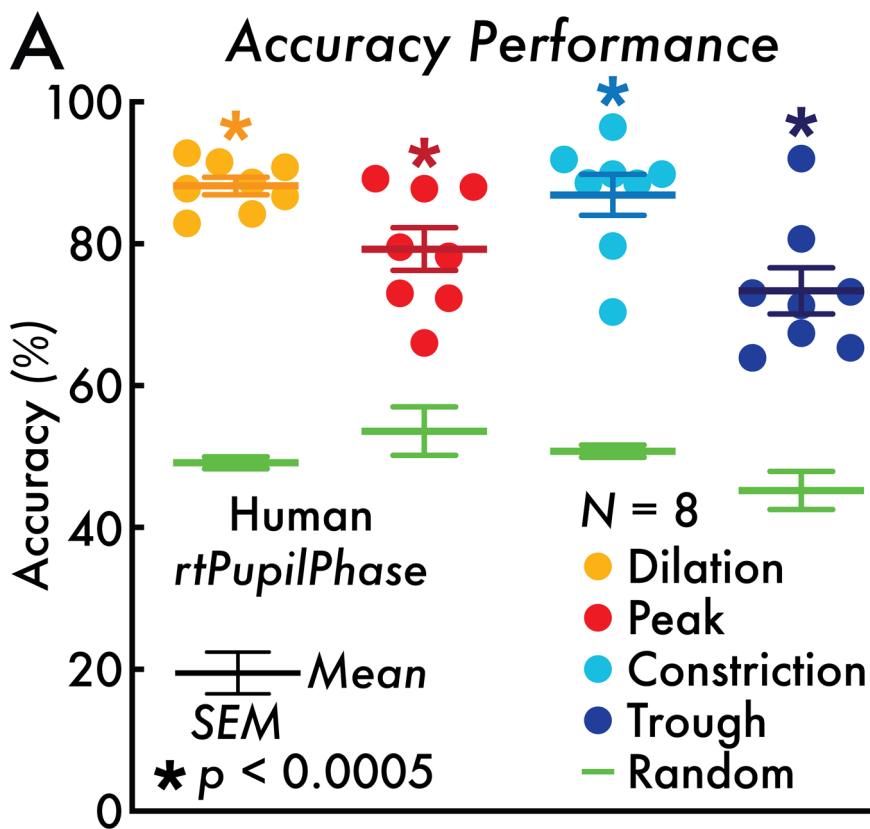
There are numerous potential applications of *rtPupilPhase*. A promising future implementation is the development of closed-loop paradigms (e.g., the real-time detection

of pupil phases triggers task events). This approach allows for targeted testing and possible causal interpretations for the interaction among pupil size and phase, neurophysiology, and behavior. For example, a study found that increasing pupil size at the time of a stimulus corresponded with improved perceptual performance, suggesting that the trend in pupil size is relevant to predict perceptual state (Eberhardt et al., 2022). Future experiments could extend on this finding by testing whether pupil phase predicts perceptual sensitivity by presenting near-threshold stimuli timed with target pupil phase events. Concurrent neuroimaging recording could help deduce the mechanism that may explain any changes in behavioral performance (e.g., perception rate and reaction time) linked with pupil phase. To encourage this kind of experimentation, we supplied a sample task script integrated with *rtPupilPhase* that could trigger an experimenter-defined task event (e.g., stimulus presentation) concurrent with the real-time detection of pupil phases.

An alternative application of *rtPupilPhase* is as a tool for pupil biofeedback. A recent study found participants can self-regulate absolute pupil size with implications on brain activity (Meissner et al., 2023). Building on this study, using *rtPupilPhase*, participants could receive real-time input of their pupil phase to regulate their pupillary fluctuations. Modifying pupil phase states may alter arousal, salience, attention, and perceptual brain network activity with corresponding consequences on behavior, cognition, emotion, and perception. Likewise, a future translational application of real-time pupillometry biofeedback is as a method to regulate brain arousal network state as a possible treatment approach for people with impaired arousal level (e.g., sleep disorders and disorders of consciousness).

When considering future implementations of *rtPupilPhase*, there are several challenges to consider. First, users must be mindful of the pupil foreshortening error—changes in recorded pupil size due to head and eye movements independent of physiological state. In addition, luminance stimulation (e.g., very dark or bright environments) may impact the dynamic range of spontaneous or evoked pupillary fluctuations with consequences on detecting pupil phase events. Correspondingly, without additional performance testing, we recommend using *rtPupilPhase* with head-stabilized pupillometry and in constant, neutral luminance environments. Also, the tested human and mouse pupil data were acquired during rest. Users who intend to implement *rtPupilPhase* during a task should confirm optimal pupil phase event detection for task-evoked pupillary fluctuations. As a proof of concept, the tested monkey pupil data were gathered during a task, suggesting *rtPupilPhase* can be robust in both rest and task contexts.

Finally, pupillary unrest is a continuous, chaotic signal that does not conform to a perfect sine wave (Rosenberg & Kroll, 1999). Therefore, there is uncertainty for the



**Fig. 3** rtPupilPhase accuracy and temporal performance. **A** The pupil phase accuracy percentage (%) for each human participant (each circle corresponds with a participant;  $N = 8$ ) is shown for the rtPupilPhase real-time detected pupil phase events versus the true pupil phase events. The random event accuracy relative to the true pupil phase event is shown in green (individual participant accuracy is not shown). The random accuracy percentage served as the baseline to statistically test against the pupil phase event accuracy (participant-level paired  $t$ -test; see *Pupil phase event detection accuracy and sensitivity performance*, [Methods](#) section). All pupil phase event accuracies (dilation = 88.16%; peak = 79.26%; constriction = 86.90%; trough = 73.37%) were statistically greater than the corresponding random event accuracy (Holm–Bonferroni-corrected,  $p < 0.05$ ;  $* p < 0.0005$ ). The mean and standard error of the mean (SEM) are depicted with error bars. **B** The distribution of pupil phase inter-event durations ( $t'$ ; see inset and *Pupil phase event detection temporal performance*, [Methods](#) section) across all detected pupil phase events up to 2 seconds (s) in binned increments of 0.1 s. The median  $t'$  was 0.067 s. The majority (67.91%) of  $t'$  values were less than 0.1 s; 16.75% between 0.1 and 0.5 s; and 15.34% greater than 0.5 s

ground-truth definitions that determine the exact boundary among the pupil phases. Here, true dilation and constriction phases were determined by the pupil size gradient, while true peak and trough phases were defined as all samples within 0.25 seconds of a local maxima or minima that exceeded a threshold prominence (see *Pupil phase event detection accuracy and sensitivity performance*, [Methods](#) section). This approach for defining pupil phases resulted in overlapping event classifications (i.e., a single pupil size sample may belong to multiple pupil phase events). Likewise, we found that the detected pupil phase events corresponded with more than one event type (e.g., 61.27% of detected dilation events were within 0.25 seconds of a true peak event; Supplementary Fig. 5). Alternative ground-truth definitions of pupil phase events would change the rtPupilPhase performance metrics. Correspondingly, rtPupilPhase users must carefully study their pupil data and monitor the behavior of rtPupilPhase with diverse performance metrics.

In conclusion, real-time pupillometry is a new approach with exciting applications. rtPupilPhase is a novel, open-source method for monitoring trends in pupil size linked with behavioral, cognitive, emotive, and perceptual states across species. Several tools are provided that allow for seamless implementation and adaptation of rtPupilPhase to achieve optimized performance for unique application goals. An immediate use of rtPupilPhase includes developing closed-loop and biofeedback paradigms where the real-time detection of pupil phase events triggers experimental stimuli. These types of paradigms are powerful to efficiently target pupil phases of interest and deduce causal relationships. Thus, rtPupilPhase introduces novel opportunities to study and implement the pupil–neurophysiology link towards achieving broad experimental and translational goals.

## Methods

**Participants** Healthy adult humans ( $N = 8$ ; mean age = 25.1 years; age standard deviation [ $SD$ ] = 4.01 years; males = 1; mean education = 17.0 years; education  $SD = 1.9$  years) were recruited from the local Bethesda, Maryland (USA) community. The Institutional Review Board of the National Institute of Mental Health approved the recruitment and consent protocols. Inclusion criteria included (1) being between 18 and 65 years old at the time of experimentation, (2) a healthy physical examination within a year of the study session, and (3) able to give informed consent. Exclusion criteria included (1) no previous or current history of neurologic or psychiatric disorders, (2) poor vision that cannot be corrected, or (3) head injuries (e.g., loss of consciousness for >30 minutes and three or more concussive injuries). Each participant underwent a health exam completed by a nurse practitioner prior to their study session.

**Fixation task** The fixation task was coded in Python and run with PsychoPy (v2022.2.4; Open Science Tools Ltd.). The task consisted of a single display: a central fixation point (a plus sign;  $0.51 \times 0.51$  degrees) on a solid gray screen. Participants were instructed to maintain central fixation throughout the task. Participants completed five 10-minute fixation task blocks with a ~2-minute break between each block. Integration of rtPupilPhase with the fixation task enabled the covert detection of pupil phase and random events (see *Real-time detection of pupil phase events* section) and accommodates future development of alternative experimental designs involving rtPupilPhase.

**Human pupillometry acquisition** Human, head-fixed pupillometry and eye tracking was acquired with a desk-top-mounted EyeLink 1000 Plus (recorded eye: right eye; offline sampling rate = 1000 Hz; version 5.50; SR Research, Inc.). The online sampling rate of the pupil size data was variable (mode sampling rate  $\approx 60$  Hz or 17 ms between samples). During pupillometry acquisition, participants were instructed to place their head in a chin and forehead rest system (SR Research Head Support; SR Research, Inc.) to maintain a fixed head position and a constant distance between the participant and pupillometer.

**Human testing equipment and facility** Human testing was conducted in a single 1.5-hour study session in a windowless, temperature-controlled behavioral testing room. The lighting in the testing room was set to a consistent level for all participants and maintained throughout the entire study session. The fixation task was administered on a behavioral laptop (MacBook Pro; 13-inch;  $2560 \times 1600$  pixels, 2019; Mac OS Catalina v10.15.7; Apple, Inc.) (Peirce, 2007). The

EyeLink 1000 Plus software ran on a Dell desktop computer (Dell OptiPlex XE2; Dell, Inc.). The behavioral laptop and the fixation task were programmed to communicate with the EyeLink desktop via an Ethernet connection. Participants viewed the fixation task on a VIEWPixx display monitor (1920 × 1200 pixels; VPixx Technologies, Inc.). The behavioral laptop monitor was mirrored to the display monitor via a DVI cable. Participants were positioned approximately 56 centimeters from the center of the display monitor, measured from the nasion.

**Mouse pupil data** The mouse pupil data were acquired from a previously published experiment (<https://zenodo.org/records/7968402>) (Shahsavarani et al., 2023). In summary, in vivo wide-field optical mapping, pupil size, locomotion, and whisking data were recorded from five adult male Thy1-jRGECO1a transgenic mice over multiple recording sessions. Throughout these sessions, the mice were head-fixed and free to exhibit spontaneous behaviors such as walking and running on a wheel without any experimental stimuli. The mouse pupil size was recorded with a BFS-U3-16S2M-CS USB 3.1 Blackfly S monochrome camera and sampled at ~20 Hz. Using the tracking software DeepLabCut (Mathis et al., 2018), pupil size was monitored by identifying eight circumferential points, then fitting a circle to these points to estimate pupil diameter. For the current experiment, eight 10-minute recording sessions were selected for each mouse. Any session in which significant portions of the pupil data were missing was not selected for inclusion in the mouse dataset.

**Monkey pupil data** The monkey pupil data consisted of two adult (~7 years old), male rhesus macaques who completed a variant of the visual reinforcement learning task previously published in Taswell et al. (2018) with simultaneous pupilometry recording. The pupil data were acquired in non-contiguous trials lasting several seconds (~2–10 seconds), with each data segment corresponding to a single task trial. One study session was selected per monkey, each including more than 1500 trials of the learning task. Only trials with pupilometry recordings lasting longer than 5 seconds were selected for each monkey. This criterion resulted in the inclusion of 184 and 202 trials for each monkey, respectively, or approximately 25 minutes of pupil data per monkey.

Head-fixed pupilometry was acquired using the MATLAB-based (MathWorks, Inc.) Monkeylogic toolbox (version 2.2; <https://monkeylogic.nimh.nih.gov>; Asaad & Eskandar, 2008) and Arrington Viewpoint eye-tracking system (recorded eye: left eye; sampling rate = 1000 Hz; Arrington Research, Inc.) run on a desktop computer (Dell OptiPlex 9020; Dell, Inc.). An infrared camera was positioned ~40 centimeters from the monkey. Pupil size was acquired in arbitrary units, linked to the voltage output of

the eye tracking system. The pupil data reported in the current study were not previously published.

**Target pupil phase events** Pupil size fluctuations consist of four main phases: (1) dilation, (2) peak, (3) constriction, and (4) trough (Fig. 1B). The *dilation* phase is when pupil size increases. The *peak* phase is when the pupil has reached a local maximum (i.e., the moment of a phase switch from a period of dilation to constriction). The *constriction* phase is when pupil size decreases. The *trough* phase is when the pupil has reached a local minimum (i.e., the moment of a phase switch from a period of constriction to dilation). During pupillary unrest—the spontaneous fluctuation of pupil size under constant environmental luminance—pupil size cycles among these four pupil phases, in part, according to neurophysiological state and other factors, including eye movements (e.g., blinks) (Yoo et al., 2021).

**Real-time detection of pupil phase events** Real-time monitoring methods are available for various physiological signals, for example, neural and cardiac potentials (Handelman, 1989; Quotb et al., 2011). Meanwhile, there are limited real-time monitoring methods for the pupil, in part, because pupil physiology presents unique challenges for developing real-time methods. First, pupil size undergoes large baseline shifts over seconds, for example, linked to states of arousal and locomotion. These low-frequency drifts limit the efficacy of applying constant pupil size thresholds for detecting pupil phases. Second, pupil size trends do not conform to a consistent profile or shape (e.g., the stereotyped membrane potential change of a neuronal action potential). Third, spontaneous and evoked pupil size changes are slow—unfolding over hundreds to thousands of milliseconds. Therefore, at the sampling rates commonly used in pupil data acquisition (>20 Hz), there are small differences in pupil size between adjacent data samples. As a result, a derivative approach (i.e., pupil size sample  $x_1 - x_2$ ,  $x_2 - x_3$ , etc.) to determine pupil phase is limited. Finally, the pupil data stream is subject to repeated artifacts and interruptions due to behaviors that occlude the pupil, including blinks, drooping eyelid (e.g., due to drowsiness), and whisking in rodents. *rtPupilPhase*—our method for detecting the phases of pupillary fluctuation in real time—overcomes these unique challenges of pupil physiology for developing real-time pupilometry methods.

*rtPupilPhase* is a Python-based, open-source software that we integrated with a fixation task (see *Fixation task* section). The main goal of *rtPupilPhase* is to analyze live-streamed pupil size data and detect the real-time occurrence of target pupil phase events: dilation, peak, constriction, and trough (Fig. 1B; see *Target pupil phase events* section). As a control condition, *rtPupilPhase* also selects pupil phase-independent or *random* events. Here, we use the random events to measure the performance of *rtPupilPhase*. Future applications of



rtPupilPhase can suppress the selection of random events or implement these events as a pupil phase-independent control or baseline condition.

The rtPupilPhase method is summarized in four main stages (Fig. 1C; see Table 1 for a list of the method parameters):

*Stage 1:* Monocular, pupil size data is live-streamed (see *Human pupillometry acquisition* section) and stored in brief, continuous intervals of pupil size data called a *pupil sample*. The pupil sample is filled with sequential pupil size data points until it comprises a total of 0.1 seconds of pupil size data (i.e., ~6 pupil size data points at ~60 Hz sampling rate). For the human pupillometry acquisition system, blinks and other interruptions in the pupil data stream (e.g., lost eye tracking due to head movement or drooping eyelid) result in a pupil size value of 0. Any pupil size value in the pupil sample equal to 0 is replaced with the designation “not a number” (NaN).

*Stage 2:* The pupil sample is simultaneously added to a *search window* and *baseline window*. Subsequently, the pupil sample is cleared, and a new pupil sample is built (see stage 1). Thus, over time, the search and baseline windows grow, comprising continuous pupil size data that are sequentially added in increments of pupil sample (i.e., 0.1 seconds). The search window is analyzed for pupil phase events (see stage 3). The baseline window is used to recurrently update the pupil size and pupil size derivative thresholds that determine the occurrence of pupil phase events within the search window (see stage 4). If one or more samples in the current search window includes a NaN, the search window is cleared, and a new search window built. The current search window is also reset if the *previous* search window contained at least one NaN sample. With this approach, rtPupilPhase limits the influence of blinks and other common human pupillometry recording artifacts in the real-time detection of pupil phase events by only considering pupil data intervals absent these artifactual occurrences.

*Stage 3:* When the search window comprises a minimum of two pupil samples (i.e., at least two cycles of stages 1 and 2 have iterated without resetting the search window), the search window data is demeaned (i.e., the mean of all the pupil size data in the search window is subtracted from all search window samples). Next, the demeaned search window pupil size data is fit with a quadratic model ( $x$ -coordinates = 0 to the number of samples in the search window minus one; NumPy function *polyfit*; <https://numpy.org>). The resulting fitted trace is a model of the pupil size data in the search window. The final pupil size value from the fitted model time course, corresponding with the final sample in the search window,

is recorded for later use to guide determining the pupil phase (see stage 4). Stages 1 through 3 iterate until a target pupil phase event is detected (see stage 4) or if the search window exceeds 5 seconds of cumulative pupil size data. In either case, the search window is emptied and built anew from subsequent pupil samples (see stages 1 and 2).

*Stage 4:* When there is at least one previous fitted model (i.e., stage 3 has iterated two or more times), the previous and current final pupil size values from the fitted model time courses are compared to determine the occurrence of a target pupil phase event. A peak event is detected when the final pupil size value of the current search window is *less than* the final pupil size value from the previous search window (final value of search window<sub>*i*</sub> < final value of search window<sub>*i-1*</sub>) and the final pupil size value from the current search window is *greater than* the pupil size 75th percentile for all peak events detected in the previous baseline window (see details below). A trough event is found when the final pupil size value of the current search window is *greater than* the final pupil size value from the previous search window (final value of search window<sub>*i*</sub> > final value of search window<sub>*i-1*</sub>) and the final pupil size value from the current search window is *less than* the pupil size 25th percentile for all trough events found in the previous baseline window (see details below). The dilation and constriction events are detected when the difference between the final pupil size values from the fitted model time courses of the current and previous search windows (final value of search window<sub>*i*</sub> – final value of search window<sub>*i-1*</sub>) is *greater than* the pupil size derivative 99th percentile or is *less than* the pupil size derivative first percentile, respectively, with the derivative percentile thresholds evaluated across all valid pupil size samples in the previous baseline window (see details below).

In the initial iterations of stage 4, the pupil size and pupil size derivative thresholds (Table 1) are set to default constants (peak pupil size threshold = 0; trough pupil size threshold = 0; dilation pupil size derivative threshold = 50; constriction pupil size derivative threshold = -50). Subsequently, these thresholds are updated when the baseline window is filled—approximately every 5 seconds. At least half of the baseline window samples must be valid pupil size values (i.e., non-NaN) to accept the current baseline window for analysis to update the pupil size and pupil size derivative thresholds. If the baseline window is rejected, the threshold values remain the same, and the baseline window is cleared and filled again (see stage 2). However, when a valid baseline window is confirmed, the baseline window pupil size data is demeaned, and all NaN pupil size samples are removed from the baseline window. The

pupil size threshold is determined by finding all peak and trough events (SciPy function *find\_peaks*; <https://scipy.org>) in the demeaned baseline window and then calculating the pupil size 75th percentile among peaks and pupil size 25th percentile of among troughs. Prior to finding troughs in the baseline window, the pupil size data are inverted (i.e., multiplied by  $-1$ ) so that finding peaks in the inverted data identifies troughs in the original, un-inverted dataset. The pupil size at each trough event is calculated with the original data. The pupil derivative thresholds are calculated by finding the derivative across all valid pupil size samples in the baseline window (NumPy function *diff*; <https://numpy.org>) and then calculating the 99th and first percentile of all derivative values.

When a pupil phase event is detected, the search window is cleared, and the procedure begins anew from stage 1. An inter-event interval (IEI) of 3 seconds is set so that *rtPupilPhase* will not log an *accepted* pupil phase event unless the IEI has been exceeded. Events detected within the IEI are logged but designated as *not* accepted. When the IEI is exceeded for any detected pupil phase event, the search window is *not* cleared; instead, additional pupil samples are added to the search window until a pupil event is detected that exceeds the IEI or the maximum length of the search window (5 seconds) is exceeded; in either case, the search window is reset. We implemented the IEI in the current demonstration of *rtPupilPhase* to limit the number of events analyzed to manage the computational load and so that the data samples contained within the pupil size, blink, and saccade fraction epochs are nonoverlapping with any other event epoch. Future application of *rtPupilPhase* can modify the IEI duration or eliminate it altogether (i.e., set the IEI to 0 seconds).

**Human simulated real-time detection of pupil phase events** Simulated *rtPupilPhase* or *sim-rtPupilPhase* is a MATLAB-based (MathWorks, Inc.), open-source software designed to simulate the *rtPupilPhase* method in a live recording using previously acquired pupil data. *sim-rtPupilPhase* was developed as a proof of concept to assess the performance of *rtPupilPhase* on pupil data from nonhuman animals. In future applications, *sim-rtPupilPhase* can serve as a tool for optimizing the *rtPupilPhase* parameters to achieve specific experimental goals and without collecting additional data. In summary, *sim-rtPupilPhase* loads previously collected pupil data and streams the data through the *rtPupilPhase* method (see *Real-time detection of pupil phase events* section; Fig. 1C). The pupil data was modeled (see stage 3 of the *rtPupilPhase* method) with the MATLAB function *fit* ( $x$ -coordinates = 1 to the number of samples in the search window; 0 to the number of samples in the search window minus 1 was also tested and achieved similar results [data not shown]; MathWorks, Inc.). To directly compare the

performance between *rtPupilPhase* and *sim-rtPupilPhase* on the human pupil data, the pupil size data were down-sampled from the offline sampling rate of 1000 to 60 Hz (i.e., the approximate online sampling rate of the human pupillometry recordings; see *Human pupillometry acquisition* section). Otherwise, the *sim-rtPupilPhase* parameters (e.g., the pupil size and pupil size derivative thresholds) were set to exactly as those used in the *rtPupilPhase* live study (Table 1).

**Mouse simulated real-time detection of pupil phase events** All pupil size samples concurrent with a locomotion event or with a value less than 0 (e.g., indicative of blinking or whisking) were replaced in the pupil data with NaN (see *Mouse pupil data* section). Otherwise, all *sim-rtPupilPhase* parameters and procedures were exactly as those used in the human *sim-rtPupilPhase* testing (Table 1; see *Human simulated real-time detection of pupil phase events* section).

**Monkey simulated real-time detection of pupil phase events** To accommodate the brief pupil data segments (<10 seconds) acquired in monkeys corresponding with task trials (see *Monkey pupil data* section), several adjustments were made to the *sim-rtPupilPhase* parameters (Table 1). First, the baseline window duration was adjusted from 5 seconds, as used in humans and mice, to 0.5 seconds. In addition, whereas in humans and mice, all event types were considered together to determine whether the IEI threshold was breached, in the monkey dataset, each pupil phase event was considered relative to its own event type to determine whether the IEI was exceeded (i.e., events of different type could fall within the IEI). This adjustment was made to increase the number of accepted pupil phase events detected in the monkey pupil data. Another adaptation made in the monkey *sim-rtPupilPhase* procedure was the initial removal of artifactual periods within each trial using the human pupil size preprocessing procedure (see *Monkey pupil data* and *Human pupil size, blink, and saccade fraction epoch extraction* sections). Preprocessing was necessary because the monkey pupil data contained numerous artifacts, including those linked to eye movements and task stimuli. Otherwise, all *sim-rtPupilPhase* parameters and procedures were exactly as those used in human *sim-rtPupilPhase* (Table 1; see *Human simulated real-time detection of pupil phase events* section).

## Statistical analysis

**Human pupil size, blink, and saccade fraction epoch extraction** Epoch extraction involved selecting segments of pupil size, blink, and saccade occurrence data centered on the pupil phase and random event times that were detected by *rtPupilPhase* and *sim-rtPupilPhase*. Prior to extracting the pupil size epochs, the pupil data were preprocessed for each

participant, including the removal of blink and other artifactual events (e.g., drooping eyelid) that result in blank periods in the pupil size data stream (*stublins.m* available at <http://www.pitt.edu/~gsiegle>) (Siegle et al., 2003). The preprocessing procedure also outputs a binary blink vector of the same length as the inputted pupil size data—blink data samples indicated with 1 and non-blink samples with 0. Similarly, a saccade binary vector was made using an established saccade detection method (Engbert & Kliegl, 2003; Engbert & Mergenthaler, 2006): saccade data samples indicated with 1 and non-saccade samples with 0. Note that the saccade binary vector was inclusive of microsaccades. Therefore, each participant contributed a preprocessed pupil size, blink binary, and saccade binary vector that extended the entire pupillometry recording session.

The preprocessed pupil size, blink binary, and saccade binary data were cut into 5001-ms epochs centered on each pupil phase and random event (i.e., 2.5 seconds before and after the event time) detected with either *rtPupilPhase* or *sim-rtPupilPhase*. The epoch was not extracted if 2.5 seconds before or after the event time exceeded the length of the pupillometry recording. The extracted pupil size epochs were demeaned (i.e., the mean pupil size across the entire epoch was subtracted from all epoch samples). After extracting all epochs, the mean across epochs was calculated within participant and events detected with *rtPupilPhase* and *sim-rtPupilPhase*, so that each participant contributed a *rtPupilPhase* and *sim-rtPupilPhase* mean pupil size, blink, and saccade fraction time course per pupil phase and random event. To interrogate the sensitivity of *rtPupilPhase* to eye movements (e.g., blinks and saccades), a subset of pupil size epochs with neither blinks nor saccades in the 0.5 seconds prior to the event time were selected and averaged separately within participant and *rtPupilPhase* and *sim-rtPupilPhase* methods (Supplementary Fig. 6A, B). The participant-level saccade time courses were smoothed using the MATLAB *smooth* function (window size = 0.1 seconds; MathWorks, Inc).

Subsequent group-level analyses involved finding the mean across participant pupil size, blink, and saccade fraction time courses within event type and *rtPupilPhase* and *sim-rtPupilPhase* detection methods (Supplement. Fig. 4A, B; Supplementary Fig. 6A, B). An alternative group-level analysis first calculated the *z*-score across participant time courses and then calculated the mean of the *z*-scored time courses across participants within event and method type (Fig. 2A, B; Supplementary Fig. 3A, B). The standard error of the mean was calculated across participants. For visualization of the pupil size, blink, and saccade fraction time courses, only the 1.5 seconds before and after the event were displayed (Fig. 2A, B; Supplementary Figs. 2B; 3A, B; 4A, B; 6).

**Mouse pupil size epoch extraction** The mouse pupil data were cut into 5001-ms epochs (101 samples at ~20 Hz sampling rate; see *Mouse pupil data* section) centered on each pupil phase and random event detected with *sim-rtPupilPhase* (i.e., 2.5 seconds before and after the event time). The epoch was not extracted if 2.5 seconds before or after the event time exceeded the length of the pupillometry recording. Next, the pupil size epochs were demeaned (i.e., the mean pupil size across the entire epoch was subtracted from all epoch samples). After extracting all epochs, the mean across epochs was calculated within mouse and event type, so that each mouse contributed a single mean pupil size time course for each event. Group-level epoch analyses involved finding the mean across mouse pupil size time courses within event type (Supplementary Fig. 4C). An alternative group-level analysis first calculated the *z*-score across mouse pupil size time courses and then calculated the mean of the *z*-scored time courses across mice (Fig. 2C; Supplementary Fig. 3C). The standard error of the mean was calculated across mice. For visualization of the pupil size time courses, only the 1.5 seconds before and after the event were displayed (Fig. 2C; Supplementary Fig. 3C; Supplementary Fig. 4C).

**Monkey pupil size epoch extraction** Prior to extracting the monkey pupil size epoch time courses, the pupil data were preprocessed using the same method applied on the human pupil data (see *Human pupil size, blink, and saccade fraction epoch extraction* section). The monkey pupil data were cut into 1001-ms epochs centered on the pupil phase and random events (i.e., 0.5 seconds before and after the event time) that were detected by *sim-rtPupilPhase* (see *Monkey simulated real-time detection of pupil phase events* section). The epoch duration was reduced for the monkey pupil data relative to the 5001-ms epochs extracted from the human and mouse datasets because the monkey data were acquired in short segments (see *Monkey pupil data* section). Therefore, cutting longer epochs exceeded the bounds of the pupil data acquired in each data segment. Accordingly, epochs were not extracted if 0.5 seconds before or after the event time exceeded the length of the pupillometry recording. Next, the pupil size epochs were demeaned (i.e., the mean pupil size across the entire epoch was subtracted from all epoch samples). Unique to the monkey dataset, the demeaned epochs were also detrended using the MATLAB *detrend* function (MathWorks, Inc.) to correct for a low-frequency drift in pupil size related to the task the monkeys were engaged. The mean across all detrended epochs within monkey and pupil phase and random events was calculated, so that each monkey contributed a single mean pupil size time course for each event. Group-level epoch analyses involved finding the mean across all monkey-mean pupil size epoch time courses within event type (Supplementary Fig. 4D). An alternative

group-level analysis first calculated the  $z$ -score across monkey epoch time courses and then calculated the mean of the  $z$ -scored epochs across monkeys for each pupil phase and random event (Fig. 2D; Supplementary Fig. 3D). The standard error of the mean was calculated across monkeys.

**Cluster-based permutation testing** Human pupil size time courses for the pupil phase events were statistically tested against the random event pupil size time course with cluster-based permutation testing (number of permutations = 250;  $p < 0.05$ ). The permutation analysis method employed in this study is a modified version of the method shared in the Mass Univariate ERP Toolbox ([https://openwetware.org/wiki/Mass\\_Univariate\\_ERP\\_Toolbox](https://openwetware.org/wiki/Mass_Univariate_ERP_Toolbox)) (Groppe et al., 2011). This approach was also used in a previous experiment to statistically analyze pupil size time courses (Kronemer et al., 2022). In summary, the cluster-based permutation testing method involves creating positive and negative null statistical distributions by participant-level permutation between the compared event types (e.g., peak versus random event). Subsequently, a one-sample  $t$ -test was performed on the non-permuted data, identifying statistically significant positive and negative clusters based on the null distributions. Clusters were defined by temporal adjacency (i.e., statistically significant data samples contiguous in time). Four cluster-based permutation analyses were evaluated each for the rtPupilPhase and sim-rtPupilPhase human pupil size time courses: (1) dilation versus random, (2) peak versus random, (3) constriction versus random, and (4) trough versus random events (Supplementary Fig. 4A, B). The mouse and monkey data were not subjected to statistical testing due to low individual animal sample sizes.

**Pupil phase event detection accuracy and sensitivity performance** The accuracy and sensitivity of rtPupilPhase in detecting pupil phase events in humans was calculated based on accepted events (i.e., those that exceeded the IEI; see *Real-time detection of pupil phase events* section). Event accuracy was evaluated by comparing the real-time detected pupil phase event versus the corresponding *true* pupil phase. The true pupil phase was determined by post hoc analysis of the pupil data. In summary, first, the human pupil data were preprocessed, including removing blinks and artifactual samples (see *Human pupil size, blink, and saccade fraction epoch extraction* section). Next, the preprocessed pupil data were smoothed using the MATLAB *smoothdata* function (Savitzky-Golay filter; window size = 0.1 seconds; MathWorks, Inc.) to eliminate high-frequency signals. The true peak and trough pupil phase events were identified using the MATLAB *findpeaks* function (MathWorks, Inc.). For trough events, prior to implementing findpeaks, the pupil size data were inverted (i.e., multiplied by  $-1$ ). Finally, the top 75% of peaks and troughs were selected based on their prominence.

For two participants, the prominence percent threshold was adjusted to 90% because visual inspection determined that lower thresholds resulted in the selection of peak and trough events with low prominence. Finally, peak and trough event binary indices were made by setting all samples within 0.25 seconds before and after each peak and trough event to an index value of 1, while all other samples outside this range were set to 0.

The true dilation and constriction pupil phase events were found by calculating the slope at every sample of the pupil size data using the MATLAB *gradient* function (MathWorks, Inc.). A dilation event binary index was created by setting all samples from the gradient output with a positive value to 1, indicating a positive slope or dilation, and a negative value to 0, indicating a negative slope or constriction. Conversely, the constriction binary index was created by setting all the samples from the gradient output with a negative value to 1 and a positive value to 0.

The accuracy of the real-time detected pupil phase events was assessed by comparing each event sample to the corresponding true pupil phase event index. An index value of 1 at the queried event sample indicated agreement between the real-time and true pupil phase events. The real-time detected event accuracy percentage was calculated within participant and pupil phase event type detected with rtPupilPhase by determining the total number of pupil phase events that were accurately detected (i.e., in agreement with the true pupil phase event indices) divided by the total number of detected pupil phase events. The result was multiplied by 100 to convert from rate to percentage units. The baseline or chance accuracy rate for each pupil phase event was determined by comparing the random event samples to each of the true pupil phase event indices (e.g., random event versus true dilation event index, random event versus true peak event index, etc.). Finally, to assess if the real-time pupil phase event accuracy was greater than the random accuracy percentage, group-level paired  $t$ -tests across participants were conducted to statistically compare pupil phase and random event accuracies (Holm–Bonferroni-corrected,  $p < 0.05$ ). A total of four  $t$ -tests were completed: (1) dilation versus random, (2) peak versus random, (3) constriction versus random, and (4) trough versus random events (Fig. 3B).

Finally, the sensitivity of the real-time detected pupil phase events was assessed using the exact method as detailed above for calculating rtPupilPhase accuracy, except each real-time detected event sample was compared to *off-target* true pupil phase event indices (e.g., comparing the real-time detected dilation event with the true peak, constriction, and trough event indices). A one-sample  $t$ -test (Holm–Bonferroni-corrected,  $p < 0.05$ ) tested if the accuracy of the real-time detected pupil phase events (i.e., on-target performance, e.g., comparing the predicted dilation event with

the true dilation event index) was greater than the off-target performance (Supplementary Fig. 5). A statistically greater on-target accuracy suggests that rtPupilPhase is sensitive to each pupil phase event type. These analyses also help to assess overlap among the pupil phase events (i.e., a detected pupil phase event belonging to two or more true pupil phase event types).

**Pupil phase event detection temporal performance** The temporal performance of rtPupilPhase is defined as the inter-event duration or the time between detected pupil phase events, independent of event type. Temporal performance is impacted by the online pupillometry sampling rate, the rtPupilPhase parameters, and behaviors that occlude the pupil (e.g., blinks). The human rtPupilPhase temporal performance was calculated for each participant by first combining the time indices for all detected pupil phase events, ignoring the IEI and random events (see *Real-time detection of pupil phase events* section), and sorting these events in chronological order. Also, intervals between fixation task blocks (i.e., ~2-minute task break periods; see *Fixation task* section) were ignored. Next, the duration of time between each event was calculated (i.e.,  $t' = \text{event time}_1 - \text{event time}_2$ ), independent of event type. The median  $t'$  value was calculated for each participant and averaged across participants to determine the estimated temporal resolution of rtPupilPhase (Fig. 3B). We chose the median to statistically assess temporal performance because there were prolonged durations between detected pupil phase events ( $t' > 0.5$  seconds in 15.34% of inter-event durations commonly the result of blinking bouts; Fig. 2B) that biased mean-based analyses. Finally, the detection frequency rate was calculated by evaluating 1 divided by the group median temporal resolution converted to units of seconds.

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**Data and Code availability** All code and data are available at <https://github.com/nimh-sfim/rtPupilPhase>.

## Declarations

**Ethics approval** All procedures involving human participants were in compliance with the National Institutes of Health Clinical Center protocol ID 93-M-0170 (ClinicalTrials.gov ID: NCT00001360) and the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. All procedures involving nonhuman animals were in compliance with the animal welfare regulations of the National Institute of Mental Health.

**Competing interests** The authors have no competing interests to declare that are relevant to the content of this article.

**Consent to participate** Informed consent was obtained from all individual participants included in this study.

**Consent for publication** Not applicable.

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**Open practices statement** The data and codes for this study are available at <https://github.com/nimh-sfim/rtPupilPhase> and this study was not preregistered.