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State-dependent brainstem ensemble dynamics and their interactions with hippocampus across sleep states

Tomomi Tsunematsu1,2,3,4, Amisha A Patel1, Arno Onken5, Shuzo Sakata1

1 Strathclyde Institute of Pharmacy and Biomedical Sciences, University of Strathclyde, 161 Cathedral Street, Glasgow G4 0RE, UK
2 Super-network Brain Physiology, Graduate School of Life Sciences, Tohoku University, Sendai 980-8577, Japan
3 Frontier Research Institute for Interdisciplinary Sciences, Tohoku University, Sendai 980-8578, Japan
4 Precursory Research for Embryonic Science and Technology, Japan Science and Technology Agency, Kawaguchi 332-0012, Japan
5 School of Informatics, University of Edinburgh, 10 Crichton Street, Edinburgh EH8 9AB, UK

Correspondence (shuzo.sakata@strath.ac.uk)

Abstract

The brainstem plays a crucial role in sleep-wake regulation. However, their ensemble dynamics underlying sleep regulation remain poorly understood. Here we show slow, state-predictive brainstem ensemble dynamics and state-dependent interactions between the brainstem and the hippocampus in mice. On a timescale of seconds to minutes, brainstem populations can predict pupil dilation and vigilance states where they exhibit longer predictable power compared with hippocampal CA1 neurons. On a timescale of sub-seconds, pontine waves (P-waves) are accompanied by synchronous firing of brainstem neurons during both rapid eye movement (REM) and non-REM (NREM) sleep. Crucially, P-waves functionally interact with CA1 activity in a state-dependent manner: during NREM sleep, hippocampal sharp wave-ripples (SWRs) precede P-waves. On the other hand, P-waves during REM sleep are phase-locked with ongoing theta oscillations and are followed by burst firing of CA1 neurons. This state-dependent global coordination between the brainstem and hippocampus implicates distinct functional roles of sleep.
Introduction


Sleep states are typically classified into two major states, non-rapid eye movement (NREM) sleep and REM sleep. While numerous brain regions and cell-types have been identified as part of sleep-regulating circuits (Brown et al., 2012, Herice et al., 2019, Jouvet, 1962, Moruzzi, 1963, Peever and Fuller, 2017, Scammell et al., 2017, Weber and Dan, 2016, Luppi et al., 2017, Adamantidis et al., 2007, Tsunematsu et al., 2014, Weber et al., 2015, Zhang et al., 2019), sleep-related neural firing and oscillations have also been described across cortical and subcortical regions (McCarley and Hobson, 1971, Hobson et al., 1975, Sakai, 1985, Steriade, 2006, Brown et al., 2012, Rasch and Born, 2013, Buzsaki, 2015, Weber et al., 2015, Scammell et al., 2017, Weber et al., 2018, Herice et al., 2019, Liu and Dan, 2019). For example, cortical slow oscillations, sleep spindles and hippocampal sharp wave-ripples (SWRs) are prominent neural events during NREM sleep whereas theta oscillations and ponto-geniculo-occipital (PGO) or pontine (P) waves are seen during REM sleep (Steriade, 2006, Montgomery et al., 2008, Buzsaki, 2015, Buzsaki, 2002, Jouvet, 1969, Steriade et al., 1993b, Callaway et al., 1987, Datta, 1997, Rasch and Born, 2013, Bizzi and Brooks, 1963). Although neural ensemble dynamics underlying these sleep-related neural events in the thalamus and the cortex including the hippocampus have been well described (Steriade, 2006, Buzsaki, 2015, Buzsaki, 2002, Steriade et al., 1993a), little is known about population activity within the brainstem. Toward a better understanding of functional roles of sleep states, it is essential to characterize state-dependent changes in brainstem network activity and their functional interactions with cortical regions across sleep states.

The brainstem, including the midbrain, pons and medulla has long been implicated in the sleep-wake cycle (Jouvet, 1962, Saper et al., 2010, Brown et al., 2012, Rasch and Born, 2013, Weber et al., 2015, Weber and Dan, 2016, Luppi et al., 2017, Scammell et al., 2017, Herice et al., 2019, Liu and Dan, 2019). It contains various nuclei, each of which consists of diverse cell-types and exhibits state-dependent firing (Brown et al., 2012, Rasch and Born, 2013, Weber et al., 2015, Weber and Dan, 2016, Luppi et al., 2017, Scammell et al., 2017, Herice et al., 2019, Liu and Dan, 2019, Weber et al., 2018, Zhang et al., 2019). However, it remains poorly explored how brainstem populations act in concert. For example, it is still unclear to what extent their activity exhibits anticipatory dynamics for ongoing vigilant states. In addition, it is also unclear whether and how brainstem populations functionally interact with various neural oscillations or events in the cortex.
across sleep states. Characterizing these physiological properties is crucial to uncover the roles of brainstem populations in sleep regulation and ultimately the functions of sleep states.

In the present study, we adopt several *in vivo* electrophysiological approaches in mice to investigate state-dependent ensemble dynamics in the brainstem, mainly the pons. We show that on a timescale of seconds to minutes, brainstem neurons show state-dependent firing with cell type-specificity. They also have a longer predictive power for vigilance states compared to those in the hippocampus. On a timescale of sub-seconds, we find state-dependent functional interactions between the brainstem and the hippocampus, with a focus on P-waves. During NREM sleep, the timing of P-waves is phase-locked with various cortical oscillations and hippocampal SWRs precede P-waves. During REM sleep, P-waves co-occur with hippocampal theta oscillations and precede burst firing of hippocampal neurons. These results imply that brainstem populations not only play a regulatory role in the sleep-wake cycle, but also contribute to global state-dependent dynamics across brain regions.

**Results**

**Brainstem population recording across sleep-wake cycles**

To investigate the state-dependency of brainstem population activity, we inserted a silicon probe into the mouse brainstem in a head-fixed condition, together with simultaneous monitoring of cortical electroencephalograms (EEGs), electromyograms (EMGs) and pupil dilation (*Figure 1*). Recorded regions spanned across multiple nuclei, including the sublaterodorsal nucleus, pontine reticular nucleus, medial preoptic nucleus, parabrachial nucleus, pontine central gray, laterodorsal tegmental nucleus and other surrounding areas according to post-mortem histological analysis (*Figure 1 – figure supplement 1*). Although a majority of neurons were recorded from the pons, we refer to recorded populations as "brainstem" neurons because some cells were located in the midbrain and medulla, but not the hypothalamus.

The sleep-wake cycle was classified based on cortical EEGs and EMGs in every 4 second. Based on the classified states, we observed clear state-dependency across measurements (*Figures. 1C-F*): wakefulness was characterized by high muscle tone (*Figure 1D*) and pupil dilation (*Figure 1F*) whereas NREM sleep was characterized by higher power of slow oscillations (*Figure 1C*) and a wider dynamic range of pupil diameter (*Figure 1F*). REM sleep was distinct from the other states, with respect to prominent theta oscillations (*Figure 1C*), low muscle tone (*Figure 1D*), higher brainstem LFPs power (*Figure 1E*) and fully constricted pupil (*Figure 1F*). The higher power of brainstem LFPs during REM sleep was preserved across all animals (7 animals, 9 recordings) (*Figure 1 – figure supplement 2*). Although most of our recordings were performed under a head-
Neuronal spiking activity in the brainstem also demonstrated rich state-dependent properties (Figure 1B). For example, a subset of neurons fired exclusively during REM sleep, indicating state-dependent population firing on a timescale of second-to-minute. In addition, we also observed frequent burst firing across neurons on a sub-second timescale during REM sleep.
analysis, we investigate state-dependent brainstem neural ensembles on two distinct timescales: a long timescale of seconds to minutes (Figures 2-4) and a sub-second timescale (Figures 5-7).

Diversity and specificity of state-dependent neural activity in the brainstem

To assess state-dependent firing of individual neurons in the brainstem on a timescale of seconds to minutes, we performed in vivo silicon probe recording (Figure 2A) from 7 head-fixed mice (9 recording sessions) and examined how individual neurons change their firing across behavioral states. Figure 2B shows representative examples of state-dependent firing from four simultaneously recorded neurons. Even within a particular state from the same animal, brainstem neurons show highly diverse and dynamic firing.

To classify neurons according to their state-dependent firing, we computed mean firing rate in each state across neurons (n = 76) and applied a hierarchical clustering algorithm (Figure 2C). We identified four functional classes: awake (AW)-on neurons (23.7 %) were more active during wakefulness compared to sleep states. REM-off neurons (17.1 %) reduced their firing during REM sleep. REM/AW-on neurons (6.6 %) were quiet during NREM sleep. The largest class (52.6 %) was REM-on neurons, which showed the highest firing rate during REM sleep. Thus, we confirmed highly diverse state-dependent firing in the brainstem.

Because the recorded neurons were distributed across various nuclei in the brainstem, it was difficult to determine their state-dependency in each nucleus. However, a subset of neurons was likely recorded from the cholinergic system, namely the pedunculopontine tegmental nucleus and the laterodorsal tegmental nucleus, which showed AW-on or REM-on activity (Figure 2 – figure supplement 1). To verify this, we performed in vivo fiber photometry of Ca\(^{2+}\) signals from pontine cholinergic neurons by expressing GCaMP6s in freely behaving mice (4 animals, 12 recording sessions) (Figure 2D). Consistent with the data from in vivo electrophysiology, cholinergic populations showed larger activity during REM sleep and wakefulness, compared to NREM sleep (F\(_{2,32} = 5.12, p = 0.012, \text{one-way ANOVA}) (Figures 2E-G). Therefore, although state-dependency of individual neuronal firing in the brainstem is diverse, we also confirmed state-dependent and cell-type-specific firing.
**Figure 2. Diverse and cell-type-specific state-dependent firing in brainstem neurons.**

(A) A diagram of the experimental approach, showing a silicon probe and a cortical EEG electrode. (B) Four examples of simultaneously recorded neurons. (C) Classification of functional classes. Firing rates across the three behavioral states were normalized as z-score for individual cells and hierarchical clustering was then applied. (D) A diagram of the experimental approach for fiber photometry-based Ca\(^{2+}\) imaging from pontine cholinergic neural populations in a freely behaving condition. (E) An example of fluorescent signals across sleep-wake cycles. Fluorescent signals (470 nm) were normalized by off-peak (405 nm) signals. red, wakefulness, blue, NREM sleep, green, REM sleep. (F) Distributions of fluorescent signals across the three behavioral states. (G) Group statistics of average fluorescent signals from 12 recordings from 4 mice (\(F_{2,32} = 5.12, p = 0.012\), one-way ANOVA). *, \(p < 0.05\) with post-hoc Tukey’s honest significant difference criterion. The following figure supplement is available for figure 2.

**Figure supplement 1.** Neurons recorded from pontine cholinergic nuclei and their state dependency.
Behavioral correlates of the sleep-wake cycle and underlying neural activity in the brainstem

Pupil diameter is an excellent biomarker of global brain state or arousal level (Aston-Jones and Cohen, 2005, Yuzgec et al., 2018, Larsen and Waters, 2018, McGinley et al., 2015) and activity in brainstem neurons, especially locus coeruleus norepinephrine neurons, correlates with pupil diameter (Aston-Jones and Cohen, 2005). However, it is still unclear how pupil dilation changes around the transition of sleep-wake states and to what extent brainstem neurons as a population can predict pupil dilation quantitatively. To address these issues, we analyzed datasets from head-fixed mice with either silicon probe recordings from the brainstem (6 animals, 6 recording sessions) or the hippocampus (2 animals, 3 recording sessions), or field potential recording from the brainstem with a bipolar electrode (6 animals, 9 recording sessions).

As previously reported (Yuzgec et al., 2018), head-fixed mice kept their eyes open, allowing us to monitor pupil dilation across states along with cortical EEG and EMG. The effects of behavioral states on pupil diameter was statistically significant (Figure 3A, $F_{2, 53} = 220.33, p < 0.0001$, one-way ANOVA), where pupil diameter was constricted during REM sleep and dilated during wakefulness.

With respect to pupil dilation dynamics across states (Figure 3B and Figure 3 – figure supplement 1), pupil diameter dynamically fluctuated during wakefulness and gradually constricted during NREM sleep. Typically, 10-20 sec before REM sleep, the pupil diameter would further decrease and was fully constricted during REM sleep, with rapid eye movement (Figure 3 – figure supplement 1).

Taking advantage of the simultaneous neural population recording and pupil monitoring, we examined how brainstem neurons can predict pupil dilation. First, we predicted pupil dilation based on the activity of individual neurons (Figure 3C) by applying a linear regression analysis. Because it was expected that the preceding neural activity can better predict pupil dilation, we systematically shifted the temporal relationship between spike trains and pupil diameter (see Methods). As expected, most of the neurons showed asymmetric profiles of R$^2$ values (Figure 3C). Although individual profiles were diverse, the average profile showed predictive activity of brainstem neurons for pupil diameter around 10 seconds in advance. We also predicted pupil diameter based on simultaneously recorded brainstem neurons (Figure 3D) by applying a multiple linear regression analysis. As with individual neurons, we observed an asymmetric profile of predictability. Thus, changes in brainstem neural activity preceded those in pupil diameter. Thereby, brainstem populations have predictive power for pupil diameter.
Longer predictability of brainstem ensembles for vigilance states

Next, we examined whether and to what extent brainstem neurons can predict sleep-wake states. To address this, first, we extracted features of neural population activity by applying non-negative matrix factorization (NMF), a technique that finds compact and easily interpretable representations of neural population activity in the form of parts-based activity patterns (Lee and Seung, 1999, Onken et al., 2016) (Figs. 4a and b) (see Methods). While overall firing rate reflected state changes (Figure 4A), NMF could extract several modules which captured state-dependent firing patterns across neurons in an unsupervised fashion. For example, module 1 represented REM-on activity whereas module 2 was activated at the end of NREM sleep and module 3 was most active
during wakefulness. Indeed, the weights in each module were consistent with state-dependency of individual neural firing (Figure 4 – figure supplement 1).

Besides modules capturing firing patterns across neurons, NMF also yielded activation coefficients of these modules. We noticed that dynamics of these activation coefficients show predictive activity: in the case of Figure 4A, the activation coefficients of modules 1 and 2 gradually built up during REM and NREM sleep, respectively. Therefore, we hypothesized that brainstem population activity exhibits not just state-dependency, but also predictive power for behavioral states (i.e., wakefulness, NREM sleep and REM sleep). To test this, we took the activation coefficients profiles from three modules and classified behavioral states by training a linear classifier, with systematic time shifting (Figure 4C). Brainstem populations showed predictive activity tens of seconds before transitions into all three behavioral states.

Figure 4. State-dependent brainstem population dynamics and their ability to predict vigilance states.

(A) Simultaneously recorded brainstem neurons across states and modules extracted with non-negative matrix factorization (NMF). (top) Firing profiles of brainstem neurons. Firing rate was normalized by the maximum firing rate and the normalized values were color-coded. Dotted lines indicate state transitions. (bottom) Average population activity (gray) and activation coefficients for each module derived by NMF. Background colors indicate behavioral states (red, AW; blue, NREM; green, REM). (B) Weights across neurons for each module. (C) Decoding of behavioral states from population activity. top, Decoding performance of brainstem and hippocampal CA1 neural populations for behavioral states as a function of time-shift. Error, SEM. bottom, Effect size as a function of time-shift.

The following figure supplement is available for figure 4.
Figure supplement 1. Weights of each module derived from NMF and individual firing profiles.
Figure supplement 2. Histological analysis of dorsal hippocampal CA1 recording.

Does this predictive activity in brainstem populations last longer, compared to other brain regions? Of many brain regions, hippocampal neurons are well known to exhibit state-dependent firing (Buzsaki, 2002, Buzsaki, 2015, Mizuseki and Miyawaki, 2017), but they less likely contribute to the
regulation of the sleep-wake cycle directly. Hence, hippocampal neurons could serve as a reference to assess the ability of brainstem populations to predict behavioral states. To examine whether brainstem populations exhibit predictive activity longer than hippocampal populations, we performed the same analysis for neural activity in the hippocampal CA1 (Figure 4C). Although CA1 neurons also had predictive power for several tens of seconds, the profile was relatively short-lasting compared to that of brainstem neurons. Thus, brainstem neurons have longer-lasting predictive power for behavioral states compared to hippocampal CA1 neurons.

Brainstem population activity underlying P-waves during NREM and REM sleep

On a timescale of seconds to minutes, brainstem neurons show diverse but specific state-dependent firing and have predictive power for pupil dilation and behavioral states. To investigate brainstem neural firing on a sub-second timescale, we focused on P-waves (Callaway et al., 1987, Datta, 1997). Although these sub-second neural events in the brainstem have long been recognized, the underlying neural ensembles and relations to other sleep-related oscillations are not fully understood.

Taking advantage of our dataset, we first examined whether the mouse brainstem exhibits P-waves like those observed in other mammalian species. We implanted a bipolar electrode in the pons (n = 16 recordings) (Figure 5A) and monitored LFPs by subtracting signals. During REM sleep, we observed large amplitude irregular neural events, which often appeared bursts (Figure 5B right). We also observed similar, but isolated neural events during NREM sleep (Figure 5B left). These neural events appeared more often during REM sleep ($p < 0.0001$, two-tailed $t$-test) (Figure 5C). Intriguingly, the frequency of these events gradually increased during NREM to REM sleep transitions and decreased during REM sleep to wakefulness transitions (Figure 5D). Because these characteristics generally resemble those in other species (Callaway et al., 1987, Datta, 1997), we concluded that these neural events are P-waves in mice.

P-waves can also be seen in silicon probe recordings (Figure 5E). Similar large-amplitude, irregular neural events were observed in subtracted and filtered LFPs (Figure 5F). Many of the simultaneously recorded brainstem neurons fired during P-waves. To assess this tendency, we pooled the peri-event firing profiles of all recorded brainstem neurons around P-waves (Figures 5G, H). The firing profiles were aligned at the trough timing of P-waves. A subset of neurons showed peak firing at the falling phase of P-waves. This tendency was consistent between NREM and REM sleep, suggesting that P-waves during NREM sleep ($P$-waves$^{NREM}$) are equivalent to P-waves during REM sleep ($P$-waves$^{REM}$), with respect to neural firing within the brainstem.
The co-firing of a subset of brainstem neurons underlies P-waves during both NREM and REM sleep. What are the impacts of such neural events onto other brain regions? Are any other sleep-related neural events associated with P-waves? Addressing these questions would provide insight into functions of P-waves. To this end, first, we investigated the relationship between P-waves and cortical EEGs (Figure 6). During NREM sleep, P-waves were associated with multiple oscillatory components. Averaged P-wave-triggered cortical EEGs exhibited multiple phasic components (Figure 6B), which consisted of delta (1-4 Hz), theta (~7 Hz) and beta (15~30 Hz) frequencies. To examine this trend further, we assessed the phase relationship between P-wave timing and cortical oscillations (Fig. 6C). We found significant phase preferences of P-wave timing ($p < 0.01$, Rayleigh test). We further assessed this phase-locking activity by computing resultant vector length (Figure 6D), which is a descriptive circular statistic and represents the length of the mean resultant vector (Berens, 2009): the closer this value is to one, the more concentrated is the phase coupling. We found larger phase modulation at delta and beta ranges.

On the other hand, P-waves$^{\text{REM}}$ exhibited distinct associations with cortical oscillations (Figures 6B-D). We observed significant phase modulation at theta range ($p < 0.01$) (Figure 6C), indicating that two prominent neural markers in REM sleep, that is, theta oscillations and P-waves, are temporally organized. We found that the effect of sleep states on these phase-locking activity was statistically significant ($F_{1,170} = 4.90$, $p < 0.05$, two-way ANOVA). We also computed effect size (Figure 6E). The effect was larger at the delta range during NREM sleep. Hence, the temporal coupling between P-waves and cortical oscillations was modified by sleep states.

Figure 5. Pontine waves (P-waves) in the mouse.

(A) A diagram of the experimental approach, with showing a bipolar electrode in the pons and a cortical EEG electrode. (B) Examples of P-waves during NREM (left) and REM sleep (right), with showing cortical EEG and EMG traces. (C) Frequency of P-waves during NREM and REM sleep ($n = 16$). ***, $p < 0.0001$, two-tailed t-test. (D) Temporal evolution of P-wave frequency. Duration of each state episode was normalized to one. Error, SEM. (E) A diagram of the experimental approach, showing a multi-shank silicon probe in the brainstem and cortical EEG electrode. (F) An example of a P-wave, showing subtracted LFPs from a probe shank, and multiple single unit activity. (G) and (H) Pooled peri-event time histograms of brainstem single units relative to P-wave timing during NREM (G) and REM sleep (H). Time zero is the timing of P-waves (trough time). Each peri-event time histogram is color-coded by normalizing the maximum firing rate for each cell. The order of single units was sorted by the peak timing in each state.
Figure 6. State-dependent interactions between P-waves and cortical oscillations.

(A) A diagram of an experimental approach showing a bipolar electrode in the pons and cortical EEG electrode.

(B) Examples of averaged event-triggered cortical EEGs and scalograms during NREM (left) and REM sleep (right). Time zero is the timing of P-waves (trough time). (C) Examples of phase-histograms. Cortical EEGs were filtered at certain frequency bands and the proportion of P-waves elicited in each phase bin was calculated. *, p < 0.01, Rayleigh test. (D) Phase modulations across frequency bands of cortical EEGs. Resultant vector length represents the mean measurement of circular spread of the phase relationship between cortical oscillations and P-waves. The effect of sleep states on resultant vector length was significant (F(1,179) = 4.90, p < 0.05, two-way ANOVA). *, p < 0.05 (post-hoc Tukey's honestly significant difference test). Error, SEM. (E) Effect size of states

Next, we investigated the relationship between P-waves and hippocampal CA1 activity (Figure 7).

We started by assessing the phase relationship between hippocampal LFPs and P-waves across frequency bands (Figure 7B). We found that the effect of sleep states on the resultant vector length was significant (F(1,79) = 4.00, p < 0.05, two-way ANOVA). While the timing of P-waves was strongly phase-locked at the theta range (~7 Hz) in both sleep states and there was no significant difference in the resultant vector length across frequencies, we observed stronger phase modulations in high frequency (≥30 Hz) components during REM sleep based on the effect size.

We further examined underlying spiking activity in the hippocampus CA1 (Figure 7C). Intriguingly, while a subset of CA1 neurons fired most strongly around the timing of P-waves during both NREM and REM sleep, the temporal order between CA1 neural firing and P-waves was state-dependent (Figure 7C): during NREM sleep, co-firing of hippocampal neurons was followed by P-waves whereas P-waves were followed by burst firing in subset of CA1 neurons during REM sleep. To test the hypothesis that co-firing of CA1 neurons during NREM sleep may reflect sharp-wave ripples (SWRs), we detected high-frequency ripple events based on hippocampal LFPs to assess the temporal relationship between ripples and P-waves^{NREM} (Figure 7D). We found that ripple events preceded P-waves during NREM sleep across all of four recordings (Figure 7D inset) (p <
Thus, P-waves are strongly associated with hippocampal activity in both sleep states. However, their associations are state-dependent.
Figure 7. State-dependent interactions between P-waves and hippocampal activity.

(A) A diagram of the experimental approach showing a multi-shank silicon probe in the hippocampus CA1, a bipolar electrode in the pons and a cortical EEG electrode. (B) Phase modulations across frequency bands of hippocampal LFPs (top) and effect size of states (bottom). The effect of sleep states on resultant vector length was significant ($F_{1,79} = 4.00, p < 0.05$, two-way ANOVA). Error, SEM. (C) Pooled peri-event time histograms of CA1 single units relative to P-wave timing in NREM (top) and REM sleep (bottom). Time zero is the timing of P-waves (trough time). Each peri-event time histogram is color-coded by normalizing the maximum firing rate for each cell. The order of single units was sorted by the peak timing in each state. (D) Frequency of hippocampal SWRs relative to P-wave timing in NREM sleep. Time zero is the timing of P-waves (trough time). After binning at 1-ms resolution, the histogram was smoothed with a 50-ms Gaussian kernel. inset, asymmetry index provides the normalized difference in the number of SWRs before and after P-waves in a 100-ms window. Larger positive values mean that the more SWRs occurred before P-waves. *, $p < 0.05$ (t-
Discussion

Although state-dependent neural ensembles have been intensively characterized in the cortex including the hippocampus, little is known about the brainstem. Here, we investigated state-dependent neural population activity in the brainstem, primarily the pons, on two distinct timescales. On a timescale of seconds to minutes, brainstem neurons show diverse state-dependent firing, with cell-type-specificity in pontine cholinergic neurons. Brainstem activity can collectively predict pupil dilation as well as behavioral states. The ability to predict behavioral states is longer lasting compared to hippocampal neurons. These relatively slow dynamics may be related to observations from optogenetic experiments where the effect of optogenetic stimulation on state transitions often emerges tens of seconds after stimulus onset (Adamantidis et al., 2007, Van Dort et al., 2015, Zhang et al., 2019, Tsunematsu et al., 2013, Tsunematsu et al., 2014).

On a timescale of sub-seconds, we characterized P-waves in the mouse, with respect to underlying neural firing as well as associated neocortical and hippocampal activity. P-waves typically appear during REM sleep and less during NREM sleep. P-waves in both sleep states are accompanied by synchronous firing of brainstem neurons, suggesting that underlying local activity during P-waves is similar between sleep states. However, their relationship to cortical neural events is state-dependent: the timing of P-waves$^{\text{REM}}$ are phase-locked to various cortical oscillations and hippocampal SWRs precede P-waves$^{\text{NREM}}$, suggesting that P-waves$^{\text{NREM}}$ are part of the brain-wide neural events triggered by SWRs. During REM sleep, P-waves are phase-locked most strongly at theta frequency in both the neocortex and hippocampus. Crucially, P-waves precede firing in a subset of hippocampal CA1 neurons, suggesting that P-waves$^{\text{REM}}$ may trigger brain-wide neural events. Thus, P-waves are part of the state-dependent coordinated activity across the brain.

Technical considerations

State-dependent activity in the brainstem has been described over the past several decades by using various methods (Pace-Schott and Hobson, 2002, Datta and Maclean, 2007, Steriade and McCarley, 1990). The present study utilized a silicon probe to monitor activity from multiple neurons simultaneously with high temporal resolution. This approach allowed us (1) to quantify state dependency of brainstem neural ensemble dynamics on a timescale of seconds to minutes, (2) to decode vigilance states based on population activity, and (3) to characterize neural population activity underlying P-waves for the first time. However, because silicon probe recording alone has a limitation to identify cell types, additional approaches, such as $\text{Ca}^{2+}$ imaging (Figure 2) or electrophysiology with optogenetic tagging (Weber et al., 2015, Yague et al., 2017, Zhang et al., 2019), can complement this study to determine how specific types of neurons contribute to state-dependent neural ensembles in the brainstem.
Slow dynamics of brainstem ensemble dynamics

Our results in Figures 3 and 4 are consistent with the notion that brainstem populations play a regulatory role in pupil dilation/constriction (Aston-Jones and Cohen, 2005, Larsen and Waters, 2018) as well as global brain states (Brown et al., 2012, Herice et al., 2019, Luppi et al., 2012, Steriade et al., 1984, Weber and Dan, 2016). Crucially, the asymmetric profile of the predictability for pupil diameter suggests that the modulation of brainstem activity precedes pupil dilation, rather than simple correlations.

The long lasting predictability of brainstem populations for behavioral states is not trivial. Intriguingly, the slow (30-60 sec) timescale recalls us the timescale observed in some of optogenetic experiments: although optogenetic stimulation can modulate neural firing at a millisecond resolution, the effect of optical stimulation on state transitions typically emerges tens of seconds after stimulus onset (Adamantidis et al., 2007, Van Dort et al., 2015, Zhang et al., 2019). The exact mechanism is still unknown, but we hypothesize that the modulation of neural activity in the brainstem occurs tens of seconds before global brain state transitions from one state to another. In other words, each state emerges from complex interactions across various regions of the brain.

P-waves in mice

Although PGO or P-waves have been studies since the 1960s in several mammalian species (Callaway et al., 1987, Datta, 1997, Bizzi and Brooks, 1963), to the best of our knowledge, we are the first to characterize P-waves in mice. Given the growing importance of mice as an animal model for sleep research (Herice et al., 2019), the confirmation of P-waves in mice is important for further interrogation, with respect to the generation mechanism and function of P-waves.

We have noticed several similarities and differences in P-waves between mice and other species. First, the waveform of P-waves in mice is generally consistent with those in other species, such as cats (Callaway et al., 1987, Jeannerod et al., 1965) and rats (Datta, 1997, Farber et al., 1980), suggesting that underlying neural ensembles may be similar across species. Indeed, the phasic firing just before (<25 ms) the trough of P-waves (Figure 5) resembles the observations in the cat (McCarley et al., 1978, Steriade et al., 1990, Sakai and Jouvet, 1980, Nelson et al., 1983). In the near future, it would be interesting to extend our approach further to explore how activity propagates across brainstem neurons during P-waves by identifying cell-types. Second, the frequency of P-waves during REM sleep is generally consistent across species (Datta, 1997). However, we have also noticed that the frequency of detected P-waves varied across our experiments. This may be explained by either the variation in REM sleep quality or electrode
positions. Further analysis of P-waves across brainstem nuclei will provide insights into their relationship with sleep homeostasis and the mechanism of P-wave genesis in mice. Datta and his colleagues performed a series of pioneering studies and reported species differences in the site of P-wave genesis between cats and rats (Datta et al., 1998, Datta and Hobson, 1995, Datta et al., 1992): the caudolateral peribrachial area was identified as the induction site of P-waves (PGO waves) in cats (Datta and Hobson, 1995, Datta et al., 1992) whereas the subcoeruleus nucleus was identified in rats (Datta et al., 1998). It would be important to revisit this issue in mice by adopting modern technologies. Third, the temporal evolution of P-wave frequency generally agrees between mice and cats: the frequency of PGO-waves gradually increases before the transition of NREM to REM sleep in cats (Steriade et al., 1989). Although it was weak, a similar tendency was observed in our recordings (Figure 5D). Rather, the frequency of P-waves increases during REM sleep. This subtle difference may be explained by anatomical differences between species (Datta, 2012). These species differences may also imply differences in the function of P-waves between species. Finally, although P-waves appear more frequently during REM sleep, it is important to note that similar neural events also occur during NREM sleep. Given state-dependent interactions between P-waves and cortical oscillations (Figures 6 and 7), the mechanisms of P-wave genesis are likely distinct.

State-dependent global coordination of neural ensembles

The temporal correlation between P-waves and hippocampal theta rhythms during REM sleep is consistent with previous studies in cats and rats (Karashima et al., 2002, Karashima et al., 2004, Karashima et al., 2005, Sakai et al., 1973). The phase-locked activity with fast gamma (80-110 Hz) in the hippocampus may relate to the recent observation that demonstrated the close association between local hippocampal theta and fast gamma events and brain-wide hyperemic events (Bergel et al., 2018). Because a number of hippocampal CA1 neurons fire immediately after P-waves (Figure 7C), P-waves may play a role in the regulation of hippocampal ensemble dynamics as well as these brain-wide events during REM sleep.

On the other hand, the picture during NREM sleep seems to be distinct. Because SWRs precedes P-waves (Figure 7D) and SWRs are known to be generated within hippocampal circuits (Buzsaki, 2015), SWRs play a leading role in brain-wide sub-second neural events including P-waves. These state-dependent brain-wide neural ensembles imply distinct functional roles of sleep states.
Methods

Animals

A total of 21 mice were used in this study (Supplementary file 1) and were housed individually with a 12 h:12 h light/dark cycle (light on hours: 7:00-19:00). Mice had ad libitum access to food and water. All experiments were performed during the light period. Their genotypes consisted of wild-type, ChAT-IRES-Cre (JAX006410), or ChAT-IRES-Cre::Ai32 (JAX012569) on C57BL/6 background. ChAT-IRES-Cre::Ai32 mice were used to identify pontine cholinergic neurons post-hoc histological analysis. For brainstem silicon probe recordings, 6 animals were used (9 recordings). For hippocampal silicon probe recordings, 2 animals were used (4 recordings). For P-wave recordings, 10 animals were used, but 4 were excluded due to electrode mispositioning or lack of histological data. 16 datasets were used for further analysis. For pupil monitoring, 14 datasets were used for further analysis. For fiber photometry, 4 animals were used (12 recordings).

The detailed information of genotypes, age, sex, body weight and the number of recordings was provided in Supplementary file 1.

Surgical procedures

For all in vivo electrophysiological experiments, mice were anesthetized with isoflurane (5% for induction, 1-2% for maintenance) and placed in a stereotaxic apparatus (SR-5M-HT, Narishige). Body temperature was maintained at 37°C with a feedback temperature controller (40–90–8°C, FHC). Lidocaine (2%, 0.1-0.3 mg) was administered subcutaneously at the site of incision. Two bone screws were implanted on the skull as electrodes for cortical EEGs and twisted wires were inserted into the neck muscle as electrodes for EMG. Another bone screw was implanted on the cerebellum as a ground/reference.

For pontine EEG recording, bipolar electrodes were bilaterally implanted in the medial parabrachial nucleus of the pons (5.1 mm posterior, 1.2 mm lateral from bregma, 3.2 mm depth from brain surface). The bipolar electrodes consisted of 75 or 100 µm diameter stainless wires (FE631309, Advent Research Materials and FE205850, Goodfellow, respectively). The tip of two glued wires were separated by 0.5-1.0 mm vertically to differentiate EEG signals. All electrodes were connected to connectors (SS-132-T-2-N, Semtec) and securely attached on the skull with dental cement. A pair of nuts was also attached on the skull with dental cement as a head-post. After the surgery, Carprofen (Rimadyl, 5 mg/kg) was administered intraperitoneously.

For brainstem or hippocampal silicon probe recording, in addition to bone screws for cortical EEGs and a ground/reference, a pair of nuts was attached on the skull with dental cement as a head-post. After the head-post surgery, the animals were left to recover for at least 5 days. During the
habituation period, the animals were placed in a head-fixed apparatus, by securing them by the head-post and placing the animal into an acrylic tube. This procedure was continued for at least 5 days, during which the duration of head-fixed was gradually extended from 10 to 120 min. A day after the habituation period, the animals were anesthetized with isoflurane and a craniotomy to insert silicon probe the brainstem and hippocampus was performed. A craniotomy on the left hemisphere (4.0 mm to 5.5 mm posterior, 1.0 to 1.3 mm lateral from bregma) for the brainstem recording and on the left hemisphere (2.0 mm posterior, 1.5 mm lateral from bregma) for the hippocampus recording were performed, respectively. To protect and prevent the brain from drying, the surface was covered with biocompatible sealants (Kwik-Sil and Kwik-Cast, WPI). The following day, the animals were placed in the head-fixed apparatus for electrophysiological recording as described below.

For fiber photometry experiments, cortical EEG and EMG electrodes were implanted as described above and connected to a 2-by-3 piece connector (SLD-112-T-12, Semtec). Two additional anchor screws were implanted bilaterally over the parietal bone to provide stability and a small portion of a drinking straw was placed horizontally between the anchor screws and the connector. The viral vector (AAV5-CAG-flex-GCaMP6s-WPRE-SV40, Penn Vector Core; titer 8.3x10^{12} GC/ml) was microinjected (500 nl at 30 ml/min) (Nanoliter2010, WPI) to target the PPT/LDT area (-4.5 mm posterior, 1 mm lateral from bregma and 3.25 mm depth from brain surface). The micropipette was left in the brain for an additional 10 minutes and then slowly raised up. An optic fiber cannula (CFM14L05, Thorlabs) was then implanted 3 mm deep from the surface of the brain and all components were secured to each other and the skull with dental cement.

**in vivo electrophysiological experiments in a head-fixed condition**

Experimental procedures were as described previously (Lyngholm and Sakata, 2019, Yague et al., 2017). Briefly, all electrophysiological recordings were performed in a single-walled acoustic chamber (MAC-3, IAC Acoustics) with the interior covered with 3 inches of acoustic absorption foam. The animals were placed in the same head-fixed apparatus, by securing them by the head-post and placing the animal into an acrylic tube. During the entire recording, the animals were not required to do anything actively. For pontine EEG recording, cortical EEG, EMG and pontine EEG signals were amplified (HST/32V-G20 and PBX3, Plexon), filtered (0.1 Hz low cut), digitized at a sampling rate of 1 kHz and recorded using LabVIEW software (National Instruments). Recording was performed for 5 hrs from 9:00 to 14:00. For brainstem or hippocampal silicon probe recording, a 32 channels 4 shank silicon probe (A4 x 8-5 mm-100-400-177 for brainstem recording or Buzsaki32 for hippocampus recording) was inserted slowly with a manual micromanipulator (SM-25A, Narishige) into the brainstem (3.75 mm – 4.3 mm from the brain surface) or the hippocampus (1.55 mm – 1.85 mm from brain surface). Probes were inserted perpendicularly with respect to the
brain surface. Broadband signals were amplified (HST/32V-G20 and PBX3, Plexon) relative to screw on the cerebellum, filtered (0.1 Hz low cut), digitized at 20 kHz and recorded using LabVIEW software (National Instruments). The recording session was initiated > 1 hr after the probe was inserted to its target depth, to stabilize neural signals. Recording preparation started from 8:00 and terminated by 15:00. For verification of silicon probe tracks, the rear of the probes were painted with Dil (~10% in ethanol, D282, Invitrogen) before insertion.

Pupil monitoring

In a subset of in vivo electrophysiological experiments under a head-fixed condition, pupil was also monitored with an off-axis infrared (IR) light source (860 nm IR LED, RS Components). A camera (acA1920-25μm, Basler Ace) with a zoom lens (M0814-MP2, computar) and an IR filter (FGL780, Thorlabs) was placed at ~10 cm from the animal's left eye. Images were collected at 25 Hz using a custom-written LabVIEW program and a National Instruments image grabber (PCIe-8242).

in vivo fiber photometry experiments in a freely behaving condition

The fiber photometry system consisted of two excitation channels. A 470 nm LED (M470L3, Thorlabs) was used to extract a Ca\textsuperscript{2+}- dependent signal and a 405 nm LED (M405L3, Thorlabs) was used to obtain a Ca\textsuperscript{2+}- independent isosbestic signal. Light from the LEDs was directed through excitation filters (FB470-10, FB405-10, Thorlabs) and a dichroic mirror to the fiber launch (DMLP425R and KT110/M, respectively). The fiber launch was connected to a multimode patch cable (M82L01, Thorlabs) which attached to an implantable optic fiber on the mouse via a ceramic mating sleeve (CFM14L05 and ADAF1, respectively). Light emissions from GCaMP6s expressing neurons were then collected back through the optic fiber, and directed through a detection path, passing a dichroic mirror (MD498) to reach a photodetector (NewFocus 2151, Newport). A National Instruments DAQ (NI USB-6211) and custom-written LabVIEW software was used to control the LEDs and acquire fluorescence data at 1 kHz. LEDs were alternately turned on and off at 40Hz in a square pulse pattern. Electrophysiology signals were recorded at 1 KHz using an interface board (RHD2000, Intan Technologies) and connected to the mouse via an amplifier (RHD2132, Intan Technologies). Mice were habituated to being handled and tethered to the freely behaving system over several consecutive days. Mice were scruffed and the straw on the headcap slotted into a custom-made clamp, to keep the head still and absorb any vertical forces when connecting the electrophysiology and fiber photometry tethers to the headcap. Once connected, mice were placed in an open top Perspex box (21.5 cm x 47 cm x 20 cm depth) lined with absorbent paper, bedding and some baby food. Recordings lasted 4-5 hours to allow for multiple sleep/wake transitions.
Histological analysis

After electrophysiological experiments, animals were deeply anesthetized with mixture of pentobarbital and lidocaine and perfused transcardially with 20 mL saline followed by 20 mL 4% paraformaldehyde/0.1 M phosphate buffer, pH 7.4. The brains were removed and immersed in the above fixative solution overnight at 4°C and then immersed in a 30% sucrose in phosphate buffer saline (PBS) for at least 2 days. The brains were quickly frozen and were cut into coronal or sagittal sections with a sliding microtome (SM2010R, Leica) or with a cryostat (CM3050, Leica) with a thickness of 50 or 100 µm. The brain sections were incubated with a NeuroTrace 500/525 Green-Fluorescence (1/350, Invitrogen) or NeuroTrace 435/455 Blue-Fluorescence (1/100, Invitrogen) in PBS for 20 min at room temperature (RT) followed by incubating with a blocking solution (10% normal goat serum, NGS, in 0.3% Triton X in PBS, PBST) for 1 hr at RT. For ChAT-IRES-Cre::Ai32 mice, to confirm the position of ChAT-expressing neurons, we performed GFP and ChAT double staining. These brain sections were incubated with mouse anti-GFP antiserum (1/2000, ABCAM) and goat anti-ChAT antiserum (1/1000, Millipore) in 3% NGS in PBST for overnight at 4°C. After washing, sections were incubated with DyLight 488-labeled donkey anti-mouse IgG (1/500, Invitrogen) and Alexa 568-labeled donkey anti-goat IgG (1/500, Invitrogen) for 2 hrs at RT. After staining, sections were mounted on gelatin-coated or MAS-coated slides and cover-slipped with 50% glycerol in PBS. The sections were examined with a fluorescence microscope (BZ-9000, Keyence).

Data analysis

Sleep scoring

Vigilance states were visually scored offline according to standard criteria (Radulovacki et al., 1984, Tobler et al., 1997). Wakefulness, NREM sleep, or REM sleep was determined in every 4 second based on cortical EEG and EMG signals using custom-made MATLAB GUI. For electrophysiological or fiber photometry experiments, the same individual scored all recordings for consistency.

Pupil analysis

Video files were processed by using DeepLabCut (Mathis et al., 2018). Each video file consisted of a 5 min segment of the recording, meaning that each experiment yields tens of video files. For training, a single file containing all states (AW, NREM sleep and REM sleep) was chosen based on the sleep score. This initial step was critical to reflect the dynamic range of pupil dilation/constriction in each experiment. After choosing the file, 20 frames were randomly selected to manually mark the left and right edges of pupil. ImageJ was used for this manual marking. Using these labeled frames, the deep convolutional neural network was then trained, and all video files were processed to detect the left and right edges of pupil. After processing, visual inspection was
performed by generating a down-sampled (50-100 times) video clip. The same procedure was applied across all recordings. To compute pupil diameter, the distance between the left and right edges of the pupil was calculated across frames. The profile was filtered (low-pass filter at 0.5 Hz) and z-scored. To compute eye movement, the middle point of pupil was determined and the distance of the middle points between two continuous frames was calculated. The profile was then normalized by the maximal value of the profile. From 20 pupil recordings (14 animals), 2 recordings from a single animal were excluded due to eye closure during most of recording period (Supplementary file 1).

Fiber photometry signal processing

Custom-written MATLAB scripts were used to compute dF/F signals. To extract 405 and 470 nm signals, illumination periods were determined by detecting synchronization pulses. For each illumination epoch, the median fluorescent signal was calculated. Because each illumination epoch consisted of pulses at 40 Hz, the fluorescent signals originally sampled at 1 kHz were effectively down-sampled to 40 Hz. Photobleaching was estimated by a single exponential curve and the difference between the fluorescent signal trace and the estimate was further low-pass filtered at 4 Hz. To estimate moving artifacts, the filtered 405 nm signals were linearly scaled based on the filtered 470 nm signals using a linear regression. To estimate dF/F signals, then the 470 nm signals were subtracted from the scaled 405 nm signals. In this study, the first 10 min segment was excluded for further analysis due to poor estimation of the photobleaching profile.

Spike train and LFP/EEG analysis

For spike sorting, Kilosort (Pachitariu et al., 2016) was used for automatic processing, followed by manual curation using phy (https://github.com/cortex-lab/phy). Clusters with ≥ 20 isolation distance were recognized as single units. The position of single units was estimated based on the channel providing the largest spike amplitude. All subsequent analysis was performed using custom-written codes (MATLAB, Mathworks).

To categorize functional classes of single units, average firing rate for each behavioral state was calculated and a hierarchical clustering approach with the Ward’s method was applied.

To predict the pupil diameter from single unit activity, spike trains were filtered (band-pass filter between 0.5 and 25 Hz) and then a liner regression analysis was performed. To evaluate the goodness-of-fit of the linear model, R-squared value was calculated. The same process was repeated by shifting the time relationship between spike trains and pupil diameter to determine an optimal time window to predict pupil diameter from spike train. Then the sequence of R-squared values were normalized by computing Z-scores.

To predict the pupil diameter from simultaneously monitored multiple single unit activities, spike trains were filtered (band-pass filter between 0.5 and 25 Hz) and a linear regression model was trained by using a regularized support-vector machine algorithm with 10-fold cross-validation.
Then cross-validated mean squared error (MSE) was computed. The same process was repeated by shifting the time relationship between spike trains and pupil diameter. The sequence of MSEs were normalized.

To find interpretable patterns in the population activity, we adopted non-negative matrix factorization (NMF) (Lee and Seung, 1999, Onken et al., 2016). NMF takes a non-negative data matrix and factorizes this matrix into two non-negative matrices. One of these matrices, the module matrix, contains patterns while the other matrix, the activation coefficient matrix, indicates how these patterns need to be weighted in order to reconstruct the original data matrix. Due to the non-negativity constraints, NMF yields a parts-based representation: one pattern cannot be canceled by another pattern. For a data matrix representing images of faces, the method yields face patterns such as eyes, eyebrows and noses in the module matrix and non-negative weights of these patterns in the activation coefficient matrix (Lee and Seung, 1999). For neural population activity, NMF can decompose spike counts into "space" (neurons) modules and activation coefficients of these modules (Onken et al., 2016). For this purpose, spike trains were discretized by binning them into 4 sec intervals, which were equivalent to the time window for sleep scoring (see above). Let \( r(t) \) denote the resulting vector of population spike counts in bin \( t \). We represented all population spike count vectors in a matrix \( R = [r(1) \ r(2) ... \ r(T)] \) of size \( N \) by \( T \), where \( N \) denotes the number of neurons and \( T \) denotes the number of time bins. We then decomposed the matrix \( R \) into two non-negative matrices \( W \) of size \( N \) by \( m \) and \( H \) of size \( m \) by \( T \) as follows: \( R = WH \), where \( m \) is the number of modules. To this end, we applied multiplicative update rules (Lee and Seung, 2001):  

\[
H_{ij} \leftarrow H_{ij} \frac{\sum_k W_{ik} R_{kj} / (WH)_{kj}}{\sum_i W_{ij}} \\
W_{ij} \leftarrow W_{ij} \frac{\sum_k H_{jk} R_{ik} / (WH)_{ik}}{\sum_i H_{ij}} 
\]

These update rules minimize the Kullback-Leibler divergence, corresponding to a Poisson noise assumption for the spike counts (Févotte and Cemgil, 2009). In each run, we randomly initialized \( W \) and \( H \) and applied the update rules up to 100 times or until convergence. For each decomposition, we performed 10 runs and selected the run with the lowest Kullback-Leibler divergence. The \( m \) columns of \( W \) then represented the \( m \) space modules and the \( m \) corresponding rows of \( H \) represented their activation coefficients for each time bin.

To select the number of space modules \( m \), we evaluated how many modules were needed so that additional modules did not significantly improve the decomposition. Our procedure was similar to that used in De Marchis et al. (De Marchis et al., 2013). We generated surrogate data by shuffling all elements of the matrix \( R \) and then decomposed the shuffled matrix like we previously decomposed the original \( R \). We quantified the quality of a decomposition using the variance accounted for (VAF) (Clark et al., 2010). Starting with one module, we incremented the number of modules until the VAF of the unshuffle data decomposition did not exceed 3/4 of the average VAF of the decompositions of 100 shuffles.
To classify three behavioral states based on the activation coefficients, a linear classifier was trained by fitting a multivariate normal density to each state with 10-fold cross validation. Then classification performance was calculated. This procedure was repeated by shifting the time relationship between the activation coefficients and sleep scores.

To detect P-waves, two EEG or LFP signals in the brainstem were subtracted and filtered (5-30 Hz band-pass filter). If the signals cross a threshold, the event was recognized as P-waves. To determine the detection threshold, a 1-min segment of the subtracted signals was extracted from the longest NREM sleep episode for a reliable estimation of stable noise level. The noise level was estimated by computing root-mean-square (RMS) values in every 10 ms time window. The threshold was defined as mean + 5 x standard deviation of the RMS values. The timing of P-waves was defined as the timing of the negative peak.

The phase analysis was essentially the same as that described previously (Yague et al., 2017). Cortical EEG or hippocampal LFP signals were used for this analysis. For hippocampal LFPs, signals from two separate channels were subtracted to minimize volume conduction. To derive band-limited signals in different frequency bands, a Kaiser finite impulse response filter was used with sharp transition bandwidth of 1 Hz, pass-band ripple of 0.01 dB and stop-band attenuation of 50 dB. For filtering, MATLAB 'filtfilt' function was used. In the present study, the following bands were assessed: [2-4], [4-7], [7-10], [10-15], [15-20], [20-30], [30-50], [50-80], [80-110], and [110-150] Hz. The instantaneous phase of each band was estimated from the Hilbert transform and the phase of P-wave occurrence was computed. To quantify the relationship between P-waves and EEG/LFP phase, the percentage of P-waves elicited in each phase bin was calculated. The resultant vector length was computed as an absolute value of mean resultant vector $r$ by using $\text{circ}_r$ function of CircStats Toolbox (Berens, 2009). Rayleigh’s test for non-uniformity of circular data was performed to assess the statistical significance ($p < 0.01$) of the non-uniformity of the P-wave vs EEG/LFP phase distribution.

To detect ripples in the hippocampus, LFP signals from the channel which detected spiking activity were used. Band-limited signals at 140-250 Hz were computed by using a Kaiser finite impulse response filter (see above). Two sequences of RMS values were calculated with two different time window: 2 sec (long RMS) and 8 ms (short RMS). If the short RMS exceeds 4 times larger long RMS for 8 ms, then signals were recognized as a ripple event. To quantify the asymmetry of the cross-correlogram between SWRs and P-waves (Figure 7D), the asymmetry index was defined as: $(N_{\text{pre}} - N_{\text{post}})/(N_{\text{pre}} + N_{\text{post}})$, where $N_{\text{pre}}$ and $N_{\text{post}}$ are the number of SWRs 100 ms before and after P-waves, respectively.
Statistical analysis

Data was presented as mean ± SEM unless otherwise stated. Statistical analyses were performed with MATLAB. In Figures 2G and 3A, one-way ANOVA with post-hoc Tukey's Honest Significant Difference (HSD) criterion was performed. In Figure 4C, repeated measures ANOVA was performed. In Figure 5C, two-tailed t-test was performed. In Figure 6C, Rayleigh test for non-uniformity was performed. In Figures 6B and 7B, two-way ANOVA with post-hoc HSD criterion was performed. In Figure 7D, two-tailed t-test was performed. To estimate effect size, Hedges' $g$ was computed using Measures of Effect Size Toolbox (Hentschke and Stuttgen, 2011).

Data availability

All sorted spike trains, sleep scores, fluorescent signals, P-wave timing and pupil information are available online (https://doi.org/10.15129/4f81777a-7b88-48f3-af4d-da484706fa5d).

Code availability

The code is available on GitHub (https://github.com/Sakata-Lab).

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Additional Information

Competing interests

The authors declare no competing interests.

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Figure Legends

Figure 2. Population activity in the brainstem across the sleep-wake cycle.

(A) A diagram of the experimental approach, showing the insertion of a silicon probe for extracellular recording in the brainstem and a screw for cortical EEG recording. Pupil dilation and EMGs were also monitored in a head-fixed condition. (B) An example of multiple electrophysiological readings across three behavioral states, including local field potentials (LFPs) in the brainstem (locally subtracted LFP signals), brainstem single unit activities (SUAs), cortical EEG, EMG and normalized pupil diameter. REM, rapid eye movement sleep; NREM, non-REM sleep; AW, wakefulness. (C) and (E) Power spectrum density of cortical EEGs (C) and brainstem LFPs (E) across three behavioral states. Spectra were computed during every 4-sec window. Errors indicate SEM. (D) and (F) Distribution of EMG signals (root mean square) (D) and normalized pupil diameter (F) across three behavioral states. Pupil diameter was normalized as z-score.

The following figure supplements are available for figure 1.

Figure supplement 1. Histological analysis.

Figure supplement 2. Power spectrum density of cortical EEGs and brainstem LFPs across all recording sessions.

Figure supplement 3. Comparisons of sleep architecture, cortical EEGs and EMGs between head-fixed and unfixed conditions.

Figure 2. Diverse and cell-type-specific state-dependent firing in brainstem neurons.

(A) A diagram of the experimental approach, showing a silicon probe and a cortical EEG electrode. (B) Four examples of simultaneously recorded neurons. (C) Classification of functional classes. Firing rates across the three behavioral states were normalized as z-score for individual cells and hierarchical clustering was then applied. (D) A diagram of the experimental approach for fiber photometry-based Ca^{2+} imaging from pontine cholinergic neural populations in a freely behaving condition. (E) An example of fluorescent signals across sleep-wake cycles. Fluorescent signals (470 nm) were normalized by off-peak (405 nm) signals. red, wakefulness, blue, NREM sleep, green, REM sleep. (F) Distributions of fluorescent signals across the three behavioral states. (G) Group statistics of average fluorescent signals from 12 recordings from 4 mice ($F_{2,32} = 5.12$, $p = 0.012$, one-way ANOVA). *, $p < 0.05$ with post-hoc Tukey's honest significant difference criterion. The following figure supplement is available for figure 2.

Figure supplement 1. Neurons recorded from pontine cholinergic nuclei and their state dependency.

Figure 3. Pupil dilation across the sleep-wake cycle and prediction of pupil dilation with brainstem populations.
(A) Mean normalized (z-scored) pupil diameter across the sleep-wake cycle (n = 18, $F_{2,53} = 220.33$, $p < 0.0001$, one-way ANOVA). ***, $p < 0.0001$, with post-hoc Tukey’s honest significant difference criterion. (B) Pupil dilation during sleep-wake state transitions (n = 18). (C) Linear regression analysis to predict pupil diameter with individual neuronal activity. (top) Normalized (z-scored) cross-validated R$^2$ values are color-coded across neurons. (bottom) The average of normalized cross-validated R$^2$ values. Error, SEM. (D) Multiple linear regression analysis to predict pupil diameter with simultaneously recorded neuronal activity. The average of normalized (z-scored) root mean square errors across datasets (n = 6). Error, SEM.

The following figure supplement is available for figure 3.

**Figure supplement 1.** Pupil dilation and eye movement across vigilance states.

**Figure 4. State-dependent brainstem population dynamics and their ability to predict vigilance states.**

(A) Simultaneously recorded brainstem neurons across states and modules extracted with non-negative matrix factorization (NMF). (top) Firing profiles of brainstem neurons. Firing rate was normalized by the maximum firing rate and the normalized values were color-coded. Dotted lines indicate state transitions. (bottom) Average population activity (gray) and activation coefficients for each module derived by NMF. Background colors indicate behavioral states (red, AW; blue, NREM; green, REM). (B) Weights across neurons for each module. (C) Decoding of behavioral states from population activity. top, Decoding performance of brainstem and hippocampal CA1 neural populations for behavioral states as a function of time-shift. Error, SEM. bottom, Effect size as a function of time-shift.

The following figure supplement is available for figure 4.

**Figure supplement 1.** Weights of each module derived from NMF and individual firing profiles.

**Figure supplement 2.** Histological analysis of dorsal hippocampal CA1 recording.

**Figure 5. Pontine waves (P-waves) in the mouse.**

(A) A diagram of the experimental approach, with showing a bipolar electrode in the pons and a cortical EEG electrode. (B) Examples of P-waves during NREM (left) and REM sleep (right), with showing cortical EEG and EMG traces. (C) Frequency of P-waves during NREM and REM sleep (n = 16). ***, $p < 0.0001$, two-tailed t-test. (D) Temporal evolution of P-wave frequency. Duration of each state episode was normalized to one. Error, SEM. (E) A diagram of the experimental approach, showing a multi-shank silicon probe in the brainstem and cortical EEG electrode. (F) An example of a P-wave, showing subtracted LFPs from a probe shank, and multiple single unit activity. (G) and (H) Pooled peri-event time histograms of brainstem single units relative to P-wave timing during NREM (G) and REM sleep (H). Time zero is the timing of P-waves (trough time).
Each peri-event time histogram is color-coded by normalizing the maximum firing rate for each cell. The order of single units was sorted by the peak timing in each state.

**Figure 6. State-dependent interactions between P-waves and cortical oscillations.**

(A) A diagram of an experimental approach showing a bipolar electrode in the pons and cortical EEG electrode. (B) Examples of averaged event-triggered cortical EEGs and scalograms during NREM (left) and REM sleep (right). Time zero is the timing of P-waves (trough time). (C) Examples of phase-histograms. Cortical EEGs were filtered at certain frequency bands and the proportion of P-waves elicited in each phase bin was calculated. *, p < 0.01, Rayleigh test. (D) Phase modulations across frequency bands of cortical EEGs. Resultant vector length represents the mean measurement of circular spread of the phase relationship between cortical oscillations and P-waves. The effect of sleep states on resultant vector length was significant (F_{1,179} = 4.90, p < 0.05, two-way ANOVA). *, p < 0.05 (post-hoc Tukey’s honest significant difference test). Error, SEM. (E) Effect size of states across frequency bands.

**Figure 7. State-dependent interactions between P-waves and hippocampal activity.**

(A) A diagram of the experimental approach showing a multi-shank silicon probe in the hippocampus CA1, a bipolar electrode in the pons and a cortical EEG electrode. (B) Phase modulations across frequency bands of hippocampal LFPs (top) and effect size of states (bottom). The effect of sleep states on resultant vector length was significant (F_{1,79} = 4.00, p < 0.05, two-way ANOVA). Error, SEM. (C) Pooled peri-event time histograms of CA1 single units relative to P-wave timing in NREM (top) and REM sleep (bottom). Time zero is the timing of P-waves (trough time). Each peri-event time histogram is color-coded by normalizing the maximum firing rate for each cell. The order of single units was sorted by the peak timing in each state. (D) Frequency of hippocampal SWRs relative to P-wave timing in NREM sleep. Time zero is the timing of P-waves (trough time). After binning at 1-ms resolution, the histogram was smoothed with a 50-ms Gaussian kernel. Inset, asymmetry index provides the normalized difference in the number of SWRs before and after P-waves in a 100-ms window. Larger positive values mean that the more SWRs occurred before P-waves. *, p < 0.05 (t-test, n = 4).
Supplementary Figure Legends

Figure 1 – figure supplement 1. Histological analysis.

(A) A sagittal section with showing the track of a silicon probe.

(B) The number of neurons recorded from brainstem nuclei in this study. MV, medial vestibular nucleus; SUV, superior vestibular nucleus; CUN, cuneiform nucleus; MRN, midbrain reticular nucleus; PAG, periaqueductal gray; PPN, pedunculopontine nucleus; RR, retrorubral area; LC, locus ceruleus; LDT, laterodorsal tegmental nucleus; PB, parabrachial nucleus; PCG, pontine central gray; PRNc, pontine reticular nucleus, caudal part; PRNr, pontine reticular nucleus, rostral part; SLD, sublaterodorsal nucleus; arb, arbor vitae; scp, superior cerebellar peduncles; VII, facial nerve; CENT2gr, lobule II, granular layer; CENT2mo, lobule II, molecular layer.

Figure 1 – figure supplement 2. Power spectrum density of cortical EEGs (A) and brainstem LFPs (B) across all recording sessions.

Spectrum was computed in every 4-sec window in each state.

Figure 1 – figure supplement 3. Comparisons of sleep architecture, cortical EEGs and EMGs between head-fixed (n = 24) and unfixed conditions (n = 12).

(A) The total duration of recording was significantly different (t-test).

(B) The fraction of NREM sleep and awake (AW) states were significantly different.

(C) The average duration of NREM sleep and AW states were significantly different.

(D) There was no significant difference in state transition probabilities.

(E) EEG spectral power was not significantly different between conditions across states.

(F) The root-mean-square (rms) of EMGs during AW state was significantly different.

Figure 2 – figure supplement 1. Neurons recorded from pontine cholinergic nuclei and their state dependency.

(A) A Nissl-stained sagittal section with Dil-labelled probe tracks (see also Figure 1 – figure supplement1A). right, an enlarged image with overlaying an estimated probe track and channel positions. Average waveforms of a LDT neuron (based on randomly picked 1000 spikes) were also overlaid. LDT, laterodorsal tegmental nucleus.
(B) State-dependent firing of the LDT neuron shown in (A). The histograms were smoothed with a 1-second Gaussian kernel.

(C) A summary of all neurons recorded from PPT and LDT. Firing rates across three behavioral states were normalized as z-score. All neurons were classified as either REM-on, AW-on or REM/AW-on neurons. The LDT neuron in (A) and (B) is the top one in this plot.

**Figure 3 – figure supplement 1.** Pupil dilation and eye movement across vigilance states.

(A) Normalized (z-scored) pupil diameter across state transitions. The duration of each state episode was normalized. Pupil diameter gradually decreased before REM sleep and stayed fully constricted during REM sleep.

(B) The average of eye movement across states. The effect of states on eye movement was significant ($F_{2,53} = 8.93, p < 0.001$, one-way ANOVA with post-hoc Tukey’s honest significant difference criterion). **, $p < 0.01$; ***, $p < 0.001$.

**Figure 4 – figure supplement 1.** Weights of each module derived from non-negative matrix factorization (A) and individual firing profiles (B).

Neurons with similar state-dependent firing patterns tend to have similar weights in each module. For example, cell#4 and #5 fire more during REM sleep and had higher weights in the module 1.

**Figure 4 – figure supplement 2.** Histological analysis of dorsal hippocampal recording.

The track of a silicon probe was confirmed in the CA1 region of the dorsal hippocampus.

**Supplementary File Legends**

**Supplementary file 1.** Summary of experimental animals and recordings in this study.

BS-Si, silicon probe recording in the brainstem. HP-Si, silicon probe recording in the hippocampus. BS-EEG, EEG recording in the brainstem. FP, fiber photometry. Exc$^1$, the animal was excluded due to electrode mispositioning. Exc$^2$, the animal was excluded due to lack of histological data. Exc$^3$, the animal was excluded due to eye closure during recording.