Feedback inhibition and its control in an insect olfactory circuit

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6 Abstract

7 Inhibitory neurons play critical roles in regulating and shaping olfactory responses in 8 vertebrates and invertebrates. In insects, these roles are performed by relatively few 9 neurons that can be interrogated efficiently, revealing fundamental principles of olfactory 10 coding. Here, with electrophysiological recordings from the locust and a large-scale 11 biophysical model, we analyzed the properties and functions of GGN, a unique giant 12 GABAergic neuron that plays a central role in structuring olfactory codes in the locust 13 mushroom body. Analysis of our in vivo recordings and simulations of our model of the 14 olfactory network suggests that GGN extends the dynamic range of KCs, and leads us to 15 predict the existence of a yet undiscovered olfactory pathway. Our analysis of GGN's 16 intrinsic properties, inputs, and outputs, in vivo and in silico, reveals basic new properties of 17 this critical neuron and the olfactory network that surrounds it.

18 Introduction

Olfactory information is transformed dramatically as it travels from the periphery to higher
order brain centers. Multiple types of olfactory receptor neurons may respond to a given odor
with vigorous bursts of action potentials, while neurons deeper in the brain, in the pyriform
cortex (vertebrates) or mushroom body (insects), may respond to the same odor with only a
spike or two (Bathellier, Buhl, Accolla, & Carleton, 2008; Cang & Isaacson, 2003; Friedrich &
Laurent, 2001; Laurent & Naraghi, 1994; Perez-Orive et al., 2002; Poo & Isaacson, 2009). In

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25 these higher order neurons, information about odors is represented sparsely by the identities 26 of the active neurons (population coding) and in the timing of the few spikes elicited in those 27 neurons (temporal coding)(Gupta & Stopfer, 2014; Perez-Orive et al., 2002; Poo & Isaacson, 28 2009; Stettler & Axel, 2009). Many studies in vertebrates and invertebrates suggest that 29 multiple mechanisms interact to mediate these transformations, including important inhibitory 30 contributions from GABAergic neurons(Large et al., 2018; Large, Vogler, Mielo, & Oswald, 31 2016; Lin, Bygrave, de Calignon, Lee, & Miesenböck, 2014; Luna & Pettit, 2010; Palmer & 32 Harvey, 2014; Papadopoulou, Cassenaer, Nowotny, & Laurent, 2011). Here, with 33 intracellular recordings and a new large-scale biophysical model that includes tens of 34 thousands of neurons and spans multiple layers of olfactory processing, we focus on a 35 singularly important inhibitory neuron to investigate the roles of input activity and feedback 36 inhibition in creating a sparse spatio-temporal odor representation in a higher order brain 37 center. Together, our recordings and models point to new functions, neural connectivity 38 patterns, and mechanisms that underlie transformations in the format of olfactory 39 information.

40 The locust olfactory system is tractable owing to its relative simplicity and is well studied. At 41 rest, olfactory receptor neurons (ORNs) are spontaneously active, evoking spontaneous 42 activity in the antennal lobe's projection neurons (PNs; Figure 1a)(Joseph, Dunn, & Stopfer, 43 2012). Odorants can increase or decrease the firing rates of ORNs, and odor-elicited spikes 44 arise in patterns that can include periods of excitation and inhibition that vary with the odor. 45 The heterogeneous responses of ORNs drive firing patterns in PNs that are further shaped 46 by inhibition from the antennal lobe's local interneurons (LN)(Raman, Joseph, Tang, & 47 Stopfer, 2010). Spikes in PNs are also coaxed into rhythmic waves by fast reciprocal 48 interactions between excitatory PNs and inhibitory LNs(Bazhenov et al., 2001; MacLeod & 49 Laurent, 1996). Odor-elicited firing patterns distributed across the population of PNs are 50 informative about the identity, concentration, and timing of the odor(Brown, Joseph, & 51 Stopfer, 2005; Laurent, Wehr, & Davidowitz, 1996; Stopfer, Jayaraman, & Laurent, 2003).

52 This information is carried by PNs to the mushroom body and the lateral horn. Within the 53 mushroom body, the primary neurons are Kenyon cells (KCs). Unlike the volubly spiking 54 PNs, the KCs are nearly silent at rest and respond very selectively to odors with very few 55 spikes(Joseph et al., 2012; Laurent & Naraghi, 1994; Perez-Orive et al., 2002). Thus, any 56 given odor evokes responses in a small fraction of the KC population, and any KC responds 57 to a small set of odors (Perez-Orive et al., 2002; Stopfer et al., 2003). This sparseness of 58 activity in KCs is thought to arise mainly from two factors: specialized membrane 59 conductances that imbue them with high firing thresholds; and a feedback circuit that tamps 60 down their spiking with cyclic inhibition(Demmer & Kloppenburg, 2009; Lin et al., 2014; 61 Papadopoulou et al., 2011; Perez-Orive et al., 2002). In the locust the main source of this 62 inhibition is the giant GABAergic neuron (GGN), one on each side of the brain(Gupta & 63 Stopfer, 2012; Leitch & Laurent, 1996; Papadopoulou et al., 2011).

64 GGN spans much of each brain hemisphere and branches very widely (Figure 1a). It is 65 reported to receive excitatory input from all 50,000 KCs at synapses within the mushroom 66 body's α lobe and, in turn, provide inhibitory feedback to all KCs 400-500 microns away within the calyx. In addition, GGN receives inhibitory input from a spiking neuron aptly 67 68 named "Inhibitor of GGN" (IG) which itself receives inhibition from GGN (Figure 1a, 69 right)(Papadopoulou et al., 2011). GGN is a non-spiking interneuron. Odor presentations, 70 spiking in KCs, and intracellular current injections have all been shown to depolarize GGN, 71 but none of these stimuli causes GGN to generate spikes; even large depolarizations 72 induced by strong intracellular current injections lead only to passive depolarizing 73 responses(Leitch & Laurent, 1996; Papadopoulou et al., 2011) (also our own observations). 74 GGN's structure is likely an important factor in its function. GGN is very large, and along its 75 path from the α lobe to the calyx, its initially thick processes divide at myriad branch points 76 into vanishingly thin fibers. Cable theory applied to neurons(Rall, 1964) predicts that a 77 passive voltage signal within such a structure will attenuate dramatically as it encounters cytosolic resistance along the neurites, will attenuate further as it divides at the neuronal 78

79 arbor's branch points, and will leak out through ionic channels in the cell membrane. 80 Together, these features made it unclear whether this giant neuron has the biophysical 81 capacity to perform its suggested function of carrying effective signals passively from the α 82 lobe to distant points in the calyx. Prior studies in invertebrates have shown that 2-5 mV 83 depolarizations in nonspiking interneurons can evoke change in membrane potential of their 84 post-synaptic neurons(Burrows & Siegler, 1978; Manor, Nadim, Abbott, & Marder, 1997). If 85 the signal through GGN attenuates to the extent that it cannot elicit responses in KCs then 86 GGN must operate through a different mechanism, perhaps purely through local interactions 87 in the calyx. To test these ideas, we developed a realistic computational model of GGN to characterize signal attenuation along this pathway. Our model showed that, although 88 89 electrical signals undergo substantial attenuation throughout its structure, signals in GGN's 90 calyceal branches appear strong enough to provide global inhibition to KCs.

91 To further understand the network determinants of GGN's responses to odors, we recorded 92 from it *in vivo* while delivering a variety of odors to the animal, and then used our large-scale 93 model to investigate the types of network activity needed to generate these patterns. We 94 identified three novel features in the olfactory network. First, to generate the types of 95 membrane potential patterns we observed in GGN, the synaptic connection strengths onto 96 KCs must be heterogeneous. Second, and surprisingly, our model predicted that a small 97 portion of KCs must respond to odors with relatively high spike rates. We tested this 98 prediction in vivo with patch clamp recordings from many KCs while presenting odors to the 99 animal's antenna. Indeed, we found that the predicted portion of KCs responded to odors 100 with relatively high rates of spiking. Third, our *in vivo* recordings of GGN revealed novel, 101 complex response patterns not previously documented, including periods of 102 hyperpolarization, that vary with the odorant. Although GGN receives reciprocal feedback 103 from IG(Papadopoulou et al., 2011), the periods of hyperpolarization could not be explained 104 by disinhibition of IG from GGN. Instead, our model predicts that this behavior could arise if,

105 in addition to receiving input from GGN, IG also receives direct excitation from another,

106 unknown odor-activated pathway.

107 Together, the results of our *in vivo* recordings and large-scale realistic computational 108 modeling provide a more complete understanding of how different parts of the olfactory 109 system interact. To generate odor-specific temporally patterned responses in GGN and in 110 the mushroom body, temporally-patterned odor evoked excitation from PNs, feedback 111 inhibition from GGN, and inhibition of GGN by odor-driven IG must all cooperate. Further, to 112 sustain adequate activity in GGN, some KCs must respond to odors with relatively high spike 113 rates.

114 Results

115 GGN morphology

116 A valuable use of computational modeling is to answer questions about biological systems 117 that are too large, complex, or difficult to address by direct physiological investigation. Earlier 118 computational studies of the insect olfactory system used relatively simple models of 119 neurons such as integrate and fire or map-based models that collapse entire neuronal 120 structures into a single point(Arena, Calí, Patané, Portera, & Strauss, 2015; Kee, Sanda, 121 Gupta, Stopfer, & Bazhenov, 2015; Papadopoulou et al., 2011; Peng & Chittka, 2017; Perez-122 Orive, Bazhenov, & Laurent, 2004). However, GGN's giant size, elaborate branching, and 123 passive membrane properties raised questions about its function that could only be 124 addressed by considering properties determined by its morphology. Thus, to understand 125 how the size and shape of GGN affects electrical signal propagation, we constructed a 126 detailed morphological model of GGN (available at neuromorpho.org).

To reconstruct the morphology of GGN we first made intracellular recordings from it *in vivo*,
filled it with dye, and obtained 3D confocal images of the dye-filled cell (Figure 1a, left; Video
S1). As previously shown, GGN has a reliable and unique location and morphology(Gupta &
Stopfer, 2012; Leitch & Laurent, 1996; Papadopoulou et al., 2011). Its soma is on the ventral

131 side of the brain, just anterior to the optic nerve. A single neurite emerges from GGN's soma, 132 travels toward the posterior and dorsal side of the brain, and splits there into two branches, 133 one innervating the α lobe and the other the mushroom body. Extending outward, these 134 branching neurites expand in width, becoming much thicker than the primary neurite. The mushroom body branch further divides into two thick processes that innervate the medial 135 136 and the lateral calyx. A thin neurite emerging from the lateral calyceal branch loops back to 137 the lateral horn, close to the soma, and splits there into many branches. We further observed 138 for the first time myriad thin fibers that emerge from the stems of the calyceal branches and 139 split into very fine feather-like neurites that wrap densely around the peduncle, with some 140 investing the peduncle core (Figure 1b). The neurites in the calyx and lateral horn are dotted 141 with many irregular bouton-like structures (Figure 1c) whereas the branches in α lobe are 142 relatively smooth (Figure 1d).

143 In two animals we traced and reconstructed the morphology of GGN from confocal image 144 stacks (Figure 1e). Analyzing these traces, we found that the maximum path length (i.e., the maximum distance between any two points on the neuronal tree when traversed along the 145 neurites) of the neuronal trees was on the order of 2mm, and the maximum physical length 146 147 (i.e., Euclidean distance between any two points on the neuron in three-dimensions) was on 148 the order of 1mm. Some neurites at their thickest were nearly 20µm in diameter. Total traced 149 branch length (i.e., the sum of the lengths of all the neurites) was about 65mm (although 150 many vanishingly thin branches were too fine to trace). Compared to 96,831 vertebrate and 151 invertebrate neurons cataloged in the neuromorpho.org database, GGN fell into the 99.75th percentile for total branch length, and the 99.95th percentile for number of branch points. It is 152 153 a really big neuron.

154 Signal attenuation in GGN

To investigate GGN's electrical properties we constructed a passive electrical model cell by
transferring the morphology tracings of the two GGNs into the NEURON

157 simulator(Carnevale & Hines, 2006). Both models produced qualitatively similar results; the 158 model we describe here was derived from the second neuron we traced because it was 159 imaged at higher resolution. To account for branches and changes in the diameters of processes that affect electrotonic distance we segmented the model GGN into 5,283 160 161 compartments. We set the membrane resistivity in the model to 33 kohm-cm² based on 162 published data obtained from other non-spiking neurons in the locust(Laurent, 1991), the specific membrane capacitance to 1 μ F/cm², the approximate value for cell 163 membranes(Curtis & Cole, 1938; Gentet, Stuart, & Clements, 2000; Hodgkin & Huxley, 164 165 1952) and the cytoplasmic resistivity to 100 ohm-cm, a typical order-of-magnitude value for 166 neurons(Hodgkin & Rushton, 1946; Roth & Häusser, 2001; Stuart & Spruston, 1998). 167 Feedback signals are thought to travel passively from GGN's α lobe branch to its calyceal 168 branches. To test the extent of passive signal attenuation through GGN's structure, we first 169 simulated voltage clamping the base of the α lobe branch of the GGN model (Figure 2a). 170 Intracellular recordings(Papadopoulou et al., 2011) (and our own) show GGN's membrane 171 potential rests at about -51 mV. Because strong odor stimuli depolarize GGN by about 10 mV in recordings made near the base of the α lobe branch(Papadopoulou et al., 2011) (also 172 173 see Figure 5a) we first stepped the clamp voltage to -40 mV and after holding it there for 450 174 ms measured the resulting depolarizations throughout the model GGN (Figure 2a inset). 175 Notably, the extent of signal attenuation was substantial and varied throughout the calyx with 176 depolarizations ranging from ~5 - 9 mV. The signal decreased with branch distance from the 177 α lobe, leaving the least amount of signal at the medial portion of the lateral calyceal branch 178 (Figure 2b, c, Video S2).

Since excitatory input typically arrives in GGN from many KCs, we then tested a more
realistic form of simulated input to the α lobe arbor of GGN by providing nonhomogeneous
Poisson spike trains through 500 excitatory model synapses; each synapse had a maximum
rate of 20 spikes/s that ramped down linearly to 0 over a 500 ms interval (Figure 2d, e). This

stimulus set was calibrated to generate a peak depolarization in the thick branches of GGN
in the same range we observed *in vivo*. This test also revealed significant attenuation of
voltage in the neuron's distant branches (Figure 2e, f).

186 For GGN neither membrane resistivity (RM) nor cytoplasmic (axial) resistivity (RA) has been measured definitively; yet, for a given morphology, these two parameters determine signal 187 188 attenuation. Thus, we explored a range of values for these two parameters with the voltage clamp simulation approach shown in Figure 2a. We based the RM value range on data 189 obtained from many types of neurons provided by the neuroelectro.org database. For RA, 190 191 neurophysiological data is sparse, so we explored broadly around the range of published 192 values(Hodgkin & Rushton, 1946; Roth & Häusser, 2001; Stuart & Spruston, 1998). As 193 expected, higher RA yielded greater signal attenuation, whereas higher RM yielded less 194 signal attenuation (Figure 2g). This analysis showed that signal transmission in GGN is 195 robust; except for the most extreme values of this parameter range, signals from the α lobe 196 remained strong enough to support synaptic transmission in the calyx. Depolarization 197 throughout GGN's calyceal arbor varied with location, as guantified in the extended lower lobe in the violin plots in Figure 2c, f and g. 198

199 Branches of GGN receiving weaker signals would be expected to provide less inhibition to 200 their postsynaptic KCs. In a simplified model in which all KCs were strongly stimulated by 201 identical input from PNs, the amount of KC spiking was indeed negatively correlated with 202 local GGN voltage deflections (Figure S3). However, in a more realistic model of the 203 mushroom body network including variable excitatory input from PNs and variable strengths 204 of inhibitory synapses between GGN and KCs, we found the negative correlation between 205 depolarizations measured at presynaptic locations throughout GGN and postsynaptic KC 206 activity was small, and likely negligible (data not shown). This suggests GGN's inhibitory 207 output has a surprisingly uniform influence upon KCs regardless of their locations.

208 Feedback inhibition expands the dynamic range of KCs

209 Feedback inhibition from GGN sparsens the odor-elicited responses of KCs by increasing 210 the KC spiking threshold and by restricting KC spiking to brief temporal windows defined by 211 the oscillatory cycle established in the AL(Gupta & Stopfer, 2014; Papadopoulou et al., 212 2011). Large-scale feedforward inhibition has previously been shown to expand the dynamic 213 range of cortical neurons(Pouille, Marin-Burgin, Adesnik, Atallah, & Scanziani, 2009). 214 Whether feedback inhibition from GGN has a similar effect on KCs is unknown. To test this, 215 we expanded our model to include, for simplicity, a single KC receiving feedback inhibition 216 from GGN (Figure 3a). To simulate the KC in this test we used a single compartmental 217 model with Hodgkin-Huxley type ion channels(Wüstenberg et al., 2004). Since just one KC 218 would have negligible effects on GGN, we applied its spiking output to GGN's α lobe branch 219 via 50,000 synapses, each with random delays between 0 and 60ms. Thus, after each spike 220 generated by the model KC, GGN received 50,000 EPSPs spread over a 60ms time window. 221 We drove the KC model with a range of tonic current injections and compared its responses 222 to those of an isolated KC model receiving the same input without feedback inhibition. As 223 expected, feedback inhibition increased the KC's threshold for spiking. Notably, though, the 224 GGN-coupled KC continued to spike over a much larger range of current injection than the 225 isolated KC, which quickly saturated to a level where it could no longer spike (Figure 3b, c). 226 This result suggests that feedback inhibition from GGN allows an individual KC to function 227 effectively over a larger dynamic range of inputs.

228 GGN responses can be complex, including hyperpolarization

229 Our recordings made *in vivo* from GGN frequently revealed depolarizations lasting

throughout an odor presentation, often with additionally depolarizing peaks corresponding to

the onset and offset of the odor (Figure 4, Animal 1, hexanol) (see also(Papadopoulou et al.,

232 2011)). Notably, our recordings from GGN also revealed more complex odor-elicited

- 233 responses than previously reported, including combinations of depolarization and
- hyperpolarization (Figure 4, Animal 1, hexanal). Moreover, we found that the same GGN

235 could respond differently when different odors were presented; for example, GGNs from 236 Animals 2 and 3 shown in Figure 4 depolarized in response to one odor and hyperpolarized 237 in response to another. Also, GGNs in different animals could respond differently to the 238 same odor (Figure 4, hexanal). Almost a guarter of the odor-GGN pairs in our in vivo 239 recordings showed reliable hyperpolarizations at some point in the odor response (40 out of 240 169). However, earlier computational models (Kee et al., 2015; Papadopoulou et al., 2011) 241 did not reproduce sustained responses in GGN, nor did they show any hyperpolarization of 242 GGN. Rather, in those models, odor-driven KCs spiking in synchronous bouts elicited 243 multiple isolated depolarizing peaks in GGN's membrane potential. To better understand the 244 mechanisms underlying GGN's odor-elicited responses (and by extension, novel features of 245 olfactory circuitry), we used our GGN model as the center of a more extensive mushroom 246 body olfactory network.

247 GGN responses suggest some KCs fire at high rates

248 We extended our detailed GGN model with a full population of 50.000 simulated KCs. KCs 249 are very small, have few dendritic branches, and generate action potentials; thus, in contrast 250 to the large, complex, and passive GGN, the morphologies of individual KCs are unlikely to 251 differentially influence their odor coding properties. Therefore, we used a relatively simple 252 NEURON version of a single compartmental KC model(Wüstenberg et al., 2004). Each 253 model KC was connected to GGN in the α lobe via an excitatory synapse, and each 254 received inhibitory input from a random segment of GGN in the calyx via a graded synapse 255 (Figure 5a). To provide excitatory input to the KCs, the firing patterns of 830 PNs were 256 simulated as spike-trains, each designed to follow the statistics of PNs recorded in 257 vivo(Jortner, Farivar, & Laurent, 2007; Mazor & Laurent, 2005). Thus, 77% of the PN spike 258 trains were assigned a spontaneous firing rate of 2.6 spikes/s; during odor stimulation, 20% 259 of these PNs were switched to 20 spikes/s modulated by the 20 Hz oscillations generated in 260 the antennal lobe and reflected in the local field potential (LFP), and 10% were inhibited (no 261 spikes) (Figure 5b). This resulted in a few highly synchronized bouts of spiking in the KC

population (Figure 5c), and corresponding isolated peaks in GGN's membrane potential
(Figure 5d). These unrealistic responses were similar to those generated by the abovementioned earlier models.

265 We suspected that more continuous input from KCs could sustain the long-lasting 266 depolarization in GGN we had observed in vivo. In our model all synapses between any two 267 cell types had the same strength. However, it has been shown in vivo that synaptic strengths 268 follow a lognormal distribution(Buzsáki & Mizuseki, 2014; Loewenstein, Kuras, & Rumpel, 269 2011; Song, Sjöström, Reigl, Nelson, & Chklovskii, 2005). After adjusting our network model 270 to include this property, some KCs became weakly inhibited, allowing them to fire more 271 volubly. Also in our model, input to the KCs emulated a fixed set of PNs constantly active 272 throughout the duration of the odor stimulus. However, in vivo, spiking patterns of PNs 273 evolve over the course of an odor presentation, and different PNs respond to the same odor 274 in different ways(Laurent & Davidowitz, 1994; Mazor & Laurent, 2005; Stopfer et al., 2003), 275 thus activating changing sets of KCs. To simulate these diverse responses, we divided the 276 model's PN population into five groups: four groups responsive to the stimulus and one 277 unresponsive. Odor-elicited spiking within each of the responsive groups started in a subset 278 of its member PNs, and then, in each successive LFP cycle, new PNs were activated (Figure 279 5e). Lacking the heterogeneity in synaptic strengths onto KCs described above, even this 280 complex activity pattern in PN population produced unrealistically synchronized bouts of 281 activity in KCs, resulting in unrealistic isolated peaks in GGN's simulated membrane 282 potential (Figure 5f). However, we found that combining heterogeneous connectivity with 283 structured PN firing patterns gave rise to GGN voltage traces that included sustained 284 depolarization and temporal dynamics more characteristic of responses we had observed in 285 vivo (Figure 5g). The distribution of firing rates of the KC population showed that, while most 286 KCs produced 0-2 odor-elicited spikes, a few KCs spiked much more (Figure 5h). Thus, our 287 analysis of GGN's voltage profile led us to predict that a few odor responses in KCs are far 288 more intense.

289 To test this in vivo, we made patch clamp recordings from 147 KCs in 114 animals, obtaining 290 results from 707 KC-odor pairs. On average, the spontaneous firing rates of these KCs were 291 very low (~0.09 Hz) and reached only somewhat higher rates during and after odor 292 termination (~0.15 and ~0.16 Hz, respectively, Figure 6a), as previously observed(Gupta & 293 Stopfer, 2014; Perez-Orive et al., 2002). Notably, though, we also found that some odor-294 elicited responses in KCs consisted of many more spikes. Figure 6b shows a representative 295 example of a hyperactive KC response, in which a 1s odor pulse elicited an average of 7 296 spikes (Figures 6c and d). Overall, the distribution of spike counts in KCs we tested was 297 clustered close to 0 but included a long rightward tail (Figure 6e), in striking agreement with 298 our prediction (Figure 5h). This result expands our view of KC activity to include a broader 299 range of odor-elicited spiking.

300 Odor evoked spiking in IG can explain GGN hyperpolarization

301 Our intracellular recordings from GGN revealed extended periods of odor-elicited 302 hyperpolarization (Figure 4), something not previously observed nor explainable by existing 303 models of GGN within its olfactory network. We hypothesized that these periods of 304 hyperpolarization might originate in the activity of IG, a neuron known to share reciprocal 305 inhibition with GGN (Figure 1a, right)(Papadopoulou et al., 2011). Specifically, we 306 hypothesized that an increase in IG activity might underlie the periods of hyperpolarization in 307 GGN, with IG's activity increase caused by disinhibition from GGN. To test this, we first tried 308 adding a simple version of IG to our model following the reciprocal connectivity plan shown 309 in Figure 1a. But, despite testing a broad range of IG properties, this configuration could not 310 generate odor-elicited hyperpolarization in GGN (data not shown). Something more was 311 needed.

The location and most properties of IG are unknown, and we were not able to identify it in our recordings. However, a previous report showed spikes in IG correlate one-to-one with IPSPs in GGN(Papadopoulou et al., 2011), suggesting we could infer IG's activity by examining GGN's membrane potential. Our recordings made *in vivo* from GGN revealed an

316 odor-elicited increase in the frequency of IPSPs in GGN's membrane potential (Wilcoxon 317 signed-rank test, N=198 pairs, W=2328.5, p << 0.001); responses from 2 animals are shown 318 in Figure 7a, and responses from 1257 trials with several odors from 47 GGNs are shown as 319 a peri-stimulus time histogram in Figures 7b and c. Assuming these IPSPs originate as 320 spikes in IG(Papadopoulou et al., 2011), these results show that IG is spontaneously active, 321 and that its responses to an odor pulse are delayed and lengthy. Further, as evident in 322 Figure 7b, IG's firing rate begins to increase before GGN's membrane potential returns to 323 baseline, suggesting that IG's odor response cannot be driven by disinhibition from GGN. 324 Therefore, we hypothesized that IG receives its odor-elicited excitatory synaptic input via a 325 different odor-driven pathway, for example, from PNs or KCs. Using our model, we could 326 indeed reproduce realistic hyperpolarization in GGN's membrane potential by adding 327 excitatory synapses to IG from either the PNs or the KCs (Figures 7d and e). Depending on 328 the PN activity pattern, our simulations produced GGN membrane potentials with 329 hyperpolarization and depolarization (Figure 7e-g).

330 A remaining question concerned the source of excitation driving spontaneous activity in IG 331 (Figure 7h, top black traces). KCs are nearly silent at rest(Gupta & Stopfer, 2014; Perez-332 Orive et al., 2002), ruling them out as the sole source of excitation to IG. PNs, though, spike 333 spontaneously because they receive direct, powerful input from spontaneously active 334 ORNs(Joseph et al., 2012), suggesting a PN-driven pathway might be responsible for 335 spontaneous activity in IG. To test this *in vivo*, we completely silenced PNs and KCs by 336 bilaterally cutting the animal's antennal nerves (Joseph et al., 2012) and then recorded 337 intracellularly from GGN. We found that spontaneous IPSPs in GGN persisted as normal in 338 preparations with silenced PNs and KCs (Figure 7h, bottom red traces), demonstrating that 339 IG's spontaneous spiking either arises intrinsically or is driven by a source other than PNs or 340 KCs.

341 Discussion

Inhibitory neurons play critical roles in regulating and shaping olfactory responses in 342 343 vertebrates and invertebrates (Kay & Stopfer, 2006). In insects, these roles are performed by 344 relatively few neurons that can be interrogated efficiently, revealing fundamental principles of 345 olfactory coding. The unique giant GABAergic neuron GGN plays a central role in structuring 346 olfactory codes in the locust mushroom body by regulating the excitability of KCs and 347 parsing their responses into rhythmic bursts. We combined intracellular recordings from 348 GGN and KCs, and developed a new morphologically detailed model of GGN as a focus of 349 analysis to investigate GGN's properties, inputs, and outputs. Further, we used a broader 350 model of the olfactory system built around GGN to explore several basic properties of the 351 olfactory network. Our new electrophysiological recordings and computational model 352 successfully reproduced the sparse activity of KCs and the membrane dynamics of GGN in 353 the locust brain while providing concrete hypotheses about how the mushroom body circuit 354 may process odor information.

355 Non-spiking interneurons in insects are often large with complex splays of neurites in 356 separate brain areas, suggesting their far-flung branches may be functionally isolated, 357 serving separate local computations (Burrows, 1981). It has been proposed that signals 358 generated within GGN's α lobe branch propagate to its calyceal branch, where they transmit 359 global inhibition to all KCs(Papadopoulou et al., 2011). But, the enormous size, extensive branching, and passive conduction characterizing GGN raised the hypothesis that GGN's α 360 361 lobe signals would attenuate to such an extent as they travel to the calyx that they would be 362 unable to effectively inhibit KCs. Our simulation of GGN's morphological and electrical 363 properties suggests that realistic levels of depolarizations of 10mv in GGN's α lobe branch 364 do indeed attenuate greatly with distance to amplitudes as low as 5mv in parts of the calyx. 365 However, earlier studies of non-spiking neurons in invertebrates showed depolarizations of 366 this amplitude should suffice to evoke neurotransmitter release. For example, (Burrows & 367 Siegler, 1978) showed that depolarizations of only about 2 mV in a non-spiking interneuron

368 in the metathoracic ganglion of the locust suffices to change the firing rate of its postsynaptic 369 motor neuron. Similarly, (Manor et al., 1997) showed in a graded synapse in the lobster 370 stomatogastric ganglion that voltage steps from -50 mV to -45 mV can reliably evoke 371 postsynaptic effects. Thus, we conclude that input from KCs at GGN's α lobe branches 372 could provide effective global inhibition to all KCs in the calyx.

373 GGN's arborizations in the calyx extend different lengths, suggesting signals arising in the α 374 lobe could attenuate more in some of its calyceal branches than in others. Our simulations indeed showed the amount of depolarization reaching GGN's distant branches varied with 375 376 their locations, but only by a few millivolts (Figure 2b). Perhaps consistent with this, APL, the 377 Drosophila analog of GGN(Lin et al., 2014) appears to provide varying levels of feedback 378 inhibition to different groups of KCs(Inada, Tsuchimoto, & Kazama, 2017). Odor-elicited 379 responses of KCs result from non-linear combinations of many factors in addition to the 380 amount of depolarization reaching presynaptic terminals of GGN; these factors include the 381 KCs' intrinsic properties, excitatory input from PNs, and the strengths of inhibitory synapses 382 from GGN. Thus, although we observed variations in the amplitudes of GGN depolarization 383 in our model's calyceal branches, they did not appear to contribute significantly to variations 384 in KC excitability. For example, KCs in the medial calyx did not consistently spike more than 385 KCs in lateral areas.

386 Our model does not address the possibility that local, reciprocal connectivity between GGN and KCs might occur in the calyx alongside global inhibition. In Drosophila, APL is known 387 388 from electron microscope image reconstructions to receive synapses from KCs in the calva. 389 possibly enabling local feedback(Eichler et al., 2017; Zheng et al., 2018). If KCs make 390 reciprocal local connections with GGN within the calyx along with convergent connections in 391 the α lobe, then the relative influence of global and local inhibition might vary with stimulus 392 intensity. We speculate that very weak olfactory stimuli that minimally activate KCs will 393 evoke in the α lobe branch of GGN only small depolarizations which would attenuate below threshold upon reaching the calyx. This would allow local inhibition to dominate, consistent 394

395 with recent observations in the Drosophila mushroom body circuit(Inada et al., 2017). In this 396 local inhibition scenario, a spiking KC would effectively inhibit only its close neighbors via 397 GGN. Combined with random connectivity from PNs, this circuitry might result in a winner-398 take-all, center-surround-type of contrast enhancement in which only the most strongly 399 driven KCs in each region of GGN's arbor can respond to an odor. On the other hand, in the 400 case of very strong olfactory stimuli (or in the absence of local KC-GGN reciprocal 401 connections in the calyx), global inhibition will dominate and KCs receiving inhibition from the 402 same region of GGN would likely fire together, reducing the contrast among their response.

403 Inhibition from GGN is known to sparsen the firing of KCs and to impose rhythmic time 404 windows on their responses (Gupta & Stopfer, 2012; Papadopoulou et al., 2011). Notably, 405 our model also revealed that feedback inhibition from GGN can expand the range of inputs 406 able to activate KCs (Figure 3). We found our isolated model KCs only generated spikes 407 when stimulated by a narrow range of current; too little current failed to evoke any response, 408 and too much current was saturating (Figure 3). In the real brain, a wide range of synaptic 409 strengths exists even within a given type of neuron, and synaptic strength can change over 410 time and with experience (reviewed in(Barbour, Brunel, Hakim, & Nadal, 2007)). It is 411 possible that ionic conductances in KCs are precisely and constantly tuned by homeostatic 412 mechanisms to match their inputs, enabling them to respond appropriately to a broad and 413 changing range of inputs (reviewed in(Marder & Goaillard, 2006)). Our results suggest that 414 feedback inhibition may also help KCs function robustly by expanding their sensitivities to a 415 wider range of inputs, enabling them to generate consistently sparse responses.

Our intracellular recordings from GGN often revealed odor-elicited periods with sustained depolarization (Figure 4), a response feature unexplainable by existing models. What inputs underly GGN's membrane potential? KCs, which provide excitation to GGN, have been shown to respond very sparsely to any given odor, with very few cells firing just one or a few spikes(Laurent & Naraghi, 1994; Mazor & Laurent, 2005; Perez-Orive et al., 2004). Our simulations showed that sparse spiking in the entire KC population cannot generate the

422 large sustained depolarizations we observed in vivo in GGN. When we adjusted the 423 excitatory and inhibitory inputs to the KCs to generate a few spikes upon activation of a fixed 424 set of PNs by odorant, the KC population responded with unrealistically strong bursts of 425 synchronous activity, resulting in unrealistic prominent peaks in GGN's membrane potential. 426 Simply increasing the excitability of KCs in a network driven by odor-evoked oscillatory 427 spiking in a fixed set of PNs succeeded in generating realistic GGN responses, but also 428 elicited spiking in an unrealistically large number of KCs in the model. We found we could 429 solve this problem by introducing variability in the strength of the synapses onto KCs (Figure 430 S4). Further, when we drove KCs with more realistic, heterogeneous patterns of excitatory 431 input from PNs, the resulting responses of GGN and the KC population generally matched 432 our observations in vivo (Figure 5). Notably, close inspection of the revised model's KC odor 433 response distribution revealed a small subset of responses with more spiking than had 434 previously been documented, thus predicting some KC responses in vivo are much stronger 435 than previously reported. Notably, our patch recordings from neurons confirmed to be KCs 436 by dye fills revealed the predicted distribution of responsiveness (Figure 6e). KCs generating 437 especially strong responses were not localized in any particular part of the calyx, nor did 438 they feature distinguishing morphologies (data not shown). It is unclear why hyperactive KC 439 responses were not previously observed in the locust mushroom body, but one possibility is 440 that unusually active neurons recorded here (but not filled) were misidentified as other cell 441 types. This small group of over-active KC responses appears to play a key role in olfactory 442 processing by driving sustained global inhibition.

Our intracellular recordings from GGN also revealed more elaborate membrane potential
temporal dynamics than previously reported, including prolonged stimulus-dependent
periods of hyperpolarization, that varied with odor and animal. In our model, simple
reciprocal inhibition of GGN by the inhibitory neuron IG could not reproduce these features.
Rather, realistic hyperpolarization of GGN's membrane potential could be caused by odorelicited activity in the inhibitory neuron IG (Figure 8). The direct source of odor-elicited

excitatory drive to IG is unknown, but could, in principle, be traced to KCs. Indeed, a version
of our model in which all KCs synapse upon IG reliably reproduced realistic odor-elicited
hyperpolarizations in GGN. Why are these hyperpolarizations elicited by only some odors in
some animals, as we saw *in vivo* (Figure 4)? Our simulations suggest that odor-specific
temporal pattern in the PN population's response(Stopfer et al., 2003) can explain this
phenomenon (Figure 7e-g).

In summary, we used biophysically detailed simulations in combination with *in vivo* electrophysiology to explore the olfactory circuit in the locust mushroom body. Our intracellular and patch recordings revealed new features of GGN, a neuron that plays a central role in shaping olfactory responses, and of the KC population, which we show to generate a small subset of hyperactive responses, as predicted by our model. These results extend our understanding of the olfactory system, highlighting ways different components interact, and providing new predictions for additional research.

462 Materials and Methods

463 Dissection and electrophysiology

464 Newly eclosed adult locusts of both sexes picked randomly from our crowded colony were 465 immobilized and the brain was exposed, desheathed and superfused with locust saline as described before(Brown et al., 2005). No sample size estimation was done beforehand. As 466 467 this was an exploratory study and odor response was specific to each GGN and odor, we 468 tried to collect data from as many animals as we could. We commonly obtained recordings 469 from one GGN in each animal, mostly one in a day, over a year. The results were similar 470 months apart. To record from GGN, a sharp glass micropipette filled with 2 or 3M potassium 471 acetate with 5% neurobiotin was inserted into the peduncle region of the mushroom body; 472 when impaled, GGN could be identified by its characteristic pattern of IPSPs in the voltage 473 record (Figure 7h). At the end of the recording session, neurobiotin was injected into the cell

iontophoretically using 0.2 nA current pulses at 3 Hz for 10 to 20 minutes, and the cell's

475 identity was confirmed by subsequent imaging.

476

477 To test whether IPSPs in GGN originate from spontaneous activity in PNs, we first silenced

the PNs by cutting both antennal nerves at the base(Joseph et al., 2012) and then searched

479 for GGN, which could still be identified by its pattern of IPSPs and by its morphology,

480 revealed by subsequent filling with neurobiotin and imaging.

481

For patch clamp recordings from KCs, the initial dissection was performed as described 482 483 above. Patch pipettes were pulled to between 7 and 12 M Ω , filled with locust internal 484 solution(Laurent, Seymour-Laurent, & Johnson, 1993) as well as a neural tracer for 485 subsequent histology (either 12 mM neurobiotin for later conjugation with an Avidin-Alexa 486 complex, or 20 µM Alexa Fluor tracer with absorption wavelengths of 488, 568 or 633). 487 Patch recordings were made in current clamp mode, and data was only analyzed if the 488 observed membrane potential was within the previously reported range for KCs (-55 to -65 mV) and if either LFP or membrane potential oscillations were observed in response to odor 489 490 stimulation. Firing rates were obtained by smoothing the PSTH with a 100 ms SD gaussian 491 window.

492

493 Stimulus delivery

For GGN recordings, odor pulses were delivered to the ipsilateral antenna as described in
(Gupta & Stopfer, 2012). The odorants included 1-hexanol at dilutions of 1% v/v, 1-hexanol,
hexanal, methyl benzoate, benzaldehyde, and cyclohexanone mixed at the dilution of 10%
v/v in mineral oil, and 100% mineral oil.

498

499 For KC recordings, the following odors were delivered similarly: 1-hexanol, hexanal,

500 cyclohexanol, 1-octananol, citral, geraniol, ethyl butyrate, 1-butanol, benzaldehyde, eugenol,

- 3-methyl-2-butenol, methyl jasmonate, decanal, methyl salicylate, linalool, limonene, pentyl
 acetate, (all 10% v/v in mineral oil, except methyl salicylate and limonene, at 40% each) and
 100% mineral oil.
- 504
- 505 Histology and immunostaining
- 506 Brains were dissected from the head capsule and fixed in 4% paraformaldehyde overnight,
- 507 then conjugated with Avidin-Alexa 568 or Avidin-Alexa 488. Some brains were first
- immunostained with mouse nc82 primary antibody (DSHB Cat# nc82, RRID:AB_2314866,
- 509 deposited to the DSHB by Buchner, E.) and Alexa 568 conjugated anti-mouse IgG
- 510 secondary antibody(Shimizu & Stopfer, 2017).
- 511
- 512 Imaging and neuronal tracing
- 513 Brains were dehydrated in an ethanol series and cleared with methyl salicylate or
- 514 CUBIC(Susaki et al., 2014), mounted in methyl salicylate or mineral oil respectively, and
- 515 imaged with a Zeiss LSM 710 confocal microscope. Two GGNs were traced in detail from
- 516 3D image stacks using NeuroLucida software (MBF Bioscience, Williston, Vermont). The
- 517 traces were converted to SWC format for further processing and cleanup using
- 518 NLMorphologyConverter (www.neuronland.org). The two traces were very similar; the one
- 519 obtained at higher resolution was used for reconstruction and modeling.
- 520

521 Statistics

- 522 For each of 198 GGN-odor pairs, average spike rates were calculated over 5 trials in
- 523 windows beginning 2 s before, and 2 s after, odor presentations. Wilcoxon-signed rank tests
- 524 from scipy package were used to compute the statistic and the two-sided *p*-value.

526 Computational model

527 GGN morphologies in SWC format were imported into NEURON and converted into passive 528 models in NEURON's hoc format. The single compartmental KC model reported by 529 (Wüstenberg et al., 2004) was translated manually into a NEURON model. The resting 530 membrane potential was set to -51 mV, as we have observed in vivo. The passive reversal 531 potential of the KCs was set to -70 mV. Custom Python scripts were written to set up 532 network models and simulation experiments using NEURON's Python interface. The 533 simulations were run on NIH's Biowulf supercomputer cluster (http://hpc.nih.gov) and 534 simulation results were saved in HDF5 based NSDF format(Ray, Chintaluri, Bhalla, & 535 Wójcik, 2015) and later analyzed with custom Python scripts. 536

537 PN activity model with a fixed responsive population

538 Modeled PN spike train rates were based on firing statistics reported in Figure 2c-e in this publication: ⁷ from which we infer 77% of PNs are spontaneously active. Odor presentations 539 540 were set to evoke spiking in ~20% of PNs, each spiking at an average rate of 20 Hz(Jortner 541 et al., 2007; Mazor & Laurent, 2005). A 20 Hz sinusoid with amplitude 0.4 times the average 542 spiking rate was further superimposed on odor-elicited spiking to model oscillatory activity 543 generated in the antennal lobe. Based on our own observations in vivo we set 10% of 544 spontaneously active PNs to respond with inhibition to odor presentations. We used a non-545 homogeneous Poisson generator to create the spike trains based on these rates. 546

547 PN activity model with a shifting responsive population

548 To test the significance of varying temporal structure in PN firing patterns, we assumed

549 ~30% of the PNs were unresponsive to odors, and divided the other 70% into 4 equally

sized groups with the following odor-elicited sequences of excitation (E) and inhibition (I):

- 551 EEI, EIE, IEI and IIE, with the last epoch occurring upon stimulus offset(Laurent &
- 552 Davidowitz, 1994). Within each group, excitation epochs featured shifting sets of active PNs,

with new PNs recruited during each LFP cycle⁷. Each group started its excitatory epoch with
activation of 70% of its members and 10% were recruited in each of the next three LFP
cycles. In this scheme at most ~30% of PNs were active at any given time during odor
presentations.

557

558 Connectivity from GGN to KCs

Each KC received one graded inhibitory synaptic input from a randomly assigned point on
GGN's calyceal branches. The strength of each synapse was adjusted to keep the KC's
membrane potential close to -60 mV when bombarded by spontaneous activity from PNs, as
observed *in vivo*(Joseph et al., 2012). The graded synapse was modeled as a NEURON
mechanism based on published descriptions(Manor et al., 1997; Papadopoulou et al., 2011).
In some simulations the individual synaptic conductances were selected from a lognormal
distribution with the mean adjusted to produce realistic KC activity.

566

567 Connectivity from PNs to KCs

Half of the PN population was randomly and independently selected as presynaptic partners for each KC. If two subsets of size *m* and *n* are randomly and independently selected from a set of size *q*, the expected size of their intersection is s = m * n / q. Thus, with 800 PNs and each KC receiving input from 400 PNs, the expected number of PNs shared by any two KCs is 400 * 400 / 800 = 200, i.e., they share about 50% of their presynaptic PNs, as shown *in vivo*(Jortner et al., 2007). In some simulations the synaptic conductances were selected from a lognormal distribution with the mean adjusted to produce realistic KC activity.

575

576

577 IG model and connectivity

578 To simulate IG, we used a single compartmental Izhikevich-type model of a regular spiking

579 (RS) pyramidal cell from the Model DB repository

580 [https://github.com/ModelDBRepository/39948] modified to include graded synaptic input 581 from GGN. To model IG's spontaneous firing, sufficient current was injected to it to generate 582 about 7 spikes/s. A single inhibitory synapse with -80 mV reversal potential connected IG to 583 one of GGN's basal dendrite segments. The strength and time constants for this synapse 584 were adjusted to produce IPSP amplitudes matching those we observed in vivo. The same 585 GGN segment was connected to IG via a graded synapse. In some simulations either the 586 output of all PNs or the output of all KCs were connected to IG via excitatory synapses. The 587 synaptic weights from KCs to IG were selected from a lognormal distribution. 588 Data Analysis 589

590 Most analysis and 3D visualization were carried out with custom Python scripts using

591 published modules including numpy, scipy, networkx, matplotlib, h5py, pandas and

592 scikitslearn.

593 Analyses of patch clamp recordings from KCs were carried out with custom MATLAB scripts. 594

595 Data and Software Availability

596 The morphological reconstruction of GGN will be made publicly available in neuromorpho 597 repository (<u>http://neuromorpho.org/</u>). The morphology, electrophysiology and simulation data 598 used in this manuscript are available at Dryad (<u>https://doi.org/10.5061/dryad.f3t3jf0</u>).

599 The code for setting up and simulating the model is available on request and will be made 600 publicly available in ModelDB repository (<u>https://senselab.med.yale.edu/ModelDB/</u>). Scripts 601 for data analysis are available at github: https://github.com/subhacom/mbnet_analysis.git.

602

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- 615 Author contributions: S.R. and M.S. designed the study. Z.A. carried out KC
- 616 electrophysiology and analyzed data. S.R. carried out GGN electrophysiology, developed
- 617 computational models and analyzed data. S.R. and M.S. wrote the manuscript.

618

- 619 **Competing interests:** The authors declare no competing interests.
- 620
- 621

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794 Figure legends

795 Figure 1 GGN is a very large neuron, one per hemisphere, spanning a large portion of the 796 locust brain. (a) Left hemisphere: Dye filled GGN (green) in a locust brain (magenta, 797 visualized with nc82 antibody) with an overlaid KC tracing (orange, filled in a different brain). 798 Dorsal: towards the viewer; ventral: into the page). Right hemisphere: Circuit diagram of the 799 locust olfactory system. Arrows show known synaptic connections, + excitatory, - inhibitory. 800 Scale bar: 200 µm. (b) Very thin, feather-like neurites from GGN wrap around and penetrate 801 the peduncle of the mushroom body, not included in our reconstruction. (c) GGN's neurites 802 in the calyx have many bouton-like protrusions (d) whereas GGN's α lobe branches are 803 relatively smooth. (b-d) scalebars: 100 µm, (e) 3D reconstruction of the same neuron shown in panel a viewed from (i) ventral and (ii) posterior side of the brain. Major branches shown 804 805 in different colors. LCA: lateral calyx, MCA: medial calyx, LH: lateral horn, a: anterior, p: 806 posterior, d: dorsal, v: ventral, l: lateral and m: medial.

807 **Figure 2** Passive voltage spread through GGN. (a) Simulation schematic: GGN's α lobe 808 branch was clamped at its stem to -40 mV (from a holding voltage of -51mV). (b) Conditions 809 described in panel a lead to different steady state depolarizations of the GGN model at 810 different locations; color indicates voltage change from resting potential; axial resistivity 811 RA=100 Ω cm; membrane resistivity RM=33 k Ω cm2. (c) Violin plots showing distribution of 812 depolarization in the α lobe and the calvceal dendrites of GGN for conditions described in 813 panel a; width of gray area indicates density, white line median, and whiskers data range. (d) 814 Schematic of simulation of multiple, random synaptic inputs to GGN: 500 synapses were 815 connected to GGN's α lobe branch. (e) Bottom: raster plot of incoming spike times at all 500 816 synapses. The spikes arrived at each synapse at random times at linearly decreasing rate, 817 starting with 20/s down to 0 after 500 ms. Top: for conditions shown in panel d, membrane 818 potentials at randomly sampled terminal neurites in different regions of GGN. (f) Violin plots 819 of peak depolarizations in the α lobe dendrites and the calyceal dendrites in model

described in panel d. (**g**) Violin plots of distribution of depolarizations in the calyx for different values of axial resistivity (RA, bottom) and membrane resistivity (RM, right) for the voltage clamp simulation described in panel a. Lines connect the median results for specified RMs (right).

824 Figure 3 Feedback inhibition from GGN extends the dynamic range of KCs. (a) Model 825 schematic: A single KC sends 50,000 excitatory synapses with random delays of 0-60 ms 826 into GGN's α lobe branch. The KC receives feedback inhibition via a graded synapse from 827 GGN's calyceal branch. A step current is injected into the KC from 500-3000ms (the end of 828 simulation). (b) Comparison of membrane potential evoked by current pulses of different 829 amplitudes in isolated KC (left) and KC with feedback inhibition (right). As the amplitude of 830 the current pulse increases, the KC's spiking first increases, and then, as the membrane 831 potential nears saturation, decreases. (c) Comparison of the number of spikes evoked in KC 832 with and without feedback inhibition during the 2500 ms current step.

Figure 4 *In vivo*, GGN's responses to odors vary with odor and animal. Examples from 3
animals and 2 odors (horizontal gray bars, 1 s) (black traces: average of 5 trials, gray:
standard error of the mean, data low-pass filtered at 49 Hz). Response features include
depolarization or hyperpolarization upon stimulus onset and/or offset, and depolarization or
hyperpolarization evoked by different odors in the same GGN.

838 Figure 5 Tuning the olfactory network by reference to GGN's olfactory responses required 839 heterogeneous synaptic strengths onto KCs and structured patterns of activity in PNs, 840 predicting a small proportion of hyperactive KC responses. (a) Schematic of mushroom body 841 network model. Each of the 50,000 KCs receives input from 50% of the 830 PNs, which are 842 modeled as spike trains. All KCs excite GGN in its α lobe branch and receive inhibition from 843 a random calvceal branch of GGN. (b-d) Model with simplified, homogenous firing patterns 844 in PNs and uniform synaptic strengths generates unrealistic membrane potential in GGN. (b) 845 Raster plot of model PN spike trains (67 shown); dots in each row mark spike times in a PN.

846 (c) Raster plot of spike trains evoked in the KCs (397 shown) when all of them receive 847 identically strong inhibitory connections from GGN. (d) Unrealistic membrane potential in 848 GGN features a few peaks corresponding to highly synchronized bouts of activity in KCs. (ef) Model in which subpopulations of PNs have different temporal patterns of spiking during 849 850 and after odor stimulation generates unrealistic membrane potential in GGN. (e) Rasters 851 show different firing patterns in different PNs. (f) Simulation of model with PN activity pattern 852 in panel e and uniform synaptic strengths onto KCs generates unrealistic membrane 853 potential in GGN. (g) Simulated membrane potential of GGN in a model with both structured 854 PN activity patterns in panel e and heterogeneous synaptic strengths gives rise to sustained 855 depolarization of GGN similar to that observed in vivo (e.g. Figure 4 animal 1). Dark gray 856 bar: 1 s odor stimulation; light gray bar: 200 ms "off response" period. (h) Histogram of KC 857 firing rates in the network model giving the realistic result shown in panel g; odors evoke in 858 most KCs 0-2 spikes/s, but in a few KCs higher firing rates.

Figure 6 *In vivo*, some KC responses are hyperactive, as predicted. (a) KC firing rate
averaged over 707 KC-odor pairs. Shaded region indicates standard error of the mean.
Black horizontal bar: 1 s odor stimulation. (b) A hyperactive response KC filled with dye
(mushroom body calyx and pedunculus outlined with dashed lines (scale bar: 50 μm) and (c)
its recorded membrane potential in response to odor stimulus, and (d) its average firing rate
elicited by this stimulus. (e) Histogram of average number of spikes in KCs across trials
upon odor presentation.

Figure 7 An additional, unidentified olfactory pathway to IG is needed to explain odor-elicited
hyperpolarization in GGN. (a) *In vivo* recordings of GGN's membrane potential from two
animals showing IPSPs (arrowheads) believed to originate as spikes in IG. Vertical scale
bar: 10 mV. (b) Peristimulus time histogram (PSTH) shows IPSP peak times from 1257
odor-trials across 47 GGNs, presumably reflecting spikes in IG. Black horizontal bar: odor
presentation in panels a and b, which share the time axis. (c) Same as panel b but showing
full responses. (d) Schematic of model with IG receiving direct excitation from KCs and

873 reciprocal inhibition with GGN. (e) Top: simulated GGN membrane potential including odor-874 elicited hyperpolarization mimics responses observed in vivo (e.g. Figure 4, Animal 3, 875 hexanal). Bottom: corresponding simulated IG membrane potential. This simulation included 876 a 200 ms synaptic delay from KCs to IG. The PN activity patterns were like those shown in 877 Figure 5. (f-g) Varying the temporal pattern of PN population activity can produce different 878 response pattern in the same network as e. (f) Raster plot of PN activity with a different 879 temporal pattern from that in e. (g) Top: simulated GGN membrane potential including odor 880 evoked de- and hyperpolarization (similar to Figure 4, Animal 1 hexanal). Bottom: 881 corresponding simulated IG membrane potential. (h) Spontaneous activity in IG does not 882 originate in the antennal lobe. Top two black traces show spontaneous IPSPs in GGN's 883 membrane voltage from two animals with intact olfactory systems. The bottom two red traces 884 are from the left and the right GGN in another animal in which the antennal lobes had been 885 silenced by cutting both antennal nerves. Vertical scale bar 5 mV, horizontal scale bar 1 s. 886 Figure 8 Updated olfactory connectivity model where odor responses in the KC population 887 are gated by feedback inhibition from GGN and inhibition of GGN via odor evoked spiking in

888 IG, which itself receives input from an unknown olfactory pathway.

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- 890 Supplemental Information
- 891

892 Video S1. Related to Figure 1: 3D view of the confocal stack of the dye filled GGN in893 Figure 1a.

894 Video S2. Related to Figure 2: 3D view of depolarizations (color coded spheres) at various
895 locations in GGN arbor in simulation described in Figure 2a.

Figure S3. Related to Figure 2: KC activity vs GGN voltage deflection in simulations where
all KCs received identical PN input. GGN->KC maximum conductance 0.7 nS and PN-

898 > KC maximum conductance 3.7 pS, GGN->KC maximum conductance 0.5 nS and PN-899 > KC maximum conductance 3.7 pS, GGN->KC maximum conductance 0.9 nS and PN-> KC maximum conductance 4.0 pS, ____ GGN->KC maximum conductance 0.9 nS and 900 901 PN-> KC maximum conductance 4.5 pS. GGN segments were grouped by peak 902 depolarization from resting potential and the total number of spiking KCs postsynaptic to 903 these segments (top) or the total number of spikes in the KCs postsynaptic to these 904 segments (bottom) were normalized by the total number of spiking and nonspiking KC post 905 synaptic to these segments.

- 906 **Figure S4. Related to Figure 5:** Model with steady activity in a fixed set of PNs (as in
- 907 Figure 5b) can produce sustained depolarization of GGN when the synaptic strengths are
- 908 lognormally distributed. Gray: 1 s odor stimulus.





















