Dynamic Configuration of Coactive Micropatterns in the Default Mode Network during Wakefulness and Sleep

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Keywords: default mode network; coactive micropattern; wakefulness and sleep; up-down states; dynamic configuration

Abstract

The default mode network (DMN) is a prominent intrinsic network that is observable in many mammalian brains. However, few studies have investigated the temporal dynamics of this network based on direct physiological recordings. Herein, we addressed this issue by characterizing the dynamics of local field potentials (LFPs) from the rat DMN during wakefulness and sleep with an exploratory analysis. We constructed a novel coactive micropattern (CAMP) algorithm to evaluate the configurations of rat DMN dynamics and further revealed the relationship between DMN dynamics with different wakefulness and alertness levels. From the gamma activity (40-80 Hz) in the DMN across wakefulness and sleep, three spatially stable CAMPs were detected: a common low-activity level micropattern (cDMN), an anterior high-activity level micropattern (aDMN) and a posterior high-activity level micropattern (pDMN). A dynamic balance across CAMPs emerged during wakefulness and was disrupted in sleep stages. In the slow-wave sleep (SWS) stage, cDMN became the primary activity pattern, whereas aDMN and pDMN were the major activity patterns in the rapid eye movement sleep (REM) stage. Additionally, further investigation revealed phasic relationships between CAMPs and the up-down states of the slow DMN activity in the SWS stage. Our study revealed that the dynamic configurations of CAMPs were highly associated with different stages of wakefulness and provided a potential three-state model to describe the DMN dynamics for wakefulness and alertness.

Impact Statement

In the current study, a novel coactive micropattern method (CAMP) was developed to elucidate fast DMN dynamics during wakefulness and sleep. Our findings demonstrated that the dynamic configurations of DMN activity are specific to different wakefulness stages and provided a three-state DMN CAMP model to depict wakefulness levels, thus revealing a potentially new neurophysiological representation of alertness levels. This work could elucidate the DMN dynamics underlying different stages of wakefulness and have important implications for the theoretical understanding of the neural mechanism of wakefulness and alertness.

1 **Introduction**

2 Multimodal imaging studies of the human brain have discovered several intrinsic
3 connectivity networks (ICNs) coexist during the resting state (Beckmann, DeLuca,
4 Devlin, & Smith, 2005; Q. Liu, Farahibozorg, Porcaro, Wenderoth, & Mantini, 2017).
5 Dynamic switching within these ICNs have demonstrated a hierarchical structure over
6 time for brain activity at rest and have been significantly associated with cognitive
7 traits (M. D. Fox et al., 2016; Vidaurre, Smith, & Woolrich, 2017). This suggests that
8 brain activity is appropriately understood in terms of the dynamic configuration
9 among ICNs. These studies have mainly considered each ICN as a whole during brain
10 dynamics while ignoring the intrinsic dynamics of individual ICNs. Indeed, individual
11 ICN also exhibits strong fluctuations in brain activity, and different ICNs are believed
12 to dominate distinct cognitive functions (Rosazza & Minati, 2011). For a specific
13 brain function, further tracking the dynamic configuration of fluctuations in brain
14 activity at the single-ICN level might be critical for revealing the underlying
15 physiological mechanism.

16 The default mode network (DMN) is one of the important ICNs, and is typically
17 believed to be related to off-task internal mentations with high activity in the resting
18 state (Gusnard, Akbudak, Shulman, & Raichle, 2001; M E Raichle et al., 2001).
19 Recent studies have reported that the DMN is also engaged and displays positive
20 contributions during several higher cognition task performances, such as the Tower of
21 London task (D. Vatansever, Menon, Manktelow, Sahakian, & Stamatakis, 2015;
22 Deniz Vatansever, Manktelow, Sahakian, Menon, & Stamatakis, 2018). Changes in

23 wakefulness could also lead to alterations of DMN activity and connectivity in
 24 humans and rodents (K. C. R. Fox, Foster, Kucyi, Daitch, & Parvizi, 2018; Lu et al.,
 25 2012; Marcus E Raichle, 2015). DMN connectivity between the frontal and posterior
 26 areas in the human brain was reduced during the slow wave sleep (SWS) stage with a
 27 low level of wakefulness (Sämann et al., 2011). However, at sleep onset and
 28 throughout the rapid eye movement sleep (REM) stage, regions in the human DMN
 29 were shown to be persistently coupled (Horovitz et al., 2008; Larson-Prior et al.,
 30 2009). These findings illustrated that DMN activity was functionally reorganized
 31 during sleep and might further reflect levels of wakefulness and alertness.
 32 Additionally, fast and ever-changing dynamics of DMN activity have also been
 33 observed in various wakefulness levels in humans, implying that the temporal aspects
 34 of spontaneous DMN activity might be associated with alertness levels (Kapogiannis,
 35 Reiter, Willette, & Mattson, 2014; Panda et al., 2016). Thus, research investigating the
 36 dynamic configuration of DMN in different stages of wakefulness using direct
 37 physiological recordings is important.

38 The DMN could also be observable in rat brains, indicating its conservation in the
 39 mammalian brain during evolution (Huang et al., 2016; Lu et al., 2012). Though there
 40 exists several difference between the brain regions in rat DMN and human DMN, the
 41 anatomical topologies of them are visually similar (Hsu et al., 2016; Marcus E
 42 Raichle, 2015). In addition, neural activity of DMN regions also activated in awake
 43 rats, and suppressing the activity in the core DMN regions could modulate rats'
 44 normal behavior (Tu, Ma, Ma, Dopfel, & Zhang, 2020; Upadhyay et al., 2011).

45 Furthermore, the information flow within anterior and posterior DMN subsystems
46 exhibited various alterations in different sleep stages and mental disorders in rats (Cui
47 et al., 2018; Jing et al., 2017). The above findings imply that the DMN might carry a
48 core function that transcends across species. Therefore, employing animal models to
49 direct record physiological DMN signals is an effective way to investigate the
50 temporal dynamics of DMN activity.

51 Several neurophysiological studies have reported that during the deep sleep stage,
52 the neurons in various brain regions exhibited highly synchronized firing rates,
53 occurring at approximately 0.5-2 Hz (Crunelli & Hughes, 2010; Gretenkord et al.,
54 2020; Lőrincz et al., 2015). This specific activity pattern was identified as the
55 up-down state, and has been considered a biomarker of low-level wakefulness in deep
56 sleep (Jercog et al., 2017; Perez-Zabalza et al., 2020). Moreover, this up-down state
57 has been demonstrated for both neuron membrane potentials and local field potentials
58 (LFPs) (Holcman & Tsodyks, 2006) and characterizes the dynamics of slow
59 oscillations during deep sleep (Ji & Wilson, 2007; Lőrincz et al., 2015). However, the
60 existence of a physiological relationship between the up-down state and DMN
61 dynamics is a topic of active interest, that deserves further exploration.

62 In the present study, we developed and applied a new dynamic activity pattern
63 method to address these challenges. The new method, named the coactive
64 micropattern analysis (CAMP), decomposed the fast dynamic activity into several
65 intrinsic CAMPs and defined the brain dynamics through the constitutions and
66 transitions among these CAMPs. We employed the CAMP analysis to elucidate the

dynamic configurations of LFPs from rat DMN in different stages during wakefulness and sleep. Our results illustrate a reorganized dynamic configurations of CAMPs for fast DMN activity in different stages of wakefulness, implying that the dynamic configurations of DMN micropatterns might provide underlying neural correlates for the wakefulness levels observed during wakefulness and sleep.

Methods and Materials

Detailed descriptions of the experimental procedures and data acquisition are described in the *Supplementary Materials*. Twenty-nine male Sprague-Dawley rats were used in our study. The DMN signals were acquired by chronically implanting fifteen electrodes into the brains of rats under deep anesthesia (Fig. 1 and Table 1). The rat DMN contained the following bilateral structures: the orbital frontal cortex (OFC), the rostral dorsal prelimbic cortex (PrL), the cingulate cortex (CG), the retrosplenial cortex (RSC), the dorsal hippocampus (HIP), the temporal lobe cortex (TE), the medial secondary visual cortex (V2) and the posterior parietal cortex (PPC). According to their anatomical coordinates (Lu et al., 2012), the PrL, OFC and CG regions were considered to be in the anterior subsystem of the DMN, whereas the RSC, HIP, PPC, TE and V2 regions were in the posterior subsystem of the DMN. In addition, we also implanted two electromyographic (EMG) electrodes bilaterally in the dorsal neck muscles. After DMN electrode implantation surgery, all rats recovered for approximately 2 weeks. During the recording session, the rats were placed in a noise-attenuated chamber and were allowed to move freely without anesthesia. All the

88 signals for the LFP, the EMG and the videos signals were simultaneously recorded
89 and continuously monitored for 72 h.

90 The dataset used in the current study was selected from the last 24 h of the total
91 recording and was separated into three stages, including resting (AWAKE), SWS and
92 REM sleep stages. The AWAKE stage of rats was defined when the rats were standing
93 or sitting quietly with low-amplitude and mixed-frequency LFP activity and relatively
94 low and stable EMG activity. The SWS stage was the sleep duration when the rats
95 were sleeping with high-amplitude and low-frequency LFP activity and low-level
96 EMG activity. The REM sleep stage was the duration when the rats were sleeping
97 with sawtooth-pattern LFP activity and flat EMG activity. For each rat, 30 segments
98 in different stages were chosen, and each segment lasted 10 s (a total of 300 s of
99 LFPs). All experimental animal procedures were approved by the Institutional Animal
100 Care and Use Committee of the University of Electronic Science and Technology of
101 China.

102 Moreover, we proposed a novel CAMP method to track fast DMN dynamics
103 during wakefulness and sleep. Briefly, this method utilizes a point process approach
104 that combines the advantages of both microstate analysis and coactive pattern analysis
105 (X. Liu & Duyn, 2013; Michel & Koenig, 2018) and extracts CAMPs based on the
106 extreme values of envelope signals at a high temporal resolution. Five steps were
107 included in the CAMP algorithm. First, the original data were bandpass filtered into
108 the gamma frequency band (40-80 Hz) and then Hilbert transformation was used to
109 obtain the envelope signals (Fig. 2b). Second, the envelope signals were normalized

110 and downsampled to improve the signal-to-noise ratio (SNR) for further analysis (Fig.
111 2c). Third, the active points for each envelope signal channel were then defined as the
112 extreme points of the envelope signals, including local maximum and minimum
113 values. Afterwards, the coactive patterns (CAPs) of the brain, which were defined as
114 brain maps in which more than one brain region displayed active points at the same
115 time point, were introduced for all stages (Fig. 2d). Fourth, a k-means clustering
116 algorithm was applied to all the CAPs to decompose the CAPs and the CAMP
117 index (Fig. 2e). Finally, the criterion based on squared Euclidean distance was applied
118 to update the CAMP and CAMP index (Fig. 2f). The last step was employed to
119 precisely determine the final spatial structures of all CAPs and the CAMP index.
120 Using the CAMP method, we decomposed three stable CAPs from gamma activity
121 during DMN dynamics to reveal the fast changes in DMN activity in different stages
122 of wakefulness. A detailed description of the CAMP analysis is provided in the
123 *Supplementary Methods*.

124 The CAMP method was separately applied to the DMN activity of each segment
125 in different stages for each rat and to the concatenated DMN activity of all rats and all
126 stages during wakefulness and sleep. The CAPs extracted from each rat in different
127 stages were further employed to test their spatial stability across rats and wakefulness
128 levels using Pearson correlation method. The results were derived from the CAPs
129 extracted from the concatenated DMN activities from all rats during wakefulness and
130 sleep unless otherwise described.

131 **Results**

132 **Three CAMPs of gamma activity in the DMN during wakefulness and sleep**

133 The CAMP analysis procedure developed in the present study is schematically
 134 illustrated in Fig. 2 and described in more detail in the *Supplementary Methods*. The
 135 concatenated gamma activities in the DMNs of all rats and all stages during
 136 wakefulness and sleep were decomposed into three distinct CAMPs, including a
 137 common low-activity level micropattern (cDMN), an anterior high-activity level
 138 micropattern (aDMN) and a posterior high-activity level micropattern (pDMN). In the
 139 cDMN, all DMN regions exhibited similar and low levels of activity (mean
 140 normalized activity: 0.2577 ± 0.0041 , Fig. 2g), indicating a potential cooperation of
 141 them in this type of CAMP. However, two different levels of activity were observed in
 142 both the aDMN and pDMN with the aDMN exhibiting relatively higher levels of
 143 activity in the anterior DMN regions (mean normalized activity: 0.3868 ± 0.0018) and
 144 lower activity in the posterior DMN structures (mean normalized activity: $0.3050 \pm$
 145 0.0060 , Fig. 2h). In the pDMN, the posterior DMN structures displayed higher levels
 146 of activity (mean normalized activity: 0.3793 ± 0.0145), whereas the anterior DMN
 147 regions exhibited relatively lower levels of activity (mean normalized activity: 0.3073
 148 ± 0.0021 , Fig. 2i). Accordingly, both the aDMN and pDMN were considered
 149 high-activity micropatterns in DMN dynamics.

150 We separately decomposed the CAMPs for each rat in every wakefulness stage
 151 individually and tested their reliability across rats and stages. All three CAMPs
 152 exhibited high stability with large correlation coefficients among different rats during

153 wakefulness and sleep (mean correlation coefficients: $r = 0.7451$, $r = 0.7535$, $r =$
 154 0.6684 for the AWAKE, SWS and REM sleep stages, respectively; Table 2). In
 155 addition, the spatial structures of these CAMPs were also similar among the AWAKE,
 156 SWS and REM sleep stages (mean correlation coefficients: $r = 0.6229$, $r = 0.7882$, $r =$
 157 0.8600 for the cDMN, aDMN and pDMN, respectively; Table 3). These findings
 158 demonstrated the high reliability and robustness of these CAMPs.

159 **Temporal features and activity levels of each CAMP during wakefulness and** 160 **sleep**

161 We computed several temporal measurements, including the total occurrence
 162 (occurrence probability), total duration (duration probability) and mean duration, to
 163 characterize the features and dynamics of these CAMPs during wakefulness and sleep.
 164 All these features represented the temporal properties of these CAMPs in different
 165 stages. Based on the comparisons, all features of cDMN displayed the largest values
 166 in the SWS stage and the smallest values in the REM sleep stage, and the two
 167 high-activity micropatterns (aDMN and pDMN) exhibited the largest values for all
 168 features in the REM sleep stage and the smallest values in the SWS stage (Fig. 3a-3c).
 169 These opposite alterations in features between low- and high-activity micropatterns
 170 suggests that these two types of CAMPs might play different physiological roles for
 171 wakefulness. Besides, all the features in three stages were remarkably different among
 172 CAMPs, improving our knowledge of the changes in wakefulness levels during
 173 wakefulness and sleep.

174 However, all of these CAMPs displayed different activities in DMN regions

175 during wakefulness and sleep. In particular, all DMN regions exhibited reduced
176 activity during SWS stages in all CAMPs (Fig. 3e-3g). Moreover, the posterior DMN
177 structures exhibited significantly reduced activity in the aDMN, while the anterior
178 DMN regions exhibited significantly reduced activity in the pDMN. All of these
179 regions showed relatively lower activity in the AWAKE stage, indicating a
180 preservation of the major activity in these two micropatterns during deep sleep (Fig.
181 3f-3g, red stars). However, all CAMPs displayed increased activity in most DMN
182 regions during the REM sleep stage. The activities in the HIP, OFC and RSC regions
183 were significantly increased during the REM sleep stage in all CAMPs, implying the
184 importance of these DMN regions for REM sleep (Fig. 3h-3j, red stars). In addition,
185 the mean activity level of each CAMP exhibited similar variation trends across
186 different stages of wakefulness. The lowest mean activity of CAMPs was observed in
187 the SWS stage, whereas the highest mean activity was observed in the REM sleep
188 stage (Fig. 3d).

189 **The features and transitions of CAMPs during wakefulness and sleep**

190 The configurations of these CAMPs involved in DMN dynamics in different
191 stages were also distinct (Fig. 4a-4c). All CAMPs presented similar features in the
192 AWAKE stage (occurrence probabilities: 32.12%, 34.12% and 33.75%; duration
193 probabilities: 31.68%, 34.15% and 34.17%; and mean duration: 29.79 ms, 24.41 ms
194 and 24.37 ms for the cDMN, aDMN and pDMN, respectively). No significant
195 differences of the features among three CAMPs were observed, indicating that their
196 roles were equivalent and that a dynamic balance in DMN activity might exist among

197 CAMPs at wakeful rest. However, the cDMN became the dominant activity pattern of
 198 DMN dynamics in the SWS stage as it had the largest occurrence probabilities
 199 (62.66%, 17.56% and 19.78% for the cDMN, aDMN and pDMN, respectively),
 200 duration probabilities (61.47%, 18.02% and 20.51% for the cDMN, aDMN and
 201 pDMN, respectively) and mean duration (55.58 ms, 21.89 ms and 22.78 ms for the
 202 cDMN, aDMN and pDMN, respectively) among all CAMPs. The predominant
 203 constituent of the low-activity micropattern suggests that all the DMN regions might
 204 have been in a stage of low activity and that DMN activity preferred a silent pattern
 205 during deep sleep. However, the two high-activity micropatterns were the main
 206 CAMPs during the REM sleep stage. All the features of aDMN and pDMN were
 207 significantly larger than those of cDMN (occurrence probabilities: 19.42%, 42.05%
 208 and 38.53%; duration probabilities: 19.33%, 41.84% and 38.83%; and mean duration:
 209 21.88 ms, 26.92 ms and 26.01 ms for the cDMN, aDMN and pDMN, respectively).
 210 The greater percentage of high-activity micropatterns during REM sleep suggests a
 211 reactivation of DMN activity in this stage. In addition, comparisons of features within
 212 two high-activity micropatterns demonstrated that the aDMN displayed significantly
 213 larger values for the three features, implying that it played a more important role in
 214 REM sleep.

215 Furthermore, the temporal concatenations of these CAMPs (i.e., the CAMP
 216 indices) in different stages also exhibited specific changes. We first performed a
 217 randomization test to examine the transition structures of these CAMP indices in
 218 different stages. The transitions among CAMPs occurred randomly in the AWAKE

219 stage ($p = 0.8157$), indicating that the transition probabilities (TPs) of pairs of CAMPs
 220 in the resting stage were proportional to their occurrences. However, these transitions
 221 did not occur randomly in the SWS ($p < 0.0001$) or REM sleep stages ($p < 0.0001$),
 222 suggesting the stabilization of the CAMP index structures during the sleep cycle and
 223 further implying the existence of several preferred transitions among CAMPs in both
 224 SWS and REM sleep stages.

225 Next, we compared the TPs for pairs of CAMPs between the two sleep stages and
 226 the AWAKE stage. We revealed similar TPs in the AWAKE stage (no significant
 227 differences among all TPs, Fig. 4d), suggesting the presence of balanced transitions
 228 among all CAMPs at rest. However, the TPs within the two high-activity
 229 micropatterns showed significant reductions in the SWS stage, whereas those between
 230 the high-activity micropatterns and the low-activity micropattern increased
 231 significantly (Fig. 4e). These changes in TPs emphasized the functional role of
 232 inhibitory activity in DMN regions in deep sleep. On the other hand, TPs in the REM
 233 sleep stage displayed different alterations, including significantly increased TPs
 234 within the high-activity micropatterns and remarkable decrease in TPs between the
 235 high-activity micropatterns and the low-activity micropattern (Fig. 4f). The increased
 236 transitions within two high-activity micropatterns revealed activation of DMN regions
 237 during REM sleep. Based on these findings, the CAMP indices and the functional
 238 roles of these CAMPs were specific for different stages. The alterations in DMN
 239 activity during wakefulness and sleep might be attributed to the specific temporal
 240 combinations of the CAMPs constituting the activity in different stages rather than the

241 spatial structures of CAMPs themselves, which were rather stable across different
242 stages.

243 **Strong phasic relationships between CAMPs and up-down states in the SWS** 244 **stage**

245 Up-down states are considered the predominant pattern of slow oscillations (0.5-2
246 Hz) during the SWS stage. Estimations of the phase distributions of each CAMP in
247 the anterior and posterior DMN slow activity regions with the Hilbert transformation
248 demonstrated that these CAMPs displayed strong phasic relationships with the
249 up-down states in the SWS stage. The cDMN preferred the down state of anterior
250 DMN activity (Fig. 5a, significant directionality: 1.97π , red line) and the up state of
251 posterior DMN activity (Fig. 5d, significant directionality: 1.16π , red line).
252 Additionally, both the aDMN and pDMN were phase locked to the up state of anterior
253 DMN activity (Fig. 5b, significant directionality: 1.21π for aDMN; Fig. 5c,
254 significant directionality: 1.18π for pDMN) and the down state of posterior DMN
255 activity (Fig. 5e, significant directionality: 0.23π for aDMN; Fig. 5f, significant
256 directionality: 0.18π for pDMN). These similar phasic relationships implied that two
257 high-activity micropatterns might belong to the same activity pattern of slow
258 oscillations during deep sleep. Thus, our proposed CAMPs may reflect the up-down
259 states of DMN slow activity in the SWS stage, and a close physiological association
260 existed between the up-down states with DMN dynamics.

261 **Discussion**

262 In the present study, we proposed a coactive micropattern (CAMP) algorithm to

263 reveal the dynamics of DMN based on the direct physiological recordings in rat
 264 during wakefulness and sleep. Our results indicated that the fast dynamics of DMN
 265 gamma activity could be decomposed into three different CAMPs. These CAMPs
 266 exhibited stable spatial structures across wakefulness and sleep, while their dynamic
 267 configurations were specific to different stages. In addition, all these CAMPs were
 268 strongly phase locked to the up-down states of slow DMN activity in the SWS stage,
 269 suggesting the temporal sequence of the neural relationship between up-down states
 270 and DMN dynamics. Our findings described the distinct dynamic configurations of
 271 DMN activity during wakefulness and sleep. The proposed a three-state model may
 272 reveal a neural mechanism by which DMN dynamics mediated wakefulness and
 273 alertness.

274 **Physiological significance of the three CAMPs**

275 Previous studies have reported a strong correlation between electrophysiological
 276 gamma activity and blood oxygen level-dependent (BOLD) signals (N. K. Logothetis,
 277 Pauls, Augath, Trinath, & Oeltermann, 2001; Nikos K. Logothetis, 2002; Magri,
 278 Schridde, Murayama, Panzeri, & Logothetis, 2012; Scheering, Koopmans, Van
 279 Mourik, Jensen, & Norris, 2016). In addition, DMN regions have also shown
 280 deactivation at gamma frequency during the performance of external tasks in several
 281 human electroencephalography (EEG) studies (Karim Jerbi et al., 2010; Ossandon et
 282 al., 2011), indicating the importance of gamma oscillation in DMN activity. Hence,
 283 we specifically focused on the fast dynamics of DMN gamma activity in the current
 284 study. The gamma activity in the rat DMN was decomposed into three stable CAMPs

285 during wakefulness and sleep. We also showed the CAMPs decomposed from DMN
 286 alpha (8-13Hz) and beta (13-30Hz) activity, which exhibited similar structures with
 287 those found in gamma band (Supplementary Fig. 5). The differences across these
 288 CAMPs further provided direct electrophysiological evidence that the DMN regions
 289 might not be simultaneously activated. Besides, different CAMPs had distinct mean
 290 durations. These phenomena revealed the differences in the activation times of
 291 anterior and posterior DMN structures in the fast dynamics and further illustrated the
 292 diversity in the latencies for both the excitation and inhibition of DMN regions (Brett
 293 L. Foster, Mohammad Dastjerdi, 2012; Foster, Rangarajan, Shirer, & Parvizi, 2015).

294 Indeed, both human and animal studies found that the DMN structure could be
 295 separated into two subnetworks, i.e., a parietal subnetwork and a prefrontal
 296 subnetwork (Cui et al., 2018; Hagmann et al., 2008; Lu et al., 2012; Wu et al., 2017).
 297 In the present study, we not only reinforced this finding from the aspect of fast DMN
 298 dynamics but also provided a possible dynamic substrate for this separation of the
 299 DMN structure. As a key component of the DMN, the orbital frontal cortex (OFC) has
 300 historically been posited to integrate interoceptive and exteroceptive information from
 301 multisensory stimuli to process information about the internal and external bodily
 302 milieu (Ongur & Price, 2000). Accordingly, we hypothesized that the high-activity
 303 micropattern aDMN might play an important role in making inferences and guiding
 304 actions in a timely and environmentally relevant manner.

305 Furthermore, the retrosplenial cortex (RSC), another key area in the DMN, has
 306 extensive connections with the hippocampal formation. The projections between the

307 RSC and hippocampal formation provide an important pathway that regulates learning,
 308 memory and emotional behavior (Wyss & Vangroen, 1992). Furthermore, the
 309 hippocampal formation is a limbic structure that forms direct or indirect connections
 310 to other DMN regions. Therefore, the high-activity micropattern pDMN detected in
 311 the present study might be associated with memory and emotional behavior.
 312 Additionally, both the aDMN and pDMN were strongly phase locked to the up state
 313 of anterior DMN activity and the down state of posterior DMN activity during the
 314 SWS stage, indicating that they may reflect similar performances for the up-down
 315 states of slow oscillations during DMN dynamics. Moreover, these two high-activity
 316 micropatterns together accounted for more than 70% of the time in the resting state,
 317 which helps explain why the brain requires high basal cerebral blood flow and
 318 metabolism for spontaneous activity (Marcus E Raichle & Mintun, 2006). It should be
 319 noted that the DMN structure could also be split into dorsal and ventral branches
 320 according to the dorsal and medial temporal regions of RSC and hippocampus in
 321 human brain (Chen, Glover, Greicius, & Chang, 2017; Shirer, Ryali, Rykhlevskaia,
 322 Menon, & Greicius, 2012). However, the rat DMN is commonly divided into the
 323 anterior and posterior subsystems for the anatomical difference with human DMN
 324 (Marcus E Raichle, 2015).

325 We also observed a low-activity micropattern (i.e., cDMN) in DMN dynamics
 326 that was widely distributed in all wakefulness stages. In the cDMN, all DMN regions
 327 displayed lower activity, indicating that the cDMN could represent the silent state for
 328 DMN activity in which all the DMN regions prefer relaxations and are prepared for

the next excitation. Moreover, the cDMN was the only coactive micropattern in which all DMN regions operated in the same manner in DMN dynamics. Thus, the appearance of cDMN suggested a working mode for DMN with low energy, but this concept requires further study.

The balance of dynamic DMN configurations supports wakefulness and alertness during wakefulness

Based on accumulating evidence, DMN activity is tightly correlated with wakefulness levels in health and disease (Buckner, Andrews-Hanna, & Schacter, 2008; Kapogiannis et al., 2014; Panda et al., 2016). In the AWAKE stage, all the CAMPs exhibited similar features, and the dynamic transitions among them were not significantly different. These similarities illustrated a balanced dynamic configuration among these CAMPs during fast gamma activity in the DMN at rest. The DMN is a key network involved in integrating high-order information from multiple sensory modalities based on numerous projections from variable somatic cortex and core limbic structures (HIP and amygdala) to the DMN regions (Heidbreder & Groenewegen, 2003; Reep, Chandler, King, & Corwin, 1994). These projections might provide the anatomical substrate for the correlation of DMN activity with alertness levels, which are largely believed to be determined by global levels of arousal regulated by the brainstem via the reticular activating system (RAS) (Delano-Wood et al., 2015). Accordingly, the identified balance of DMN dynamics might be a competitive product between the integration and differentiation of DMN activity in maintaining wakefulness and alertness during resting state (Cavanna, Vilas,

351 Palmucci, & Tagliazucchi, 2018; Tononi, 2004). Furthermore, this balance of dynamic
352 configurations also indicated that the DMN might function in multistable regimes and
353 revealed the potential neural mechanism by which DMN activity supported
354 wakefulness and alertness in the resting state (Andrews-Hanna, 2012; Buckner et al.,
355 2008).

356 **Functional reorganization of dynamic DMN configurations during sleep**

357 Compared to the resting state, the SWS stage was consistently accompanied with
358 reduced brain activity, whereas commensurate brain activity has been reported in the
359 REM sleep stage (Horovitz et al., 2008). Consistent alterations in the average brain
360 activity associated with CAMPs during DMN dynamics were also observed in our
361 study, suggesting that the activities of CAMPs might also reveal the changes in
362 wakefulness during wakefulness and sleep. However, the reduced activities of all
363 CAMPs might not sufficiently explain the decrease in DMN activity observed during
364 deep sleep due to the stable spatial structures of these CAMPs during wakefulness and
365 sleep. The decrease in activity might result from the increased occurrence probability
366 of the cDMN and the decreased probabilities of other two high-activity CAMPs.
367 These inversely changed occurrence probabilities in different CAMPs revealed the
368 neural mechanism of reduced brain activity given that the DMN regions were shown
369 to prefer the low-activity state during deep sleep (Bazhenov, Timofeev, Steriade, &
370 Sejnowski, 2002; Diekelmann & Born, 2010).

371 The balance of dynamic DMN configurations was also disrupted during sleep,
372 indicating the functional reorganization of DMN dynamics. The reorganization of

373 DMN activity might be associated with the alteration of different wakefulness levels
374 in different sleep stages (Tononi, 2004). In the REM sleep stage, the dynamic
375 transitions between the aDMN and pDMN increased, indicating more communication
376 between anterior and posterior DMN regions. The communications displayed the
377 top-down and bottom-up mechanisms in DMN structure, both of which are important
378 for the information processing in the brain (Buschman & Miller, 2007; Theeuwes,
379 2010). Thus, we speculate that the communications between anterior and posterior
380 DMN regions might help elucidate the neurophysiological basis underlying the
381 preservation of the wakefulness level in the REM sleep stage.

382 In the SWS stage, the dynamic transitions between the low-activity micropattern
383 and two high-activity micropatterns increased significantly. Moreover, different types
384 of micropatterns corresponded to distinct up-down states in slow oscillations among
385 DMN regions. Accordingly, the transitions between the low-activity micropattern and
386 two high-activity micropatterns in DMN dynamics could be deemed as the transitions
387 within up-down states. The dominant transitions of up-down states in deep sleep
388 further suggested the physiological importance of these increased dynamic transitions.
389 However, the dynamic transitions within the two high-activity micropatterns
390 decreased in the SWS stage. These reductions supported our hypothesis that
391 communications between anterior and posterior DMN regions are important for levels
392 of wakefulness and alertness given that wakefulness and alertness are almost lost
393 during deep sleep. The loss of wakefulness and alertness might not be caused by the
394 change in a single type of dynamic transition within pairs of CAMPs. We

395 hypothesized that the balance of dynamic DMN configurations was the underlying
396 key neural mechanism supporting wakefulness and alertness, which emerged during
397 wakefulness and disappeared during sleep. The coordination and cooperation of all
398 CAMPs played a core role for the ability of the DMN in supporting wakefulness and
399 alertness.

400 Based on these findings, we propose a three-state model to describe the
401 relationship between DMN micropatterns and wakefulness levels observed during
402 wakefulness and sleep. As shown in Fig. 6, the three CAMPs involved in DMN
403 dynamics are the basis of this model, and their interactions refer to the underlying
404 mechanism regulating the wakefulness level observed in distinct stages. Equal
405 communications among the three CAMPs support conscious awareness in the
406 AWAKE stage. The communications between the low-activity micropattern (i.e.,
407 cDMN) and each high-activity micropattern (i.e., aDMN and pDMN) are important
408 for the SWS stage characterized by a low level of wakefulness. During the REM sleep
409 stage, communications within high-activity micropatterns are predominant.

410 According to the proposed three-state model, we hypothesize that preservation of
411 wakefulness and alertness not only requires information transition between anterior
412 and posterior DMN regions, but also need a state that all DMN regions remain silent
413 and relaxed. Information transition within anterior and posterior DMN regions is
414 mediated by up-down and bottom-up mechanisms and vital for supporting
415 wakefulness and alertness. The absence of this process could lead to the loss of
416 alertness in the SWS stage, and this process alone would result in the wakefulness

level of the REM sleep stage, which is more wakeful than the SWS stage and less wakeful than the AWAKE stage. This phenomenon highlights the importance of the silent pattern for all DMN regions during the resting state with wakefulness and alertness.

Wakefulness and alertness in humans not only depend on the anterior-posterior integration with DMN regions but also involves fronto-parietal task-positive executive and attention networks. Moreover, the connections between DMN and task positive networks also play critical roles in supporting wakefulness and alertness. Given the limitation of neuroimaging measure, the current work only describes the associations between DMN dynamics and wakefulness levels. The roles of integrations between DMN and other networks could not be explored at present. Further work could validate our model with DMN activity during the wakefulness-sleep cycle and further track the roles of integrations among different ICNs across different levels of wakefulness and alertness with human EEG signals.

Methodological perspectives

Consistent with the promising microstate analysis of EEG/LFP signals (Michel & Koenig, 2018), the CAMP analysis reported herein also assumes that brain activity consists of several distinct instantaneous patterns. The difference is that the CAMP method focuses on the nature of brain activity in different regions and extracts micropatterns from the envelope signals. Envelope signals imply temporal alterations of brain power, and their decomposition directly reveals brain rhythm dynamics. In addition, the coactive patterns analyzed in the CAMP method were selected based on

the distributions of extreme values in the envelope signals, which differs from the method used in microstate analysis. Local extreme values in envelope signals represent the instantaneous higher/lower activities of brain regions followed by contrasting changes in activity. The derived coactive patterns were thus considered to represent the activity patterns leading to inversion of activity among regions in specific brain networks. Therefore, we postulate that the proposed CAMP method will help researchers elucidate coactive micropatterns in specific brain networks and reveal additional underlying information about fast brain dynamics.

Limitations

Although we reveal several interesting findings in the current work, some limitations exist that should be taken into consideration. First, the rat DMN is slightly anatomically different from the human DMN, and our findings in rat DMN dynamics need to be validated in the human DMN during wakefulness and sleep. In addition, the present work reveals the dynamic configurations of DMN activity exclusively in the gamma band, and different frequency bands have distinct physiological roles. The relationships between the DMN dynamics in other frequency bands with wakefulness levels should be investigated in future studies.

Conclusion

The DMN is believed to be associated with neural mechanisms of wakefulness and alertness levels, whereas fast dynamics of DMN activity based on direct physiological recordings in different stages of wakefulness remain unclear. We highlighted that the fast dynamics of DMN activity during wakefulness and sleep

461 shared structurally stable CAMPs, whereas their dynamic configurations were specific
462 to different levels of wakefulness. Our results indicated the reorganization of DMN
463 dynamics during wakefulness and sleep, and provided a three-state model to reveal
464 the fundamental neural associations between DMN activity and wakefulness levels.

465 **Acknowledgments**

466 We thank Professor Pedro A. Valdes-Sosa for the valuable discussions and
467 suggestions regarding this work.

468 **Authorship Confirmation Statement**

469 Y.X., D.Y., C.Z., and D.G. designed the research; Y.C., M.L., and W.J. performed
470 the research; Y.C., M.L., B.B., and H.L. analyzed the data; and C.Y., B.B., D.G., and
471 D.Y. wrote the paper.

472 **Authors' Disclosure Statement**

473 The authors declare that no competing financial interests exist.

474 **Funding Statement**

475 This study was supported by the National Natural Science Foundation of China
476 (grant nos. 81861128001, 61527815, 31771149, 61761166001, 61871420, 11975194
477 and 81901366), the Sichuan Science and Technology Program (grant no.
478 2018HH0003), and the 111 project (grant no. B12027).

479 **References**

480 Andrews-Hanna, J. R. (2012). The Brain's Default Network and its Adaptive Role in
481 Internal Mentation. *Neuroscientist*, 18(3), 251–270.
482 <https://doi.org/10.1016/j.neuroimage.2013.08.045>.The

483 Bazhenov, M., Timofeev, I., Steriade, M., & Sejnowski, T. J. (2002). Model of
484 thalamocortical slow-wave sleep oscillations and transitions to activated states.
485 *The Journal of Neuroscience*, 22(19), 1.

486 Beckmann, C. F., DeLuca, M., Devlin, J. T., & Smith, S. M. (2005). Investigations
487 into resting-state connectivity using independent component analysis.
488 *Philosophical Transactions of the Royal Society B: Biological Sciences*,
489 360(1457), 1001–1013. <https://doi.org/10.1098/rstb.2005.1634>

490 Brett L. Foster, Mohammad Dastjerdi, and J. P. (2012). Neural populations in
491 human posteromedial cortex display opposing responses during memory and
492 numerical processing. *Proceedings of the National Academy of Sciences*, 109,
493 15514–15519.
494 <https://doi.org/10.1073/pnas.1206580109/-/DCSupplemental>.www.pnas.org/cgi/doi/10.1073/pnas.1206580109

496 Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain’s default
497 network: Anatomy, function, and relevance to disease. *Annals of the New York*
498 *Academy of Sciences*, 1124, 1–38. <https://doi.org/10.1196/annals.1440.011>

499 Buschman, T. J., & Miller, E. K. (2007). Top-Down Versus Bottom-Up Control of
500 Attention in the Prefrontal and. *Science*, 315(March), 1860–1863.
501 <https://doi.org/10.1126/science.1138071>

502 Cavanna, F., Vilas, M. G., Palmucci, M., & Tagliazucchi, E. (2018). Dynamic
503 functional connectivity and brain metastability during altered states of
504 consciousness. *NeuroImage*, 180, 383–395.

505 <https://doi.org/10.1016/j.neuroimage.2017.09.065>

506 Chen, J. E., Glover, G. H., Greicius, M. D., & Chang, C. (2017). Dissociated patterns
507 of anti-correlations with dorsal and ventral default-mode networks at rest.
508 *Human Brain Mapping*, 38(5), 2454–2465. <https://doi.org/10.1002/hbm.23532>

509 Crunelli, V., & Hughes, S. W. (2010). The slow (1 Hz) rhythm of non-REM sleep: A
510 dialogue between three cardinal oscillators. *Nature Neuroscience*, 13(1), 9–17.
511 <https://doi.org/10.1038/nn.2445>

512 Cui, Y., Yu, S., Zhang, T., Zhang, Y., Xia, Y., Yao, D., & Guo, D. (2018). Altered
513 activity and information flow in the default mode network of pilocarpine-induced
514 epilepsy rats. *Brain Research*, 1696, 71–80.
515 <https://doi.org/10.1016/j.brainres.2018.05.012>

516 Delano-Wood, L., Bangen, K. J., Sorg, S. F., Clark, A. L., Schiehser, D. M., Luc,
517 N., ... Bigler, E. D. (2015). Brainstem white matter integrity is related to loss of
518 consciousness and postconcussive symptomatology in veterans with chronic mild
519 to moderate traumatic brain injury. *Brain Imaging and Behavior*, 9(3), 500–512.
520 <https://doi.org/10.1007/s11682-015-9432-2>

521 Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews*.
522 *Neuroscience*, 11(2), 114–126. <https://doi.org/10.1038/nrn2762>

523 Foster, B. L., Rangarajan, V., Shirer, W. R., & Parvizi, J. (2015). Intrinsic and
524 task-dependent coupling of neuronal population activity in human parietal cortex.
525 *Neuron*, 86(2), 578–590. <https://doi.org/10.1016/j.neuron.2015.03.018>

526 Fox, K. C. R., Foster, B. L., Kucyi, A., Daitch, A. L., & Parvizi, J. (2018). Intracranial

527 Electrophysiology of the Human Default Network. *Trends in Cognitive Sciences*.
528 <https://doi.org/10.1016/j.tics.2018.02.002>

529 Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Essen, C. Van, Raichle, M.
530 E., ... Raichle, M. E. (2016). Networks Linked references are available on
531 JSTOR for this article□: The human brain is intrinsically organized into
532 dynamic , anticorrelated functional networks. *Proceedings of the National*
533 *Academy of Sciences of the United States of America*, (May).

534 Gretenkord, S., Olthof, B. M. J., Stylianou, M., Rees, A., Gartside, S. E., & LeBeau, F.
535 E. N. (2020). Electrical stimulation of the ventral tegmental area evokes
536 sleep-like state transitions under urethane anaesthesia in the rat medial prefrontal
537 cortex via dopamine D1-like receptors. *European Journal of Neuroscience*, 52(2),
538 2915–2930. <https://doi.org/10.1111/ejn.14665>

539 Gusnard, D. A., Akbudak, E., Shulman, G. L., & Raichle, M. E. (2001). Medial
540 prefrontal cortex and self-referential mental activity: Relation to a default mode
541 of brain function. *Proceedings of the National Academy of Sciences of the United*
542 *States of America*, 98(7), 4259–4264. <https://doi.org/10.1073/pnas.071043098>

543 Hagmann, P., Cammoun, L., Gigandet, X., Meuli, R., Honey, C. J., Van Wendeen, J.,
544 & Sporns, O. (2008). Mapping the structural core of human cerebral cortex.
545 *PLoS Biology*, 6(7), 1479–1493. <https://doi.org/10.1371/journal.pbio.0060159>

546 Heidbreder, C. A., & Groenewegen, H. J. (2003). The medial prefrontal cortex in the
547 rat: Evidence for a dorso-ventral distinction based upon functional and
548 anatomical characteristics. *Neuroscience and Biobehavioral Reviews*, 27(6),

549 555–579. <https://doi.org/10.1016/j.neubiorev.2003.09.003>

550 Holcman, D., & Tsodyks, M. (2006). The emergence of up and down states in cortical
551 networks. *PLoS Computational Biology*, 2(3), 174–181.
552 <https://doi.org/10.1371/journal.pcbi.0020023>

553 Horovitz, S. G., Fukunaga, M., De Zwart, J. A., Van Gelderen, P., Fulton, S. C.,
554 Balkin, T. J., & Duyn, J. H. (2008). Low frequency BOLD fluctuations during
555 resting wakefulness and light sleep: A simultaneous EEG-fMRI study. *Human*
556 *Brain Mapping*, 29(6), 671–682. <https://doi.org/10.1002/hbm.20428>

557 Hsu, L.-M., Liang, X., Gu, H., Brynildsen, J. K., Stark, J. A., Ash, J. A., ... Yang, Y.
558 (2016). Constituents and functional implications of the rat default mode network.
559 *Proceedings of the National Academy of Sciences*, 113(31), E4541–E4547.
560 <https://doi.org/10.1073/pnas.1601485113>

561 Huang, S. M., Wu, Y. L., Peng, S. L., Peng, H. H., Huang, T. Y., Ho, K. C., & Wang,
562 F. N. (2016). Inter-Strain Differences in Default Mode Network: A Resting State
563 fMRI Study on Spontaneously Hypertensive Rat and Wistar Kyoto Rat.
564 *Scientific Reports*, 6(February), 1–9. <https://doi.org/10.1038/srep21697>

565 Jercog, D., Roxin, A., Barthó, P., Luczak, A., Compte, A., & De La Rocha, J. (2017).
566 UP-DOWN cortical dynamics reflect state transitions in a bistable network.
567 *ELife*, 6, 1–33. <https://doi.org/10.7554/eLife.22425>

568 Ji, D., & Wilson, M. A. (2007). Coordinated memory replay in the visual cortex and
569 hippocampus during sleep. *Nature Neuroscience*, 10(1), 100–107.
570 <https://doi.org/10.1038/nn1825>

- 571 Jing, W., Guo, D., Zhang, Y., Guo, F., Valdés-Sosa, P. A., Xia, Y., & Yao, D. (2017).
572 Reentrant information flow in electrophysiological rat default mode network.
573 *Frontiers in Neuroscience*, 11(FEB), 1–12.
574 <https://doi.org/10.3389/fnins.2017.00093>
- 575 Kapogiannis, D., Reiter, D. A., Willette, A. A., & Mattson, M. P. (2014). Dynamic
576 functional connectivity of the default mode network tracks daydreaming.
577 *NeuroImage*, 100, 112–119.
578 <https://doi.org/10.1016/j.neuroimage.2012.09.029>.Posteromedial
- 579 Karim Jerbi, R., V. J., Tomas , , O., Dalal, S. S., Julien Jung, D. H., Minotti, L., ...
580 Lachaux, and J.-P. (2010). Exploring the electrophysiological correlates of the
581 default-mode network with intracerebral EEG. *Frontiers in Systems*
582 *Neuroscience*, 4(June), 1–9. <https://doi.org/10.3389/fnsys.2010.00027>
- 583 Larson-Prior, L. J., Zempel, J. M., Nolan, T. S., Prior, F. W., Snyder, A., & Raichle,
584 M. E. (2009). Cortical network functional connectivity in the descent to sleep.
585 *Proceedings of the National Academy of Sciences of the United States of*
586 *America*, 106(11), 4489–4494. <https://doi.org/10.1073/pnas.0900924106>
- 587 Liu, Q., Farahibozorg, S., Porcaro, C., Wenderoth, N., & Mantini, D. (2017).
588 Detecting large-scale networks in the human brain using high-density
589 electroencephalography. *Human Brain Mapping*, 38(9), 4631–4643.
590 <https://doi.org/10.1002/hbm.23688>
- 591 Liu, X., & Duyn, J. H. (2013). Time-varying functional network information extracted
592 from brief instances of spontaneous brain activity. *Proceedings of the National*

593 *Academy of Sciences of the United States of America*, 110(11), 4392–4397.
594 <https://doi.org/10.1073/pnas.1216856110>

595 Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., & Oeltermann, A. (2001).
596 Neurophysiological investigation of the basis of the fMRI signal. *Nature*,
597 412(6843), 150–157. <https://doi.org/10.1038/35084005>

598 Logothetis, Nikos K. (2002). The neural basis of the blood-oxygen-level-dependent
599 functional magnetic resonance imaging signal. *Philosophical Transactions of the*
600 *Royal Society B: Biological Sciences*, 357(1424), 1003–1037.
601 <https://doi.org/10.1098/rstb.2002.1114>

602 Lörincz, M. L., Gunner, D., Bao, Y., Connelly, W. M., Isaac, J. T. R., Hughes, S. W.,
603 & Crunelli, V. (2015). A distinct class of slow (~0.2–2 Hz) intrinsically bursting
604 layer 5 pyramidal neurons determines UP/DOWN state dynamics in the
605 neocortex. *Journal of Neuroscience*, 35(14), 5442–5458.
606 <https://doi.org/10.1523/JNEUROSCI.3603-14.2015>

607 Lu, H., Zou, Q., Gu, H., Raichle, M. E., Stein, E. A., & Yang, Y. (2012). Rat brains
608 also have a default mode network. *Proceedings of the National Academy of*
609 *Sciences of the United States of America*, 109(10), 3979–3984.
610 <https://doi.org/10.1073/pnas.1200506109>

611 Magri, C., Schridde, U., Murayama, Y., Panzeri, S., & Logothetis, N. K. (2012). The
612 Amplitude and Timing of the BOLD Signal Reflects the Relationship between
613 Local Field Potential Power at Different Frequencies. *The Journal of*
614 *Neuroscience*, 32(4), 1395–1407.

615 <https://doi.org/10.1523/JNEUROSCI.3985-11.2012>

616 Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the

617 temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*,

618 *180*(November 2017), 577–593.

619 <https://doi.org/10.1016/j.neuroimage.2017.11.062>

620 Ongur, D., & Price, J. (2000). The Organization of Networks within the Orbital and

621 Medial Prefrontal Cortex of Rats, Monkeys and Humans. *Cerebral Cortex*, *10*(3),

622 206–219. <https://doi.org/10.1093/cercor/10.3.206>

623 Ossandon, T., Jerbi, K., Vidal, J. R., Bayle, D. J., Henaff, M.-A., Jung, J., ... Lachaux,

624 J.-P. (2011). Transient Suppression of Broadband Gamma Power in the

625 Default-Mode Network Is Correlated with Task Complexity and Subject

626 Performance. *Journal of Neuroscience*, *31*(41), 14521–14530.

627 <https://doi.org/10.1523/JNEUROSCI.2483-11.2011>

628 Panda, R., Bharath, R. D., Upadhyay, N., Mangalore, S., Chennu, S., & Rao, S. L.

629 (2016). Temporal Dynamics of the Default Mode Network Characterize

630 Meditation-Induced Alterations in Consciousness. *Frontiers in Human*

631 *Neuroscience*, *10*(July), 1–12. <https://doi.org/10.3389/fnhum.2016.00372>

632 Perez-Zabalza, M., Reig, R., Manrique, J., Jercog, D., Winograd, M., Parga, N., &

633 Sanchez-Vives, M. V. (2020). Modulation of cortical slow oscillatory rhythm by

634 GABAB receptors: an in vitro experimental and computational study. *Journal of*

635 *Physiology*, *598*(16), 3439–3457. <https://doi.org/10.1113/JP279476>

636 Raichle, M E, MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., &

- 637 Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the*
638 *National Academy of Sciences of the United States of America*, 98(2), 676–682.
639 <https://doi.org/10.1073/pnas.98.2.676>
- 640 Raichle, Marcus E. (2015). The Brain ’ s Default Mode Network. *Annual Review*
641 *Neuroscience*, (April), 413–427.
642 <https://doi.org/10.1146/annurev-neuro-071013-014030>
- 643 Raichle, Marcus E, & Mintun, M. A. (2006). Brain work and brain imaging. *Annual*
644 *Review of Neuroscience*, 29, 449–476.
645 <https://doi.org/10.1146/annurev.neuro.29.051605.112819>
- 646 Reep, R. L., Chandler, H. C., King, V., & Corwin, J. V. (1994). Rat posterior parietal
647 cortex: topography of corticocortical and thalamic connections. *Experimental*
648 *Brain Research*, 100(1), 67–84. <https://doi.org/10.1007/BF00227280>
- 649 Rosazza, C., & Minati, L. (2011). Resting-state brain networks: Literature review and
650 clinical applications. *Neurological Sciences*, 32(5), 773–785.
651 <https://doi.org/10.1007/s10072-011-0636-y>
- 652 Sämann, P. G., Wehrle, R., Hoehn, D., Spoormaker, V. I., Peters, H., Tully, C., ...
653 Czisch, M. (2011). Development of the brain’s default mode network from
654 wakefulness to slow wave sleep. *Cerebral Cortex*, 21(9), 2082–2093.
655 <https://doi.org/10.1093/cercor/bhq295>
- 656 Scheering, R., Koopmans, P. J., Van Mourik, T., Jensen, O., & Norris, D. G. (2016).
657 The relationship between oscillatory EEG activity and the laminar-specific
658 BOLD signal. *Proceedings of the National Academy of Sciences of the United*

659 *States of America*, 113(24), 6761–6766.

660 <https://doi.org/10.1073/pnas.1522577113>

661 Shirer, W. R., Ryali, S., Rykhlevskaia, E., Menon, V., & Greicius, M. D. (2012).

662 Decoding subject-driven cognitive states with whole-brain connectivity patterns.

663 *Cerebral Cortex*, 22(1), 158–165. <https://doi.org/10.1093/cercor/bhr099>

664 Theeuwes, J. (2010). Top-down and bottom-up control of visual selection. *Acta*

665 *Psychologica*, 135(2), 77–99. <https://doi.org/10.1016/j.actpsy.2010.02.006>

666 Tononi, G. (2004). *An information integration theory of consciousness*. *BMC*

667 *neuroscience* (Vol. 5). BioMed Central. <https://doi.org/10.1186/1471-2202-5-42>

668 Tu, W., Ma, Z., Ma, Y., Dopfel, D., & Zhang, N. (2020). Suppressing Anterior

669 Cingulate Cortex Modulates Default Mode Network and Behavior in Awake

670 Rats. *Cerebral Cortex*, 1–12. <https://doi.org/10.1093/cercor/bhaa227>

671 Upadhyay, J., Baker, S. J., Chandran, P., Miller, L., Lee, Y., Marek, G. J., ... Day, M.

672 (2011). Default-Mode-Like Network Activation in Awake Rodents. *PLoS ONE*,

673 6(11). <https://doi.org/10.1371/journal.pone.0027839>

674 Vatansever, D., Menon, D. K., Manktelow, A. E., Sahakian, B. J., & Stamatakis, E. A.

675 (2015). Default mode network connectivity during task execution. *NeuroImage*,

676 122, 96–104. <https://doi.org/10.1016/j.neuroimage.2015.07.053>

677 Vatansever, Deniz, Manktelow, A., Sahakian, B. J., Menon, D. K., & Stamatakis, E.

678 A. (2018). Default Mode Network Engagement beyond Self-Referential Internal

679 Mentation. *Brain Connectivity*, 8(4), 245–253.

680 <https://doi.org/10.1089/brain.2017.0489>

- 681 Vidaurre, D., Smith, S. M., & Woolrich, M. W. (2017). Brain network dynamics are
682 hierarchically organized in time. *Proceedings of the National Academy of*
683 *Sciences*, 201705120. <https://doi.org/10.1073/pnas.1705120114>
- 684 Wu, X. jie, Zeng, L. L., Shen, H., Yuan, L., Qin, J., Zhang, P., & Hu, D. (2017).
685 Functional network connectivity alterations in schizophrenia and depression.
686 *Psychiatry Research - Neuroimaging*, 263(March), 113–120.
687 <https://doi.org/10.1016/j.psychresns.2017.03.012>
- 688 Wyss, J. M., & Vangroen, T. (1992). Connections between the retrosplenial cortex
689 and the hippocampal-formation in the rat - a review. *Hippocampus*, 2(1), 1–12.
690 <https://doi.org/10.1002/hipo.450020102>

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■ epidural electrode ● depth electrode

708

709 **Figure 1.** The placement of 15 intracranial electrodes.

710

711

Figure 2. Schematic of the CAMP procedure and three CAMPs of gamma activity in the DMN during wakefulness and sleep. (a) The original LFPs. (b) The envelope signals (blue lines) were extracted by applying the Hilbert transform to the bandpass-filtered signals (gray lines). (c) All the envelope signals were downsampled (blue lines), and the extreme values were detected as the active points for each channel (red dots). The dotted lines suggest the coactive points in which more than N (N=7 in the present study) active points were observed across DMN regions. (d) The coactive patterns were the maps of activity of all DMN regions at coactive points. (e) The k-means clustering algorithm was applied to all coactive patterns to detect the CAMPs. (f) A criterion was employed to remove several coactive points and increase the aggregation of the CAMPs. The final CAMPs and CAMP index detected in this step were subjected to further analyses. (g) Spatial structure of the common low-activity level micropattern (cDMN). (h) Spatial structure of the anterior high-activity level micropattern

724 (aDMN). (i) Spatial structure of the posterior high-activity level micropattern (pDMN).

Figure 3. Comparisons of the temporal features and activity levels of each CAMP during wakefulness and sleep. (a) Comparisons of the total occurrence of each CAMP in different stages of wakefulness. The dots represent the values obtained from 29 rats, and the black stars indicate significant differences with a corrected $p < 0.001$. (b) Comparisons of the total duration. (c) Comparisons of the mean duration. (d) Comparisons of the mean DMN activity during wakefulness and sleep for different CAMPs. (e-j) Comparisons of activity in DMN nodes for different CAMPs across different stages of wakefulness: (e and h) cDMN, (f and i) aDMN, and (g and j) pDMN. Gray dots indicate decreased normalized activity and black dots indicate increased normalized activity. The size of the dot reflects the value of the difference, and the red stars indicate significance differences with a corrected $p < 0.001$.

737

738 **Figure 4.** Characteristics of CAMPs and the transitions among them in different stages of
739 wakefulness during wakefulness and sleep. (a) Comparisons of the occurrence probability
740 for all CAMPs in the three stages. The black dots indicate the values of the occurrence
741 probability obtained from 29 rats in different CAMPs and stages. The black stars indicate

742 significant differences with a corrected $p < 0.001$. (b) Comparisons of the duration probability.
743 (c) Comparisons of the mean duration. (d-f) The transition structures among CAMPs for the
744 AWAKE (d), SWS (e) and REM sleep stages (f). All the numbers indicate the mean TPs
745 calculated for the 29 rats and the standard deviation. The numbers in blue indicate a
746 significantly lower transition probability than observed in the AWAKE stage, and the numbers
747 in red indicate a significantly higher transition probability. The significance level is a
748 corrected $p < 0.001$.
749

750

751 **Figure 5.** Phase locking relationship between each CAMP with slow oscillations in the SWS
752 stage. (a-c) The phase locking relationships between the cDMN (a), aDMN (b) and pDMN (c)
753 with the slow oscillations in anterior DMN regions. (d-f) The phase locking relationships
754 between the cDMN (d), aDMN (e) and pDMN (f) with the slow oscillations in posterior
755 DMN regions. The red lines showed the significant directionality with Rayleigh test $p < 0.001$.

756

757 **Figure 6.** The three-state model of the **alertness** levels during wakefulness and sleep. The
 758 AWAKE stage requires the cooperation of all three CAMPs, while the SWS stage requires
 759 communications between the low-activity micropattern (cDMN) and the high-activity
 760 micropatterns (aDMN or pDMN). The REM sleep stage requires interactions within the two
 761 high-activity micropatterns.

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