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### 1 Gradients in the cerebellar cortex enable Fourier-like transformation and

### 2 improve storing capacity

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#### 20 Abstract

21 Cerebellar granule cells (GCs) making up majority of all the neurons in the 22 vertebrate brain, but heterogeneities among GCs and potential functional 23 consequences are poorly understood. Here, we identified unexpected gradients 24 in the biophysical properties of GCs. GCs closer to the white matter (inner-zone 25 GCs) had higher firing thresholds and could sustain firing with larger current inputs. Dynamic clamp experiments showed that inner- and outer-zone GCs 26 27 preferentially respond to high- and low-frequency mossy fiber inputs, 28 respectively, enabling to disperse the mossy fiber input into its frequency 29 components as performed by a Fourier transformation. Furthermore, inner-zone 30 GCs have faster axonal conduction velocity and elicit faster synaptic potentials in 31 Purkinje cells. Neuronal network modeling revealed that these gradients improve 32 spike-timing precision of Purkinje cells and decrease the number of GCs required 33 to learn spike-sequences. Thus, our study uncovers biophysical gradients in the 34 cerebellar cortex enabling a Fourier-like transformation of mossy fiber inputs.

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#### 35 Introduction

Digital audio compression (e.g., 'MP3'; Javant et al., 1993) and image 36 37 compression (e.g., 'JPEG'; Wallace, 1992) rely on Fourier transformations, which 38 decompose a signal (e.g., sound amplitude as a function of time or image 39 intensity as a function of space) into its frequency components (power as a 40 function of frequency). By storing these frequency components with different 41 precision depending on psychophysical demands of hearing and seeing, the 42 overall storage capacity can be increased dramatically. In principle, neuronal 43 networks consisting of neurons with varied electrophysiological properties could 44 be suitable for Fourier-like transformations of information. This could benefit 45 processing in neuronal circuits by increasing the signal-to-noise ratio of input 46 signals or by selecting only relevant spectral components of a signal. 47 Interestingly, there are indications that for example pyramidal neurons in visual 48 cortex and in the hippocampus are tuned to different inputs or different input 49 strengths (Cembrowski and Spruston, 2019; Fletcher and Williams, 2019; Soltesz 50 and Losonczy, 2018). However, whether these neuronal networks perform a 51 Fourier-like transform on their inputs remains unknown.

52 Controlling the timing and precision of movements is considered to be one of the 53 main functions of the cerebellum. In the cerebellum, the firing frequency of 54 Purkinje cells (PCs) (Heiney et al., 2014; Herzfeld et al., 2015; Hewitt et al., 55 2011; Medina and Lisberger, 2007; Payne et al., 2019; Sarnaik and Raman, 56 2018; Witter et al., 2013) or the timing of spikes (Brown and Raman, 2018; 57 Sarnaik and Raman, 2018) have been shown to be closely related to movement. 58 Indeed, cerebellar pathology impairs precision in motor learning tasks (Gibo et 59 al., 2013; Martin et al., 1996) and timing of rhythmic learning tasks (Keele and 60 lvry, 1990). These functions are executed by a remarkably simple neuronal 61 network architecture. Inputs from mossy fibers (MFs) are processed by GCs and 62 transmitted via their parallel fiber (PF) axons to PCs, which provide the sole 63 output from the cerebellar cortex. GCs represent the first stage in cerebellar 64 processing and have been proposed to provide pattern separation and

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65 conversion into a sparser representation of the MF input (recently reviewed by 66 (Cayco-Gajic and Silver, 2019). These MF inputs show a wide variety of signaling 67 frequencies, ranging from slow modulating activity to kilohertz bursts of activity 68 (Arenz et al., 2008; Rancz et al., 2007; Ritzau-Jost et al., 2014; van Kan et al., 69 1993). Interestingly, in cellular models of the cerebellum, each MF is considered 70 to be either active or inactive with little consideration for this wide range of 71 frequencies (Albus, 1971; Marr, 1969). Furthermore, in these models, GCs are 72 generally considered as a uniform population of neurons.

73 Here we show that the biophysical properties of GCs differ according to their 74 vertical position in the GC layer. GCs located close to the white matter (inner-75 zone) selectively transmit high-frequency MF inputs, have shorter action 76 potentials and a higher voltage threshold to fire an action potential compared with 77 GCs close to the PC layer (outer-zone). This gradient of GC properties enables a 78 Fourier-like transformation of the MF input, where inner-zone GCs convey the 79 high-frequency and outer-zone GCs the low-frequency components of the MF 80 input. These different Fourier-like components are sent to PCs by specialized 81 downstream signaling pathways, differing in PF axon diameters, action potential velocity and PC excitatory postsynaptic potential (EPSP) kinetics. Computational 82 83 simulations show that the biophysical gradients in the GC and molecular layer 84 significantly reduce the number of GCs required to learn a sequence of firing frequencies and accelerate the time required to switch between firing 85 86 frequencies.

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#### 88 Results

#### 89 A gradient in the biophysical properties of inner- to outer-zone GCs

90 To investigate whether GCs are tuned for different frequencies we first 91 investigated the intrinsic membrane properties of GCs from different depths 92 within the GC layer in lobule V of the cerebellum of P21-30 mice. We divided the 93 GC layer into three zones and performed whole-cell current-clamp recordings

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94 from inner- (closest to the white matter), middle- and outer-zone (closest to PCs) 95 GCs (Figure1A.B). Upon current injection, inner-zone GCs were less excitable 96 compared with outer-zone GCs (Figure 1C). On average, the relationship 97 between the mean number of action potentials and the injected current were 98 surprisingly different for inner- and outer-zone GCs (Figure 1D): inner-zone GCs 99 needed higher current injections to fire an action potential (inner:  $56.8 \pm 2.6$  pA 100 vs. middle: 51.2 ± 2.0 pA vs. outer: 39.4 ± 2.0 pA; n = 38, 31, and 38, 101 respectively; P<sub>ANOVA</sub> < 0.0001; Figure 1E) and to achieve the maximum firing rate 102 compared with middle- and outer-zone GCs (inner: 224.6 ± 9.8 pA vs. middle: 103 190.8 ± 9.6 pA vs. outer: 174.3 ± 9.0 pA, respectively: PANOVA = 0.0007; Figure 104 **1F**). Consistently, inner-zone GCs had a more depolarized threshold for action 105 potential generation compared with middle- and outer-zone GCs (-38.0 ± 0.7 mV 106 vs.  $-38.2 \pm 0.8$  mV vs.  $-41.4 \pm 0.6$  mV; P<sub>ANOVA</sub> = 0.001; Figure 1G) and a lower 107 input resistance (486 ± 27 M $\Omega$  vs. 494 ± 27 M $\Omega$  vs. 791 ± 63 M $\Omega$ ; P<sub>ANOVA</sub> = 108 <0.0001; Figure 1H). Furthermore, the capacitance of inner-zone GCs was 109 significantly larger compared to the outer-zone GCs (inner: 5.8 ± 0.2 pF vs. 110 middle: 5.8  $\pm$  0.2 pF vs outer: 4.6  $\pm$  0.1 pF; P<sub>ANOVA</sub> = <0.0001 Figure 1I). In 111 agreement with these findings we observed depolarization block in inner-zone 112 GCs at higher current inputs than for outer-zone GCs (Figure 1C,D). 113 Furthermore, a larger delay of the first spike was observed in inner- compared 114 with outer-zone GCs ( $P_{T-Test} = 0.01$ ; Figure 1J;  $P_{ANOVA} = 0.0001$ ; Figure 1K). The 115 delay with 60 pA current injection was  $48 \pm 6$  ms for inner-,  $38 \pm 4$  ms for middle-, 116 and  $23 \pm 2$  ms for outer-zone GCs (n = 32, 25, and 37, respectively; note that 6 117 out of 38 inner-zone GC did not fire an action potential at 60 pA). Finally, the 118 action potential half-width of GCs differed significantly between the three zones 119 (inner:  $122 \pm 2 \mu s v s$ . middle:  $137 \pm 4 \mu s v s$ . outer:  $143 \pm 4 \mu s$ ;  $P_{ANOVA} = 0.0001$ ; 120 Figure 1L).

To test whether these gradients are specific to lobule V, we investigated GCs in lobule IX. Here, we observed very similar gradients to lobule V (**Figure 1—figure supplement 1**). In short, outer-zone GCs were more excitable and had broader spikes compared with inner-zone GCs. Interestingly, the absolute values

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125 between lobule V and IX differed (Figure 1—figure supplement 1), consistent 126 with previously described differences in, e.g., the firing frequency in vivo between 127 these two lobules (Witter and De Zeeuw, 2015a; Zhou et al., 2014) and in the 128 differential density of Kv4 and Cav3 channel expression in GCs across different 129 lobules (Heath et al., 2014; Rizwan et al., 2016; Serôdio and Rudy, 1998). Taking 130 the large functional difference between spino- and vestibulo-cerebellum into 131 account (Witter and De Zeeuw, 2015b), these data suggest that different 132 biophysical properties of GCs is likely a conserved mechanism throughout the 133 entire cerebellar cortex, potentially tuning GCs to different frequencies.

134 Development can have large effects on the physiology of neurons, and GCs in 135 particular undergo profound changes during development (Dhar et al., 2018; 136 Lackey et al., 2018). To exclude confounding effects of developmental stage, we 137 tested whether these gradients were also present at a later developmental stage. 138 Recordings obtained from GCs in lobule V in animals between 80 and 100 days 139 of age showed the very similar gradients as in young animals (Figure 1—figure 140 supplement 2). Together, these data show a prominent gradient in the 141 electrophysiological properties of GCs over the depth of the granule cell layer, 142 and that this gradient can consistently be found in different lobules and ages.

#### 143 Voltage-gated potassium currents are larger at inner-zone GCs

144 To investigate possible causes for the gradient in the biophysical properties, we 145 investigated voltage-gated potassium (Kv) currents by performing voltage-clamp 146 recordings in outside-out patches from somata of inner- and outer-zone GCs in 147 lobule V (Figure 2A). The maximum Kv current was significantly higher in inner-148 zone GCs (282  $\pm$  29 pA, n = 48) compared with outer-zone GCs (221  $\pm$  28 pA, n 149 = 54,  $P_{Mann-Whitney}$  = 0.02; Figure 2B). Neither the steady-state activation curve 150 (Figure 2C) nor the degree of inactivation (Figure 2D) was different between the 151 two GC populations. Furthermore, steady-state inactivation, which was 152 investigated with different holding potentials, was similar between inner- and 153 outer-zone GCs (Figure 2-figure supplement 1). These data suggest that 154 inner- and outer-zone GCs have a similar composition of Kv channels, but inner-

155 zone GCs have a higher Kv channel density. The here observed larger Kv 156 currents in inner-zone GCs are consistent with the short action potential duration 157 of inner-zone GCs (cf. Figure 1). Thus, our data provide a biophysical 158 explanation for the observed gradient in GC properties.

#### 159 **MF inputs are differentially processed by inner and outer GCs**

160 The gradient within the GC layer creates an optimal range of input strengths for 161 each GC. To test how this gradient impacts the processing of synaptic MF inputs, 162 we performed dynamic clamp experiments to test whether different MF input 163 frequencies differentially affect spiking in inner- and outer-zone GCs (Figure 3A). 164 We first recorded excitatory postsynaptic currents (EPSC) from GCs located at 165 inner- or outer-zone of lobule V after single MF stimulation. We found no 166 significant differences in the amplitude nor in the kinetics of EPSCs in inner- and 167 outer-zone GCs (Figure 3—figure supplement 1).

168 Individual MFs span the entire depth of the GC layer, contacting both inner- and 169 outer-zone GCs (Krieger et al., 1985; Palay and Chan-Palay, 1974). 170 Furthermore, GCs are electronically extremely compact neurons and can be 171 considered as a single compartment (D'Angelo et al., 1993; Delvendahl et al., 172 2015; Silver et al., 1992). Therefore, we could use the dynamic clamp technique 173 to implement the conductance of identical MF signals in inner- and outer-zone 174 GCs based on the measured EPSC kinetics. We first applied input of a single MF 175 with Poisson-distributed firing-frequencies ranging between 30 and 500 Hz for 176 300 ms duration while changing the resting membrane potential to simulate the 177 large variability of membrane potential of GCs observed in vivo (Chadderton et 178 al., 2004). In line with the observed gradients in the electrophysiological 179 properties of GCs, inner-zone GCs fired fewer action potentials compared with 180 outer-zone GCs in response to low-frequency MF inputs at a membrane potential 181 of ~-90 mV (Figure 3B,C). In contrast, inner-zone GCs fired more action 182 potentials compared with outer-zone GCs in response to high-frequency MF 183 inputs at a membrane potential of ~-70 mV. In vivo, such a depolarization would 184 be caused by less inhibition and/or additional MF inputs. These data suggest that

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185 outer- and inner-zone GCs are specialized for low- and high-frequency MF186 inputs, respectively.

#### 187 Fourier-like transformation of MF input frequency

188 To further test whether inner- and outer-zone GCs can extract different frequency 189 components from a MF input signal, which would resemble a Fourier-190 transformation, we varied the MF input frequency sinusoidally between 30 and 191 300 Hz (Figure 4A). At a holding potential of -70 mV, inner-zone GCs responded 192 preferentially to high-frequency MF inputs up to 300 Hz, while outer-zone GCs 193 responded preferentially to low-frequency inputs up to 100 Hz. To estimate the 194 optimal frequency at which inner- and outer-zone GCs preferentially fire action 195 potentials, we calculated the phase angle (see Methods). The mean phase 196 angle, at which GC preferentially fired, was  $145.9 \pm 10.4^{\circ}$  for inner-zone (n = 13) 197 and  $102.5 \pm 18.3^{\circ}$  for outer-zone GCs (n = 9) (P<sub>T-TEST</sub> = 0.04), representing an 198 average firing frequency of 217 and 100 Hz for inner- and outer-zone GCs, 199 respectively. Thus, the gradient in the biophysical properties enables the 200 cerebellar GC layer to split incoming MF signals into different frequency bands 201 and thereby to perform a Fourier-like transformation of the compound MF input 202 signal.

#### 203 The position of PFs is correlated with the position of GC somata

204 A Fourier-like transformation in the GC layer (i.e. a separation of the spectral 205 components of MF signals) could be particularly relevant if downstream 206 pathways are specialized for these spectral components. Early silver-stainings 207 and drawings from Ramón y Cajal indicate that inner-zone GCs give rise to PFs 208 close to the PC layer and outer-zone GCs give rise to PFs close to the pia 209 (Eccles, 1967; Ramón y Cajal, 1911 but see Espinosa and Luo, 2008; Wilms and 210 Häusser, 2015). To test this possibility, we examined the ascending and parallel 211 branches of the GC axon. First, we investigated whether there is a correlation 212 between the relative positions of the PF in the molecular layer and the GC 213 somata in the GC layer. Dil was injected in vivo into the GC layer to label GCs 214 and their axons. Several GCs were clearly stained 24h after Dil injection (Figure

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215 5A), and the position of their soma and PF in the cerebellar cortex could be 216 measured (Figure 5B-D). Even though the length of the ascending GC axon 217 showed considerable variation (196  $\pm$  5.5 µm, range: 144 to 291 µm, n = 39 218 axons in n = 6 mice), after normalization for the thickness of the molecular and 219 GC layers, GC soma position was significantly correlated with the position of the bifurcation in the GC axon (Figure 5C,D; R<sup>2</sup>=0.86, P<0.001). These data show 220 221 that inner- and outer-zone GCs preferentially give rise to inner- and outer-zone 222 PFs, respectively.

# 223 Inner-zone PFs have larger diameter and higher action potential224 propagation velocity

225 Next, we tested whether PFs, like GCs, have different properties depending on 226 the position within the molecular layer. First, we compared the PF diameters in 227 electron microscopic images of parasagittal sections of mouse cerebellum lobule 228 V and found significantly larger diameters for inner-zone PFs compared to 229 middle- and outer-zone PFs (182  $\pm$  2.6 nm, n = 703 vs. 159  $\pm$  2.0 nm, n = 819 vs. 230 145  $\pm$  1.7 nm, n = 1085 Figure 6A-C; P<sub>ANOVA</sub> < 0.0001), which is in agreement 231 with previous investigations reported in cat (Eccles et al., 1967), monkey (Fox 232 and Barnard, 1957), and rats (Pichitpornchai et al., 1994).

233 Axonal diameter is often a strong predictor for axonal conduction speed (Jack et 234 al., 1983). We therefore recorded compound action potentials of PFs in lobule V 235 and compared their conduction speed in the inner-, middle- and outer-zone of the 236 molecular layer (Figure 6D-F). We detected a significantly higher velocity in inner-zone PFs compared with in middle- or outer-zone PFs (0.33  $\pm$  0.004 m s<sup>-1</sup>, 237 n = 8 vs.  $0.31 \pm 0.005$  m s<sup>-1</sup>, n = 6 vs.  $0.28 \pm 0.005$  m s<sup>-1</sup>, n = 8; Figure 6F; 238 239  $P_{ANOVA} < 0.0001$ ). The absolute velocity and the gradient in the velocity from 240 inner- to outer-zone PFs agree well with previous studies (Baginskas et al., 2009; 241 Vranesic et al., 1994). These results suggest that the inner-zone PFs are 242 specialized for fast signaling, which is consistent with the concept that inner-zone 243 GCs are tuned for high-frequency inputs (cf. Figure 1 and 2).

In addition to the above results obtained from lobule V, similar gradients in both
axon diameter and axon conduction speed were found in lobule IX (Figure 6—
figure supplement 1). This suggests that gradients in axon diameter and axon

247 conduction speed are general features of the cerebellar cortex.

A possible confounder of our results could be an overrepresentation of large-248 249 diameter Lugaro cell axons within inner-zone PFs (Dieudonne and Dumoulin, 250 2000). However, this would predict that the histogram of the axon diameters 251 shows two distinct peaks with varying amplitude. Instead, we observed a single 252 bell-shaped distribution in each PF zone (Figure 6-figure supplement 2), 253 arguing that the measured differences between axon diameters were not due to 254 varying contributions from Lugaro cell axons, but reflect the differences between 255 inner-, middle- and outer-zone PFs.

#### 256 PCs process inner-, middle-, and outer-zone PF inputs differentially

257 Our data thus far indicate that GCs and PFs are adapted to different MF input 258 frequencies and conduction velocity, respectively. This arrangement could in 259 principle provide PFs with functionally segregated information streams that are 260 differentially processed in PCs. To investigate this possibility, we made whole-261 cell current-clamp recordings from PCs in sagittal slices of the cerebellar vermis. 262 PCs were held at a hyperpolarized voltage to prevent spiking and to isolate 263 excitatory inputs. Electrical stimulation of the PFs was alternated between inner-, 264 middle- and outer-zones and adjusted to obtain similar amplitude EPSPs in all 265 zones (Figure 7A,B). Stimulation of inner-zone PFs resulted in EPSPs (Barbour, 266 1993; Roth and Häusser, 2001) with shorter rise and decay times compared with 267 EPSPs obtained from stimulating outer-zone PFs (rise<sub>20-80</sub>: inner:  $0.57 \pm 0.04$  ms, 268 n = 12; middle:  $0.93 \pm 0.17$  ms, n = 4; outer:  $1.83 \pm 0.33$  ms, n = 12 (P<sub>ANOVA</sub> = 269 0.009; decay: inner: 21.9 ± 1.5 ms, middle: 39.7 ± 1.1 ms outer: 40.8 ± 4.1 ms; 270 P<sub>ANOVA</sub> = 0.0004, **Figure 7C**). These results suggest that inner-zone PF inputs 271 undergo less dendritic filtering in PCs compared with outer-zone PF inputs (De 272 Schutter and Bower, 1994a, b; Roth and Häusser, 2001) but see (De Schutter 273 and Bower, 1994c). To investigate high-frequency inputs to PCs, we elicited five

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EPSPs at 100 Hz and 500 Hz (**Figure 7D,E**). Individual EPSPs evoked from inner-zone PFs showed clear individual rising phases and peaks between each stimulus and less summation compared with outer-zone PFs (**Figure 7D-F**). These results suggest that inner-zone PFs can transmit timing information more faithfully compared with outer-zone PFs and thus control spike timing of PCs more precisely.

# The observed neuronal gradients increase storing capacity and improve temporal precision of PC spiking

Thus far we have described a prominent gradient in the electrophysiological properties of GCs over the depth of the GC layer that enables inner- and outerzone GCs to preferentially respond to high- and low-frequency inputs, respectively. The different frequency components are transferred via specialized PFs, which enable PCs to interpret high-frequency signals rapidly at the base of their dendritic trees and low-frequency signals slowly at more distal parts of their dendritic trees (**Figure 8A**).

289 To address the functional implications of these gradients in the GC and 290 molecular layer, we performed computational modeling of a neuronal network of 291 the cerebellar cortex with integrate-and-fire neurons. The model consisted of one 292 PC and varying number of GCs and MFs (Figure 8A). GCs received randomly 293 determined MF inputs with either tonic (Arenz et al., 2008; van Kan et al., 1993) 294 or bursting (Rancz et al., 2007) in vivo-like spiking sequences. By changing the 295 synaptic weights of the GC to PC synapses, the PC had to acquire a target 296 spiking sequence with regular 80-, 40- and 120-Hz firing (Figure 8B). The 297 algorithm for changing the synaptic weights was a combination of a learning 298 based on climbing-fiber-like punishments and an unbiased algorithm 299 minimization algorithm (see Methods).

We first compared a model without gradients, where the parameters were set at the average of the experimentally determined values, with a model including all experimentally determined gradients (black and red, respectively, throughout

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303 Figure 8). To measure the difference between the final PC spiking and the target 304 sequence we calculated van Rossum errors using a time constant of 30 ms 305 (Rossum, 2001) Figure 8C-E). With increasing number of GCs, the final PC 306 spiking sequence resembled the target sequences increasingly better, as 307 illustrated by an average spiking histogram from many repetitions with different 308 random sets of MF inputs for models consisting of 100 and 1000 GCs (Figure 309 **8B**). As expected, the average minimal van Rossum error (for many repetitions 310 with different random sets of MF inputs) decreased with increasing number of 311 GCs (Figure 8C). For all sizes of the GC population, the average minimal van 312 Rossum error was significantly smaller in the model containing all the 313 experimentally determined gradients compared with the model without any 314 gradients. For example, to obtain the spiking precision of the model containing 315 400 GCs with all gradients, the model without gradients required 800 GCs (cf. 316 red arrows in **Figure 8C**). This indicates that for a cerebellum exploiting gradients 317 in the GC layer, the number of GCs can at least be halved to obtain a certain 318 temporal precision compared with a cerebellum containing no gradients.

To investigate the relative contribution of each of the gradients, we tested models containing each gradient in isolation, resulting in intermediate van Rossum errors (blue, yellow, and green in **Figure 8C,D**). The average relative differences between the models across all sizes of the GC populations suggest an almost additive behavior of the individual gradients to the overall performance (**Figure 8E**).

To further investigate the interplay of the different gradients, we investigated a model containing all gradients, but the connectivity between GCs, PF action potential speed, and PC EPSP kinetics were randomly intermixed (red dashed lines in Figure 8C-E). The network benefits from these intermixed gradients, but maximum optimization can only be obtained with correct connectivity (**Figure 8E**).

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331 The time constant of the van Rossum error can be decreased or increased to 332 investigate spike timing or slower changes in firing rate, respectively. The impact 333 of the gradients increased with increasing time constant (Figure 8-figure 334 supplement 1A,B), indicating that rate coded signaling especially benefits from 335 the here described gradients. To specifically test the effect of gradients on the 336 cerebellum's ability to switch between firing frequencies, we made sigmoid fits 337 around the times of firing rate changes. The transition time ( $t_{T}$ ; see methods) 338 from these fits showed that models with all gradients showed on average 20% 339 faster switching between firing frequencies than models without any gradients (Figure 8—figure supplement 1C-F). 340

341 To further test the influence of gradients on efficient cerebellar processing, we 342 repeated the modeling experiments but used a target sequence with a firing 343 pause (i.e. 80, 0, and 120 Hz instead of 80, 40, and 120 Hz) resulting in similar 344 van Rossum errors and transition time (Figure 8—figure supplement 1G-M). A 345 pause in firing enabled us to quantify the temporal error at the start and the end 346 of the pause (Figure 8—figure supplement 1N-Q), because these spike times 347 have been proposed to be of particular relevance for behavior (Hong et al., 348 2016). Both measures (transition time and temporal error in pause beginning and 349 end) revealed similar results compared with the van Rossum measure, indicating 350 that the speed of 'frequency-switching' and the temporal spiking precision of PCs 351 critically depend on the here described gradients. Thus, our modeling results 352 show that experimentally determined gradients improve the spiking precision, 353 accelerate 'frequency-switching', and increase the storing capacity of the 354 cerebellar cortex.

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#### 356 Discussion

In this study, we describe a gradient in the biophysical properties of superficial to deep GCs, which enables the GC layer to perform a Fourier-like transformation of the MF input. Furthermore, we show that the downstream pathways from GCs

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to PCs are specialized for transmitting the frequency band for which the corresponding GCs are tuned to. Finally, computational modeling demonstrates that both the gradients in the GC layer and the specialized downstream pathways improve the spiking precision, accelerate the change of firing frequency of PCs, and increase storing capacity in the cerebellar cortex.

#### 365 **Fourier-like transformation in the cerebellar cortex**

366 Our data demonstrate that outer-zone GCs preferentially fire during MF input with 367 low frequency ('low-frequency' GCs, magenta in Figure 9A), whereas inner-zone 368 GCs preferentially fire during MF input with high frequency ('high-frequency' 369 GCs, green in Figure 9A). The separation of a signal into its frequency 370 components resembles a Fourier transformation (Figure 9B). The analogy with a 371 Fourier transformation has the limitations that (1) a single MF cannot transmit two 372 frequencies simultaneously but only separated in time (cf. example in Figure 9A) 373 and (2) concurrent inputs from two MFs with different frequencies synapsing onto 374 a single GC cannot be separated. Yet, our data indicate that the entire GC layer 375 with several MFs sending various frequencies to numerous GCs can execute a 376 Fourier-like transformation. In analogy to the dispersion of white light in an optical 377 prism into its spectral components, the broadband MF signal is separated into its 378 spectral components with inner- to outer-zone GCs preferentially transmitting the 379 high- to low frequency components, respectively. Such a separation offers the 380 chance to process each frequency component differentially. Indeed, in the 381 molecular layer, the high-frequency components of the MF signal are sent via 382 rapidly conducting axons to proximal parts of the PC dendritic tree. This allows 383 fast (phasic) signals to have a strong and rapid impact on PC firing. On the other 384 hand, low-frequency components of the MF signal are conducted more slowly 385 and elicit slower EPSPs, allowing slow (tonic) signals to have a modulatory 386 impact on PC firing. Our data indicate that, in analogy to the increased storing 387 capacity of digital audio and image compression (Javant et al., 1993; Wallace, 388 1992), the combination of a Fourier-like transformation in the GC layer and 389 specialized downstream signaling pathways in the molecular layer dramatically 390 reduces the number of required GCs for precise PC spiking (cf. Figure 8).

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391 Furthermore, our data support the 'adaptive filter' theory of the cerebellum, where 392 broadband MF input is differentially filtered by GCs (Dean et al., 2010; Fujita, 393 1982; Singla et al., 2017). Within this framework, our data indicate a gradient in 394 the band-pass filtering properties of GCs. Furthermore, our data could provide an 395 additional explanation for improved motor learning by elevated background 396 activity of MFs (Albergaria et al., 2018), because the elevated MF activity will 397 help overcoming the high threshold of inner-zone GCs, which rapidly and 398 effectively impact PCs via fast conducting PFs at the proximal dendrite.

#### 399 Axes of frequency specialization in the cerebellum

400 There are at least two axes of heterogeneity in the cerebellar cortex. First, Zebrin 401 stripes can be observed as parasagittal zones ('medio-lateral' axis) in cerebellar 402 cortex (Apps et al., 2018). Firing rate, firing regularity, synaptic connectivity and 403 even synaptic plasticity seems to differ between PCs in zebrin positive and 404 negative zones (Valera et al., 2016; Wadiche and Jahr, 2005; Xiao et al., 2014; 405 Zhou et al., 2014). Second, there is a lobular organization ('rostro-caudal' axis) 406 as shown here by the functional differences between lobules V and IX (Figure 407 1-figure supplement 1). GCs in lobule IX are tuned to lower frequencies than 408 GCs in lobule V. These findings are largely in line with previous investigations 409 (Heath et al., 2014; Witter and De Zeeuw, 2015a; Zhou et al., 2014), where the 410 anterior cerebellum was identified to process high-frequency or bursting signals. 411 while the vestibulo-cerebellum mainly processed lower frequency or slowly-412 modulating inputs. Furthermore, the optimal time intervals for introduction of 413 spike timing dependent plasticity differ between the vermis and the flocculus 414 (Suvrathan et al., 2016).

In addition to these two known axes of heterogeneity, we described an axis that is orthogonal to the surface of the cerebellar cortex. This 'depth' axis causes inner-zone GCs to be tuned to higher frequencies than outer-zone GCs. This frequency gradient along the 'depth'-axes is in line with recently described connections of MFs and PC, which specifically target GCs close to the PC layer (Gao et al., 2016; Guo et al., 2016). These connections send slow feedback

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421 signals to the outer-zone GCs, which — according to our framework — are 422 ideally suited to process such slow modulatory signals. Independent of these 423 specialized feedback pathways, MFs exhibit heterogeneity (Chabrol et al., 2015; 424 Bengtsson and Jörntell, 2009). Our data indicate that each type of the 425 heterogeneous MF inputs is split into its frequency components along the depth 426 axis. Our results furthermore predict that superficial GCs, such as the ones 427 imaged recently in the investigation of eye-blink conditioning and reward 428 representation in the cerebellar cortex (Giovannucci et al., 2017; Wagner et al., 429 2017), would preferentially convey low-frequency signals to PCs and might not 430 be representative for the full range of frequencies present over the depth of the 431 GC layer.

Thus, including this new 'depth' axis, there are three orthogonal axes along which the cerebellar cortex is tuned for preferred frequency, indicating the importance of proper frequency tuning of the circuitry.

#### 435 **The role of inhibition**

436 In the current study we did not investigate molecular layer interneurons, which 437 can have large impact on PC spiking (Blot et al., 2016; Dizon and Khodakhah, 438 2011; Gaffield and Christie, 2017; Mittmann et al., 2005; Sudhakar et al., 2017). 439 However, the spatial arrangement of stellate and basket cell interneurons is 440 consistent with our framework. Although the dendrites of molecular layer 441 interneurons can span the entire molecular layer, the dendrites of basket cells 442 seem to be preferentially located at the inner-zone of the molecular layer 443 (Palkovits et al., 1971; Rakic, 1972), which positions them ideally to receive rapid 444 high-frequency signals of inner-zone PFs. Consistently, they impact PC firing 445 rapidly and efficiently via their pinceaus (Blot and Barbour, 2014). Furthermore, 446 the dendrites of a subset of stellate cells (with their somata located in the outer-447 zone molecular layer) are preferentially located at the outer-zone molecular layer 448 (Palkovits et al., 1971; Rakic, 1972), which positions them ideally to receive 449 modulatory low-frequency signals and elicit slow IPSPs in PCs. Furthermore, 450 molecular layer interneurons seem to represent a continuum along the vertical

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451 axis, with a correlation between the vertical location of the soma, axonal boutons, 452 and dendrite location (Sultan and Bower, 1998), which is consistent with the 453 here-described continuum of biophysical properties along the vertical axis of the 454 cortex. Incorporating molecular layer interneurons, their synaptic plasticity and 455 their potential gradients into the frequency-dispersion framework may show a 456 further increase in the dynamic range of frequency separation within the 457 cerebellar cortex over what we have described here (Gao et al., 2012).

#### 458 Functional implications for the cerebellum

In general, our anatomical and electrophysiological data, combined with our modeling results, show that inner-zone GCs convey high-frequency signals from MFs via rapid pathways to PCs with little filtering. This is in contrast to outer-zone GCs that are tuned to lower frequencies, and which signals undergo more filtering in the PC. These results suggest that the sparse code of GCs (Albus, 1971; Billings et al., 2014; Marr, 1969) is in part caused by different frequency tuning of GCs.

466 MF firing frequencies range from <1 to ~1000 Hz (Arenz et al., 2008; Chadderton 467 et al., 2004; Jörntell and Ekerot, 2006; Rancz et al., 2007; van Kan et al., 1993). 468 Many previous modeling studies investigating cerebellar function considered the 469 activity of each MF as a constant digital value (Albus, 1971; Babadi and 470 Sompolinsky, 2014; Brunel et al., 2004; Clopath et al., 2012; Marr, 1969), a 471 constant analog value (Chabrol et al., 2015; Clopath and Brunel, 2013), or spike 472 sequences with constant frequency (Billings et al., 2014; Cayco-Gajic et al., 473 2017; Steuber et al., 2007). We focused on the time-varying aspects of MF 474 integration in GCs, and therefore implemented a model with a corresponding 475 large range of MF input frequencies that could change over time. It would be 476 interesting to elucidate in, as much previous models, consisting of more uniform 477 MF inputs, would benefit from the here-observed biophysical gradients.

To implement these gradients in a model we used a simplified cerebellar circuitry that does not consider active dendrites (Llinás and Sugimori, 1980) or the tonic

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480 activity of PCs (Raman and Bean, 1997). It will therefore be interesting to 481 investigate if the here-observed gradients in the GC and molecular layer improve 482 the performance of more complex models of the cerebellar cortex (De Schutter 483 and Bower, 1994a; Garrido et al., 2013; Masoli et al., 2015; Medina et al., 2000; 484 Rossert et al., 2015; Spanne and Jörntell, 2013; Steuber et al., 2007; Sudhakar 485 et al., 2017; Walter and Khodakhah, 2009; Yamazaki and Tanaka, 2007). 486 Furthermore, it remains to be investigated whether gradients in the GC layer also 487 improve models that aim to explain tasks such as eye-blink conditioning (Mauk 488 and Buonomano, 2004) and vestibulo-ocular reflexes (du Lac et al., 1995)

489 Our model simulated the learning that PCs undergo to acquire specific firing 490 frequencies in response to GC input. PC firing rate and spiking precision have 491 been shown to be closely related to movement (Brown and Raman, 2018; 492 Sarnaik and Raman, 2018). Our results show that the same temporal spiking 493 precision or the same frequency switching speed can be obtained with 494 approximately half the number of GCs when GC gradients are implemented 495 (Figure 8). Taking into account the large number of cerebellar GCs in the brain 496 (Herculano-Houzel, 2009; Williams and Herrup, 1988), a significant reduction in 497 the number of GCs could represent an evolutionary advantage to minimize 498 neuronal maintenance energy (Howarth et al., 2012; Isler and van Schaik, 2006). 499 Therefore, the dramatic increase in storing capacity for precise PC spiking 500 provides an evolutionary explanation for the emergence of gradients in the 501 neuronal properties.

#### 502 Functional implications for other neural networks

503 Based on the described advantages of the Fourier transformation for rapid and 504 storing-efficient information processing, we hypothesize that other neural 505 networks also perform Fourier-like transformations and use segregated 506 frequency-specific signaling pathways. To our knowledge this has rarely been 507 shown explicitly, but similar mechanisms might operate, for example, in the 508 spinal cord network: descending motor commands from the pyramidal tract send 509 broadband signals to motoneurons with different input resistances resulting from

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510 differences in size. This enables small motoneurons to fire during low-frequency 511 inputs and large motoneurons only during high-frequency inputs (Henneman et 512 al., 1965). Furthermore, specialized efferent down-stream signaling pathways 513 innervate specific types of muscles with specialized short-term plasticity of the 514 corresponding neuromuscular junctions (Wang and Brehm, 2017).

515 In the hippocampus, frequency preferences of hippocampal neurons are well 516 established enabling segregation of compound oscillatory input into distinct 517 frequency components (Pike et al., 2000). Furthermore, there is increasing 518 evidence that previously considered homogeneous population of neurons exhibit 519 gradients in the neuronal properties (Cembrowski and Spruston, 2019), such as 520 the intrinsic electrical properties and synaptic connectivity in CA3 pyramidal 521 neurons (Galliano et al., 2013). The heterogeneity furthermore enables functional 522 segregation of information streams for example in CA1 pyramidal neurons 523 (Soltesz and Losonczy, 2018). Finally, in the neocortex, gradients in anatomical 524 and biophysical properties were recently uncovered (Fletcher and Williams, 525 2019).

526 In summary, our findings contribute to the growing body of evidence that the 527 neurons of a cell layer can exhibit systematic functional heterogeneities with 528 differential tuning of neurons along gradients. Our data furthermore suggest that 529 such gradients facilitate complex transformation of information, such as Fourier-530 like transformations, to cope with a broad temporal diversity of signals in the 531 central nervous system.

532

#### 533 Material and Methods

#### 534 Electrophysiology

Parasagittal 300-µm thick cerebellar slices were prepared from P21–P30 (young
animals) or from P80-P100 (old animals) C57BL/6 mice of either sex as
described previously (Ritzau-Jost et al., 2014);(Delvendahl et al., 2015). Animals
were treated in accordance with the German and French Protection of Animals

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539 Act and with the guidelines for the welfare of experimental animals issued by the 540 European Communities Council Directive. The extracellular solution for the 541 whole-cell measurements contained (in mM): NaCl 125, NaHCO<sub>3</sub> 25, glucose 20, 542 KCl 2.5, CaCl<sub>2</sub> 2, NaH<sub>2</sub>PO<sub>4</sub> 1.25, MgCl<sub>2</sub> 1 (310 mOsm, pH 7.3 when bubbled with 543 Carbogen (95%O<sub>2</sub>/5%CO<sub>2</sub>)). For outside-out measurements of potassium 544 currents (Figure 2), 150 µM CdCl<sub>2</sub> and 1 µM TTX were added to the external 545 solution to block voltage-gated calcium channels and sodium channels, 546 respectively. The intracellular solution contained in mM: K-Gluconate 150, NaCl 547 10, K-Hepes 10, Mg-ATP 3, Na-GTP 0.3, EGTA 0.05 (305 mOsm, pH 7.3). A 548 liquid junction potential of +13 mV was corrected for. All electrophysiological 549 measurements were performed with a HEKA EPC10 amplifier (HEKA Elektronik, 550 Lambrecht/Pfalz, Germany) under control of the Patchmaster software. All 551 measurements were performed at 34–37°C.

552

#### 553 *Current clamp recordings in GCs*

Action potentials were evoked in current-clamp mode by current pulses (amplitude 20–400 pA, duration 300 ms). To determine the input resistance, subthreshold current pulses were applied from -20 to + 20 pA in 2 pA steps. The resistance of the solution-filled patch-pipettes was between 6–12 M $\Omega$  and the mean series resistance was not compensated during the measurement. Data were sampled at 200 kHz.

560

#### 561 Outside-out recordings in GCs

To reliably clamp potassium currents from the soma of GCs (**Figure 2**), potassium currents were measured in outside-out patches pulled from the soma of inner and outer GCs by applying 10 ms voltage steps from –90 to +60 mV with 10 mV increments at an intersweep interval of 1 s. The intersweep holding potential was –90 mV. Data were sampled at 100 kHz.

567

#### 568 Compound action potentials in PFs

569 For the detection of compound action potentials in PFs, two pipettes (tip

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resistances 1–4 MΩ) filled with extracellular solution and connected to the patchclamp amplifier were positioned within the molecular layer of horizontally cut slices of the cerebellar vermis. The average distance between two recording electrodes was  $143 \pm 5 \mu m$ . Compound action potentials were evoked by voltage stimulation (100 V) for 100 µs with a third pipette connected to an accumulator powered stimulation device (ISO-Pulser ISOP1, AD-Elektronik, Buchenbach, Germany). 40 to 80 stimulations delivered at 1 Hz were averaged and analyzed.

577

#### 578 Excitatory postsynaptic potentials in PC

579 Excitatory postsynaptic potentials (EPSPs) in PC were elicited by voltage 580 stimulation of the PFs within the inner, middle or outer third of the molecular layer 581 from horizontally cut cerebellar slices (Figure 7). 10 µM SR95531 was added to 582 the external solution to block  $GABA_A$  receptors. The stimulation pipette was filled 583 with extracellular solution, and the voltage was adjusted between 6 to 25 V to 584 elicit EPSPs with an amplitude between 1 and 2 mV. EPSPs were measured 585 after a single 100 µs voltage stimulation or 5 stimulations (100 µs duration) at a 586 frequency of 100 and 500 Hz. Averages of 30 trains per stimulation protocol were 587 used for data analysis.

588

#### 589 Excitatory postsynaptic currents in GCs

To measure evoked EPSCs from GCs (**Figure 3—figure supplement 1**), 90-100 days-old mice were used. GCs from inner- or outer-zone from lobule V were held at resting conditions and MF axons were stimulated at 1 Hz with a second pipette. The average stimulation voltage was  $36 \pm 3$  V for outer-zone GCs and 37 $\pm 3$  V for inner-zone GCs.

595

#### 596 Dynamic Clamp of MF conductance in GCs

597 In order to analyze the response of GCs on *in-vivo* like MF inputs, we used a 598 dynamic clamp implemented with the microcontroller Teensy 3.6 599 (https://www.pjrc.com) as described by Desai et al. (Desai et al., 2017). The 600 Teensy was programmed using the Arduino integrated development environment

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601 with the code provided by Desai et al (2017) and modified for our need as 602 described in the following.

603

604 The time course of MF conductance was

605 
$$G_{EPSC}(t) = G_{max} A_{norm} \left( -e^{-\frac{t}{\tau_r}} + \sum_{i=1}^3 a_i e^{-\frac{t}{\tau_i}} \right)$$

606 where the exponential rise time ( $\tau_r$ ) was 0.1 ms, the decay time constants ( $\tau_1$ ,  $\tau_2$ , 607 and  $\tau_3$ ) were 0.3, 8, and 40 ms, respectively, and the relative amplitude of the decay components  $(a_1, a_2, and a_3)$  were 0.7, 0.26, and 0.04, respectively. The 608 609 peak conductance ( $G_{max}$ ) was 1 nS (Hallermann et al., 2010) and the 610 normalization factor  $(A_{norm})$  was 0.518, which was numerically calculated to 611 obtain a peak amplitude of 1. The kinetics of the MF conductance were chosen to 612 reproduce the measured mixed AMPA and NMDA EPSC kinetics of single 613 EPSCs (Figure 3-figure supplement 1) and trains of EPSCs (Baade et al., 614 2016). The short-term plasticity during Poisson sequence of spikes was 615 implemented by changing  $G_{max}$  according to a simple phenomenological model 616 (Tsodyks and Markram, 1997) assuming a release probability pro of 0.4 (Ritzau-617 Jost et al., 2014). Facilitation was implemented as an increase in the release 618 probability according to  $p_r = p_r + 0.2^*(1 - p_r)$  and decaying back to  $p_{r0}$  with a time 619 constant of 12 ms (Saviane and Silver, 2006). Depression was implemented 620 according to a recovery process with a time constant of 25 ms, which 621 approximates a biexponential recovery process of 12 ms and 2 s (Hallermann et 622 al., 2010; Saviane and Silver, 2006). The resulting short-term plasticity 623 reproduced previously obtained data with regular spiking ranging from 20 to 1000 624 Hz (Baade et al., 2016; Hallermann et al., 2010; Ritzau-Jost et al., 2014).

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The microcontroller was programmed to implement the MF conductance and its short-term plasticity with Poisson distributed spike times with a constant frequency ranging from 30 to 500 Hz for 300 ms (Figure 3). In each cell, each frequency was applied five times.

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To investigate the response to sinusoidally varying input frequencies (Figure 4), the target frequency of the Poisson process (F) was varied on a logarithmic scale according to:

634 
$$F(t) = exp\left(\log(F_{min}) + \left(\log(F_{max}) - \log(F_{min})\right)\left(0.5 + 0.5sin(2\pi t/T)\right)\right)$$

635 where the minimal and maximal frequency ( $F_{min}$  and  $F_{max}$ ) were 30 and 300 Hz, 636 respectively, and the duration of the sine wave cycle (T) was 1 s. In each cell, 10 637 cycles were applied consecutively. The histogram of the spike times (Figure 4B) 638 was averaged across the last six cycles of all cells. The vector strength and 639 phase angle (Kan et al., 1993) were calculated as the absolute value and the 640 argument of the complex number  $\rho$  ( $i = \sqrt{-1}$ ):

$$\rho = \frac{1}{N} \sum_{n=1}^{N} e^{i2\pi \frac{t_n}{T}}$$

642 where  $t_n$  are the spike times of all *N* spikes per experiment and *T* the cycle 643 duration (1 s).

644

#### 645 Electron Microscopy

Four C57BL/6 mice of either sex with an age between P23–P28 were sacrificed, 646 647 followed by transcardial perfusion with saline and consecutively a fixative 648 containing 4% paraformaldehyde and 2% glutaraldehyde in phosphate-buffered 649 saline (PBS). After removal of the brain, the tissue was allowed to post-fix over 650 night at 4°C and sagittal sections of the cerebellum were prepared at a thickness 651 of 60 µm using a Leica microtome (Leica Microsystems, Wetzlar, Germany). The 652 sections were stained in 0.5% osmium tetroxide in PBS for 30 min followed by 653 dehydration in graded alcohol and another staining step with 1% uranyl acetate 654 in 70% ethanol. After further dehydration, the tissue was embedded in durcupan 655 (Sigma-Aldrich), which was allowed to polymerize for 48 h at 56°C between 656 coated microscope slides and cover glasses. Regions of interest were identified 657 by light microscopy, cut and transferred onto blocks of durcupan to obtain ultra-

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658 thin sections using an Ultramicrotome (Leica Microsystems). Ultra-thin sections

659 were transferred onto formvar-coated copper grids and stained with lead citrate.

660 Ultrastructural analysis was performed using a Zeiss SIGMA electron microscope

661 (Zeiss NTS, Oberkochen, Germany) equipped with a STEM detector and ATLAS662 software.

663

#### 664 Measurement of parallel-fiber axon diameter

Electron micrographs were manually analyzed in a blind manner (numbered by masked randomization) and each micrograph was divided into eight identically sized fields. The diameter of each parallel-fiber axon was measured as the longest chord in one or two of these fields. Cross sections with visible active zones or mitochondria were excluded from analysis.

670

### 671 Dil Injections and GC tracking

672 Six P20 CD1 mice were anesthetized with isoflurane (4%). An incision of the skin 673 to expose the skull and a hole was manually drilled using a 25G needle above 674 the desired injection site. Injections of small amounts of Dil (1,1-dioctadecyl-675 3,3,3,3 tetramethylindocarbocyanine perchlorate, ThermoFisher Scientific, 10% 676 in N,N-dimethylformamide) were performed using a broken glass pipette 677 connected to a picospritzer II (Parker Instrumentation). 24 h after injection, 678 animals were sacrificed and transcardially perfused with 4% paraformaldehyde in 679 PBS. The cerebellum was dissected, fixed overnight, and embedded in 4% 680 agarose in PBS. 150-µm thick sections were then cut in the transverse or sagittal 681 plane using a vibratome (VT1000, Leica microsystems). Z-Stacks (1 µm steps) 682 were acquired using a confocal microscope (Leica SP5 II, 63x objective). GCs 683 were traced from their some to the axonal bifurcation of PFs. (Average stack 684 depth: 84  $\pm$  20  $\mu$ m). GC axons were reconstructed using the 'Simple Neurite 685 Tracer' plugin (Longair et al., 2011) in Fiji (ImageJ, NIH, USA). This plugin 686 allowed us to assess the continuity of axons between several cross-sections. GC 687 ascending axons were then fully traced and measured within the Z-limits of 688 image sections. The size of the different layers of cerebellar cortex was

reconstructed in each Z-stack. To avoid variability, all distances were normalizedto the corresponding molecular layer height.

691

#### 692 Data analysis

693 Data were analyzed using custom-written procedures in Igor Pro software 694 (WaveMetrics, Oregon, USA). Intrinsic properties of GCs were determined from 695 the injected currents that elicited the largest number of action potentials. The action potential threshold was defined as the membrane voltage at which the first 696 derivative exceeded 100 V s<sup>-1</sup>. the minimal action potential peak was set as -20 697 698 mV and the minimal amplitude to 20 mV. All action potentials with a half-width 699 smaller than 50 µs and larger than 500 µs were excluded. Action potential 700 frequency and half-width were calculated from the first three action potentials. 701 Membrane capacitance, resting membrane potential and series resistance were 702 read from the amplifier software (HEKA) after achieving the whole-cell 703 configuration. Input resistance (R<sub>in</sub>) was analyzed from alternating subthreshold 704 current injections from -20 to 20 pA (2 pA steps). The voltage was plotted against 705 injected current and a spline interpolation was performed to obtain the slope at 706 the holding membrane potential (0 pA current injection).

Peak-current from outside-out patches was determined from voltage steps (-90 to +60 mV) with Fitmaster software (HEKA). Steady-state inactivation was determined from the last 2 ms of the respective sweep. Cells were only included if 50 pA <  $I_{max}$  < 1 nA to exclude potential whole-cell measurements and membrane-vesicles.

712

Final EPSP measurements from PCs and EPSC measurements from GCs were analyzed with the Fitmaster software (HEKA). For PC EPSPs, 20-80% rise time and time to peak were determined from the average of 30 individual single EPSPs. GCs EPSCs were averaged from 25 traces. To obtain the decay kinetics, single EPSPs/EPSCs were fitted with either one or two exponentials. The weighted time constant was calculated as:

25

 $A_{slow} \tau_{slow} + A_{fast} \tau_{fast}$ 

$$t_{w} = \frac{1}{A_{slow} + A_{fast}}$$
  
720 Paired-pulse ratio was determined between the first and the 5<sup>th</sup> EPSP after  
721 stimulation with 100 Hz trains. Single EPSCs from inner- and outer-zone GCs

stimulation with 100 Hz trains. Single EPSCs from inner- and outer-zone GCs 121 722 were averaged and fitted with two exponentials. The decay kinetics and 723 amplitude of the grand-average was used to implement the MF EPSCs for the 724 Dynamic Clamp.

725

#### 726 Neuronal networking modeling

727 The neuronal network consisted of varying numbers of MF inputs, GCs and one 728 PC and was implemented in Matlab (The MathWorks, Inc, Natick, 729 Massachusetts, R2017a). For each simulation, a random set of MF inputs was 730 generated. This input was then fed to a layer of integrate-and-fire GCs. A 731 modeled PC then used the output of these GCs for trial-to-trial learning. The PF-732 to-PC synaptic weights were optimized with the aim to make the PC spiking 733 sequence similar to the target sequence. In the following, each component of the 734 model is explained in detail.

735

#### 736 MF inputs

737 To simulate *in vivo* like MF firing patterns, half of the MFs fired tonically (van Kan 738 et al., 1993) and the other half fired bursts (Rancz et al., 2007). All MF spike 739 trains were modeled first by generating a 'threshold trace'. For tonically firing 740 MFs, this threshold trace was a Gaussian function with a peak and standard 741 deviation chosen from uniform distributions ranging between 10 and 100 Hz and 742 0.2 and 0.5 s respectively, and a peak time point between 0 and 0.5 s. For burst 743 firing MFs, the threshold trace was an exponential function with a peak randomly 744 chosen between 600 and 1200 Hz, a decay time constant of 30 ms and a peak 745 between 0 and 0.5 s. The threshold trace was then evaluated against random 746 numbers from a uniform distribution to determine the occurrence of a spike. To 747 accelerate the simulations the sampling time interval was 1 ms.

26

#### 749 GC properties

GCs were implemented as integrate and fire models with the following parameters: the membrane resistance was linearly varied between 450 M $\Omega$  for inner GCs to 800 M $\Omega$  for outer GCs (Figure 1H) and the threshold was linearly varied between -37 mV for inner GCs to -42 mV for outer GCs (Figure 1G). For the models without the GC gradient, these values were set to the mean of the values for the inner and outer GC (i.e. 625 M $\Omega$  and -39 mV). The reset potential was set to -90 mV and the membrane potential to -80 mV.

757

#### 758 *PF properties*

759 To simulate a different action potential propagation speed, the GC spike times 760 were delayed by a value linearly varied between 0 for inner and 3 ms for outer 761 GCs. The delay was calculated as the difference in conduction time required to travel 5 mm with a speed of 0.28 and 0.33 m s<sup>-1</sup> (Figure 4F). Even with this 762 763 anatomically rather too large PF length (Harvey and Napper, 1991), the PF 764 propagation speed has only a small impact on the model performance (see e.g. 765 blue lines and bars in Figure 7C-E), arguing against a big impact of PF 766 conduction delays (Braitenberg et al., 1997) at least in our model approach.

767

#### 768 Synaptic connections and properties

769 Each MF was connected to 10 GCs and each GC received 2 MF inputs, i.e. the 770 number of MF was 1/5 of the number of GCs. Since our model consists only of 771 'active' MFs, we chose only 2 and not 4 MFs per GCs (Billings et al., 2014). The 772 MF to GC synapse was implemented as a model with one pool of vesicles with a 773 release probability of 0.5 and a vesicle recruitment time constant of 13 ms 774 (Hallermann et al., 2010). Synaptic facilitation was implemented by increasing 775 the release probability after each spike by 0.2 decaying to the resting release 776 probability with a time constant of 12 ms (Saviane and Silver, 2006). The 777 synaptic conductance had exponential rise and decay time constants of 0.1 and 778 2 ms, respectively, and a peak amplitude of 1.9 nS (Silver et al., 1992). 779 Correspondingly, the GC to PC synapse was implemented as a model with one

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780 pool of vesicles with a release probability  $(p_{r0})$  of 0.4 and a vesicle recruitment 781 time constant of 50 ms. Synaptic facilitation was implemented by increasing the 782 release probability after each spike by 0.2 decaying to the resting release 783 probability with a time constant of 50 ms (Doussau et al., 2017; Isope and 784 Barbour, 2002; Valera et al., 2012). The synaptic conductance had exponential 785 rise time constant between 0.5 and 2 ms and decay time constant between 17.5 786 and 70 ms for inner- and outer-zone GCs, respectively (Figure 6). The peak 787 amplitude was adjusted to equalize the charge of the EPSC and to generate an 788 approximately correct number of PC spikes (with the initial start values, i.e. all 789 GC to PC synaptic weight factors = 1) by linearly varying between 0.5 and 0.15 790 nS for inner- and outer-zone GCs, respectively.

791

#### 792 PC properties

The PC was implemented as an integrate and fire model with a membrane resistance of 15 M $\Omega$ , resting membrane potential of -50 mV, and a firing threshold of -45 mV. Spontaneous firing of PCs (Raman and Bean, 1997) was not implemented, and the only inputs to drive PCs to threshold were the GC-to-PC EPSCs.

798

#### 799 Target sequence and van Rossum measure

800 Based on *in vivo* firing patterns (Witter and De Zeeuw, 2015a), an arbitrary target 801 firing sequence of 80, 40, and 120 Hz for 300, 100, and 100 ms, respectively, 802 was chosen. The distance between the PC and the target spiking sequence was 803 quantified with the van Rossum error (van Rossum, 2001). Both spiking 804 sequences were convolved with an exponential kernel with a decay time constant 805 of 30 ms (or values ranging from 2 to 300 ms in (Figure 8-figure supplement 806 **1A,B**). The van Rossum error was defined as the integral of the square of the 807 difference between these two convolved traces. We also tested another 808 algorithm to calculate the van Rossum error (Houghton and Kreuz, 2012), which 809 C++ code was taken from http://pymuvr.readthedocs.io/ and incorporated into 810 Matlab via the MEX function and results were comparable.

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811

#### 812 Learning and minimization algorithm

813 For each random set of MF inputs, the GC to PC synaptic weights were changed 814 according to the following algorithm with the aim to minimize the van Rossum 815 error between the PC spiking sequence and the target sequence. The initial 816 values of the synaptic weights were 1, and values were allowed to change 817 between 0 and 100. First, an algorithm was used that was based on supervised 818 learning (Raymond and Medina, 2018) to punish the GCs that have spikes that 819 precede unwanted PC spikes. Subsequently, an unbiased optimization of the GC 820 to PC synaptic weight was performed using the patternsearch() algorithm of 821 Matlab to minimize the van Rossum error. To increase the chance that a global 822 (and not local) minimum was found, the minimization of the routine was repeated 823 several times with random starting values. Other optimization routines such as a 824 simplex [(fminsearch() of Matlab) or a genetic algorithm (ga() of Matlab)] revealed 825 similar results. To exclude the possibility that the differences in the minimal van 826 Rossum error between models with and without gradients were due to a bias in 827 our learning algorithm, we performed a set of simulations with networks 828 consisting of less than 100 GCs, in which we skipped the learning algorithm and 829 only used unbiased minimization algorithm. This resulted in similar difference in 830 the minimal van Rossum error between models with and without gradients, 831 indicating that the learning algorithm was not biased towards one type of model. 832 For networks with consisting of more than 100 GCs the pre-learning was required 833 to facilitate the finding of the global minimum.

834

#### 835 Analysis of modeling results

300 different sets of random MF inputs were used to determine 300 statistically independent minimal van Rossum values for each of the models with different number of GCs and different number of implemented gradients (illustrated as mean ± SEM in Figure 7C). Comparing different models with the same set of MF input (using the nonparametric paired Wilcoxon signed-rank statistical test) the difference was significant (p<0.001) for all of the models and all number of GCs.

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The van Rossum errors were then normalized to the mean of the error of the model without gradients (Figure 7D). The values in **Figure 8D** were fitted with cubic spline interpolation using the logarithm of the number of GCs as abscissa.

845

To quantify the transition time between two target frequencies of the PC, the spike histogram was fitted with the equation

848 
$$f(t) = 80 + \frac{-80 + 40}{1 + e^{-(t-200)/t_T}} + \frac{-40 + 120}{1 + e^{-(t-300)/t_T}}$$

849 where *f* is the spike frequency in Hz and *t* the time in ms. The transition time  $t_T$ 850 corresponds to the 23% to 77% decay and rise time for the transition from 80 to 851 40 Hz and from 40 to 120 Hz, respectively.

852

#### 853 Sensitivity of model parameters

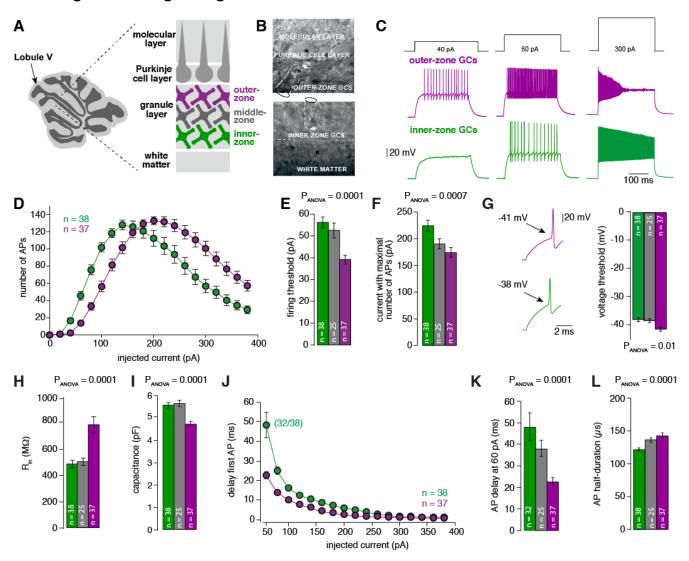
854 We verified that our conclusions do not critically depend on specific parameters 855 of the model. For example, decreasing the simulation time interval from 1 ms to 856 100 µs, resulted in difference of the best van Rossum error of 21% between 857 models with and without gradients consisting of 100 GC, compared with a 858 difference of 17% between the corresponding models with the default simulation 859 time interval of 1 ms (cf. Figure 8D). With 4 MFs per GCs (not 2) the difference 860 of the best van Rossum error was 15% between models with and without 861 gradients consisting of 100 GC (17% with 2 MF per GC). With a membrane 862 resistance of the PC of 100 M $\Omega$  (not 15 M $\Omega$ ) the difference of the best van 863 Rossum error was 23% between models with and without gradients consisting of 864 100 GC (17% with 15 M $\Omega$ ). Finally, changing the target sequence to 80, 0, and 865 120 Hz (not 80, 40, and 120 Hz) resulted in very similar results as obtained with 866 the original target (compare Figure Figure 8C-E with Figure 8-figure 867 supplement 1 H-J and Figure 8—figure supplement 1 D-F with Figure 8 figure supplement 1 K-M). 868

869

#### 870 Statistical testing

All data are expressed as mean ± SEM. The number of analyzed cells is
 indicated in the figures. To test for statistically significant differences of normally

distributed data, we performed ANOVA or Student's t-tests and provided the P value ( $P_{ANOVA}$ , and  $P_{T-TEST}$ , respectively) above the bar-graphs. To test the differences between single groups we performed a Tukey post-hoc test and provided the corresponding P value in the figure legend ( $P_{Tukey}$ ). For not normally distributed data we performed a Mann-Whitney test.

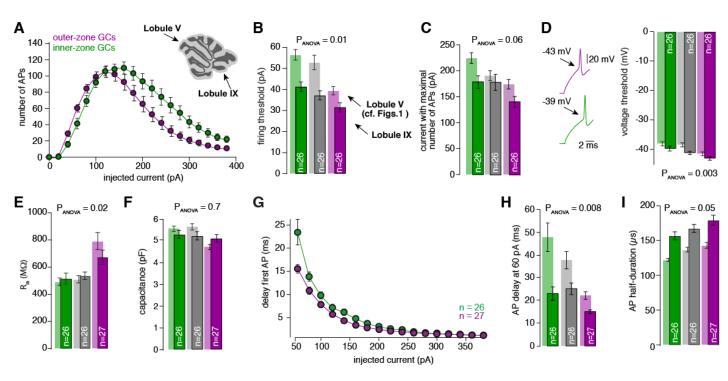


#### 879 Figures and figure legends:

## Figure 1: A gradient in the biophysical properties of inner- to outer-zone GCs

- 883 Α. Scheme of a parasagittal slice from the cerebellar cortex were lobule V 884 is indicated bv an arrow. Enlargement shows a schematic 885 representation of the white matter, the GC, PC and molecular layer of 886 the cerebellar cortex. Throughout the manuscript, inner-zone GCs 887 (close to the white matter) are depicted in green, the middle-zone GCs 888 in grey, and the outer-zone GC (close to the PCs) in magenta.
- B. Example differential-interference-contrast (DIC) microscopic images of
  acute cerebellar slices during recordings from outer- (top) and an
  inner-zone GCs (bottom). The pipette is indicated with dashed line.

- 892 C. Example current-clamp recordings from an outer-zone GC (magenta,
  893 top) and an inner-zone GC (green, bottom) after injection of increasing
  894 currents (40 pA, 60 pA and 300 pA).
- B95 D. Number of action potentials from inner- (green, n = 38) and outer(magenta, n = 37) zone GCs plotted against the injected current. Note
  that the maximum number of action potentials is similar but outer-zone
  GCs achieved the maximum firing rate with a lower current injection.
- 899 E. Average current threshold for action potential firing of inner- (green),
  900 middle- (grey) and outer-zone GCs (right) (P<sub>Tukey</sub> = 0.0001 for inner- vs
  901 outer-zone GCs).
- 902 F. Average current needed to elicit the most number of action potentials
  903 for of inner- (green), middle- (grey) and outer-zone GCs (magenta)
  904 (P<sub>Tukey</sub> = 0.0005 for inner- vs outer-zone GCs).
- 905G.Left: example action potentials from an inner- and outer-zone GC with906the indicated (arrows) mean voltage-threshold for firing action907potentials. Right: Comparison of the average voltage threshold for908action potential firing ( $P_{Tukey} = 0.002$  for inner- vs outer-zone GCs).
- 909 H. Average input resistance of inner- (green), middle- (grey) and outer910 zone GCs (P<sub>Tukey</sub> = 0.0001 for inner- vs outer-zone GCs).
- 911I.Average capacitance of inner-, middle- and outer-zone GCs (P<sub>Tukey</sub> =9120.0001 for inner- vs outer-zone GCs).
- 913J.Delay time of the first action potential plotted against the injected914current. Note, only 32 of 38 inner-zone GCs were firing action potential915at a current injection of 60 pA.
- 916K.Delay of the first action potential of inner- (green), middle- (grey) and917outer-zone GCs at a current injection of 60 pA ( $P_{Tukey} = 0.0001$  for918inner- vs outer-zone GCs).
- 919L.Average action potential half-duration of inner- (green), middle- (grey)920and outer-zone GCs (P<sub>Tukey</sub> = 0.0001 for inner- vs outer-zone GCs).
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923 Figure 1—figure supplement 1: The gradient in the biophysical properties 924 of GCs and PFs is preserved throughout the cerebellar cortex.

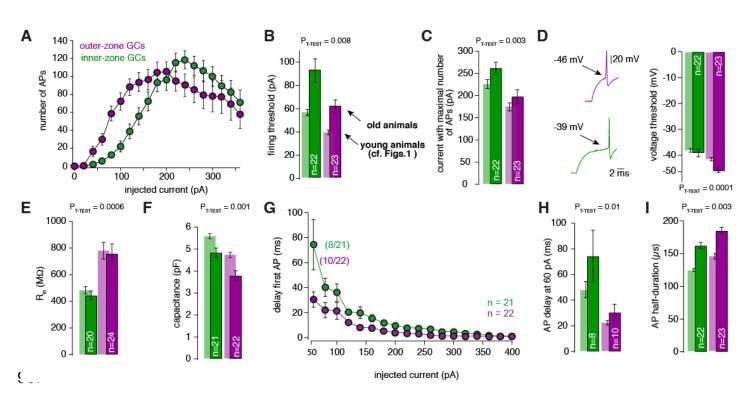
- A. Number of action potentials (APs) from inner (green) and outer (magenta) zone GCs plotted against the injected current. The maximum number of action potentials is similar but with more current injection, inner-zone GCs fire more action potentials. Inset: An image of a cerebellar slice shows were the lobule V and lobule IX are indicated by arrows.
- 931 Β. Bar graphs represent the firing threshold of GCs from inner (dark-932 green), middle (dark-grey) and outer-zone (dark-magenta). The light-933 colored bar graphs in the background are the data from lobule V 934 shown in Figure 1. Firing threshold is higher in inner- compared to 935 outer-zone GCs from lobule IX, and with the same current injection, GCs from lobule IX fire action potentials faster compared to lobule V. 936 937 The numbers of recorded GCs for lobule IX (n) are indicated ( $P_{Tukey}$  = 938 0.007 for inner- vs outer-zone GCs).
- 939 C. Average current needed to elicit the maximum number of action
  940 potentials for of inner- (green), middle- (grey) and outer-zone GCs
  941 (magenta) (P<sub>Tukey</sub> = 0.002 for inner- vs outer-zone GCs).
- 942D.Left: example action potentials from an inner- and outer-zone GC with943the indicated (arrows) mean voltage threshold for firing action

34

944 potentials. Right: Voltage threshold to elicit action potentials in inner-, 945 middle- and outer-zone GCs from lobule IX compared with data from 946 lobule V. Voltage threshold for outer-zone GCs is lower compared to 947 inner-zone GCs from lobule IX ( $P_{Tukey} = 0.002$  for inner- vs outer-zone 948 GCs).

- 949E.Input resistance of GCs from outer-zone of lobule IV is higher950compared to inner- and middle zone GCs. But there is no difference951between the input resistance of GCs from lobule V and IX ( $P_{Tukey} =$ 9520.02 for inner- vs outer-zone GCs).
- 953F.Average capacitance of inner-, middle- and outer-zone GCs. In954contrary to lobule V there is no difference in the capacitance of GC955from inner-, middle, or outer-zone ( $P_{Tukey} = 0.7$  for inner- vs outer-zone956GCs).
- 957 G. Delay of the first action potential plotted against the injected current.
- 958 H. Delay of the first action potential after a current injection of 60 pA from
  959 inner-, middle- and outer-zone GCs from lobule IX compared to lobule
  960 V (P<sub>Tukey</sub> = 0.05 for inner- vs outer-zone GCs).
- 961I.The action potential half-duration of inner-zone (dark-green) GCs from962lobule IX is shorter compared to middle (dark-grey)- and outer-zone963(dark-magenta) GCs. Compared to lobule V (faded-green, faded grey964and faded magenta), the GCs from lobule IX showed a broader action965potential half-width ( $P_{Tukey} = 0.09$  for inner- vs outer-zone GCs).

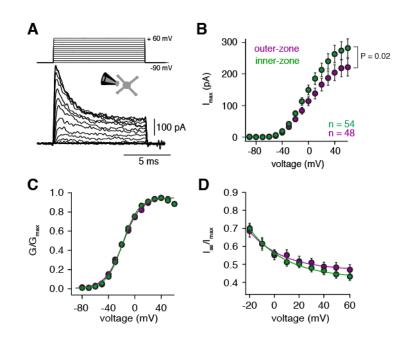
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## Figure 1—figure supplement 2: The gradient in the biophysical properties of GCs and PFs is also found in 3-month-old animals.

- 970A.Number of action potentials (APs) from inner (green) and outer971(magenta) zone GCs plotted against the injected current. The972maximum number of action potentials is similar, but with more current973injection, inner-zone GCs fire more action potentials. For all the974measurements GCs from lobule V were used.
- 975B.Bar graphs represent the firing threshold of GCs from inner (dark-<br/>green), and outer-zone (dark-magenta). The light-colored bar graphs<br/>in the background are the data from lobule V in young (21-30 days-<br/>old) animals shown in Figure 1. Firing threshold is higher in inner -<br/>compared to outer-zone GCs from old animals.
- 980C.Average current needed to elicit the maximum number of action981potentials for of inner- (green), and outer-zone GCs (magenta).
- 982D.Left: example action potentials from an inner- and outer-zone GC with983the indicated (arrows) mean voltage-threshold for firing action984potentials. Right: voltage threshold to elicit action potentials in inner-,985middle- and outer-zone GCs from old animals compared with data986from young animals.
- 987 E. Input resistance of GCs from outer-zone is higher compared to inner988 zone GCs. But there is no difference between the input resistance of
  989 GCs from young and old animals.

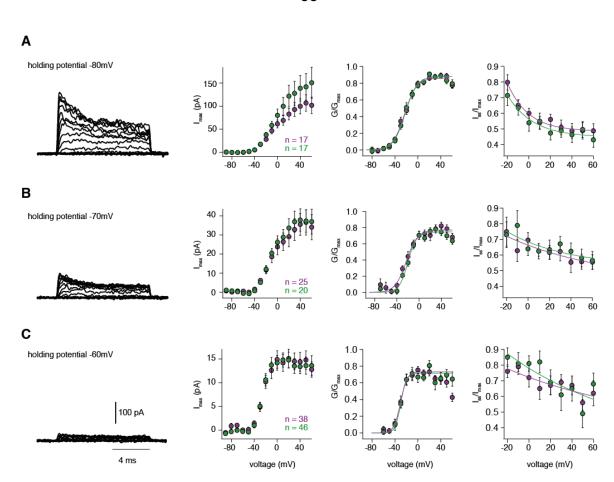
- F. Average capacitance of inner- and outer-zone GCs. In agreement with
  the data from the young animals, inner-zone GCs have a higher
  capacitance compered to outer-zone GCs.
- 993G.Delay of the first action potential plotted against the injected current.994Since the mean current threshold is higher compared to young995animals only 8 out of 21 GCs from inner- and 10 out of 22 GCs from996outer-zone already fired action potentials at a current injection
- 997 H. Delay of the first action potential after a current injection of 60 pA from
  998 inner-, middle- and outer-zone GCs from lobule IX compared to lobule
  999 V.
- 1000I.The action potential half-duration of inner-zone (dark-green) GCs from1001old animals is shorter compared with outer-zone (dark-magenta) GCs.
- 1002



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### 1004 Figure 2: Voltage-gated potassium currents are larger at inner-zone GCs

- 1005A.Example potassium currents from outside-out patches of cerebellar1006GCs evoked by voltage steps from -90 to +60 mV in 10 mV increments1007with a duration of 10 ms. All recordings were made in the presence of10081  $\mu$ M TTX and 150  $\mu$ M CdCl<sub>2</sub> to block voltage-gated sodium and1009calcium channels, respectively.
- 1010B.Average peak potassium current (I<sub>max</sub>) plotted versus step potential of1011inner (green) and outer-zone (magenta) GCs. Significance level was1012tested with a Mann-Whitney Test and the P value is indicated in the1013figure. Note, that the P value shows the significance level at 60 mV.
- 1014C.Average normalized peak potassium conductance (G/G<sub>max</sub>) versus1015step potential of inner (green) and outer-zone (magenta) GCs.
- 1016D.Average steady-state current (Iss, mean current of the last 2 ms of the101710ms depolarization) normalized to the peak current (Imax) versus step1018potential of inner (green) and outer-zone (magenta) GCs.



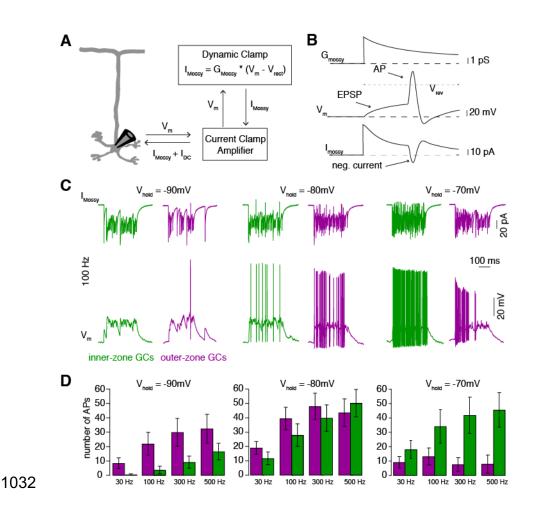
## Figure 2—figure supplement 1: Steady-state activation and inactivation are similar for inner and outer GCs.

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A – C left: Example potassium currents from outside-out patches of cerebellar
GCs evoked by voltage steps from -90 to +60 mV in 10 mV increments with a
duration of 10 ms. The intersweep holding potential varied between -80 mV (A), 70 mV (B) and -60 mV (C). Panels show the corresponding current-voltage
relationship (first panel) of inner-zone (green) and outer-zone (magenta) GCs,
the normalized conductance (second panel) and the normalized inactivation
behavior (third panel). The number of measured cells are indicated in the figure.

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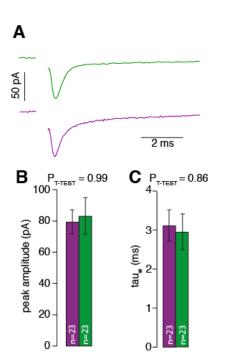


#### 1033 Figure 3: MF inputs are differentially processed by inner and outer GCs 1034

- A. Schematic representation of the Dynamic Clamp system.
- 1036B.Illustration of MF conductance  $(G_{mossy})$ , GC membrane potential  $(V_m)$ ,1037and MF current  $(I_{mossy})$  for the dynamic clamp technique. Note the1038prediction of a negative current during the action potential as apparent1039in the experimental traces in panel C.
- 1040C.Example dynamic clamp recordings of inner- (green) and outer-zone1041(magenta) GCs at different holding potentials (-90 mV left; -80 mV1042middle and -70 mV right) at a stimulation frequency of 100 Hz. Upper1043trace represents the poisson-distributed MF-like EPSCs. Lower trace1044shows the measured EPSPs and action potentials.
- 1045D.Average number of measured action potentials (APs) after mossy-fiber1046like EPSC injection at different frequencies and the indicated holding1047potentials.

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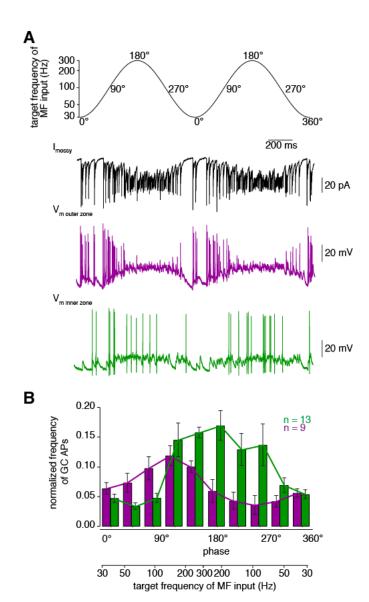
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#### Figure 3—figure supplement 1: MF input is similar for inner- and outer-1051 1052 zone GCs.

- 1053 Examples of single EPSCs measured from inner- (green) and outer-Α. 1054 zone GCs (magenta) after 1Hz stimulation of MF axons. Stimulation 1055 artifacts were removed.
- 1056 Average amplitude of EPSCs from inner- (green) and outer-zone GCs. Β.
- 1057 C. Weighted decay time (see material and methods) of EPSCs from 1058 inner- (green) and outer-zone (magenta).





### 1061 Figure 4: Fourier-like transformation of MF input frequency

- 1062ATarget frequency of the dynamic clamp MF-like sinusoidal EPSC input1063current. The frequencies ranged from 30 to 300 Hz and the duration1064was 1s. The degree values denote the phase angle. Black: example1065trace of poisson-distributed MF-like input current. Magenta and green:1066Dynamic clamp measurement of outer- and inner-zone GCs,1067respectively, after stimulation with a MF-like current shown in black at a1068holding potential of approximately -70 mV.
- 1069 B Histogram of the normalized frequency of action potentials (APS) fired
- 1070 by GCs at different time intervals during 1s stimulation with poisson-
- 1071 distributed MF-like currents shown in A. Each bar represents a time
- 1072 window of 100 ms. Green: inner-zone GCs, magenta: outer-zone GCs.

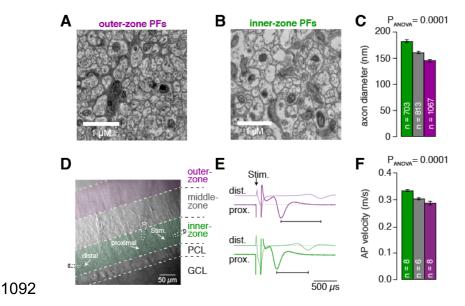
Α В ML PCL GCL Granule cell distance from O D 1.0 normalized distance to ML 0 purkinje cell layer (%) 20 nolecular 0.5 40 0.0 60 80 -0.5 aranule n = 39100 0 20 40 60 80 100 ò Distance of bifurcation from purkinje cell layer (%)

### 1075 Figure 5: The position of PFs is correlated with the position of GC somata

- 1076A.Example of GCs labeled with Dil 24 h post injection. Numerous GCs1077from inner-, middle-, and outer-zone were labeled.
- 1078B.Example of traced axons from different GCs from the outer zone. The1079axon was traced (red) from the cell soma to the bifurcation side in the1080molecular layer. Stained cell bodies of PFs are also visible (white). *ML:*1081molecular layer; *PCL:* Purkinje cell layer; *GCL:* granule cell layer.
- 1082C.The distance between labeled GCs and the PC layer strongly1083correlated with the distance between the axon bifurcation and the PC1084layer (Pearson's correlation coefficient r = -0.862; p<0.001). Solid black</td>1085line depicts the linear interpolation and the grey lines represent SEM of1086the fit. The number of recorded GCs (n) is indicated.
- 1087D.Position of the GC somata from the granular layer of each traced cell1088linked to the position of the bifurcation side in the molecular layer. To1089avoid variability, all the distances were normalized to the1090corresponding molecular layer hight.

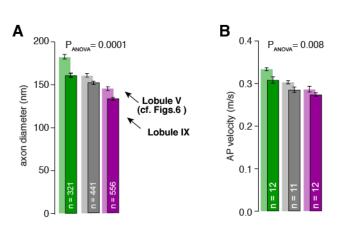
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# 1093Figure 6: Inner-zone PFs have larger diameter and higher action potential1094propagation velocity.

- A. Electron microscopic image of the outer (A) and inner zone (B) of sagittalsections through the molecular layer.
- 1097C. Summary of axon diameters in the inner (green), middle (grey), and outer1098zone (magenta) of the molecular layer ( $P_{Tukey} = 0.0001$  for inner- vs outer-1099zone GCs).
- D. DIC image of the molecular layer superimposed with a schematic illustration of the experimental setup to measure compound action potentials from PFs. Compound action potentials were evoked by a stimulus electrode (left) and recorded by a proximal and distal recording electrode (middle, right).
- E. Example traces used to determine the conduction velocity between inner-,
  middle-, and outer-zone PFs. The time difference between the compound
  action potential arriving at the proximal electrode (solid traces) and the
  distal electrode (faint traces) was used to determine the velocity. The time
  was shorter for inner-zone PFs (green) compared with outer-zone PFs
  (magenta).
- 1111 F. Summary of action potential (AP) velocity in inner-, middle- and outer-1112 zones (P<sub>Tukey</sub> = 0.0001 for inner- vs outer-zone GCs).
- 1113 1114

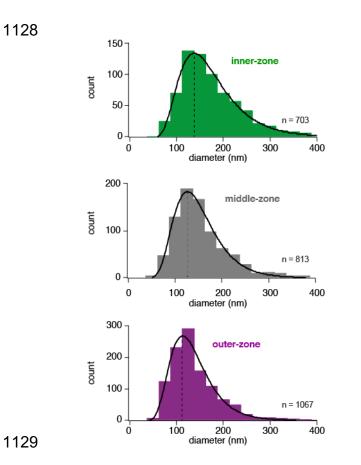


1115 1116

1117 Figure 6—figure supplement 1: Differences in axon diameter and action 1118 potential velocity are also found in lobule IX.

- 1119A.Summary of axon diameters in the inner (green), middle (grey), and1120outer zone (magenta) of the molecular layer ( $P_{Tukey} = 0.0001$  for inner-1121vs outer-zone GCs). The light-colored bar graphs in the background1122are the data from lobule V shown in Figure 6.
- 1123B.Summary of action potential (AP) velocity in inner-, middle- and outer-1124zones of PF from molecular layer of lobule IX (P<sub>Tukey</sub> = 0.0001 for1125inner- vs outer-zone GCs).
- 1126

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### 1130 Figure 6—figure supplement 2: Histogram of the axon diameters.

1131 Histograms of the diameter of inner-, middle- and outer-zone axons in the

1132 molecular layer, indicating that the change in axon diameter is not due to an

1133 increased fraction of larger diameter axons from non-GC cells (e.g. Lugaro cells).

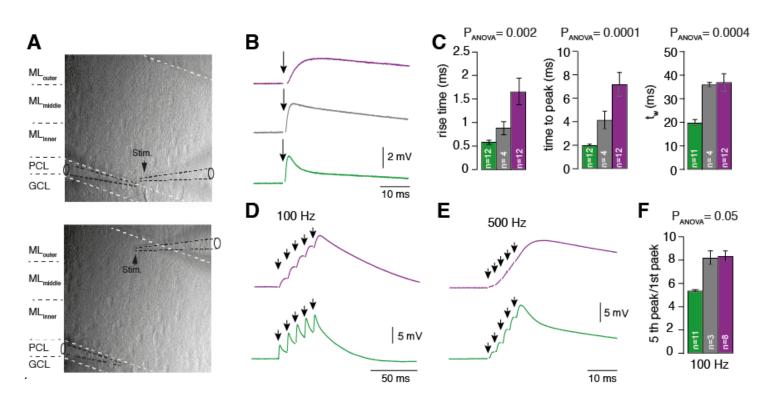
1134 Instead the entire distribution of the axon diameters is shifted between zones.

1135 Data were fit with a skewed Gaussian function:  $a e^{\left[-\log (2)\left(\left(\log\left(1+2b\frac{d-d_0}{ds}\right)/b\right)^2\right)\right]}$ ,

1136 where *a* is the amplitude, *d* the diameter, and *d0* the diameter at the peak. *ds* 

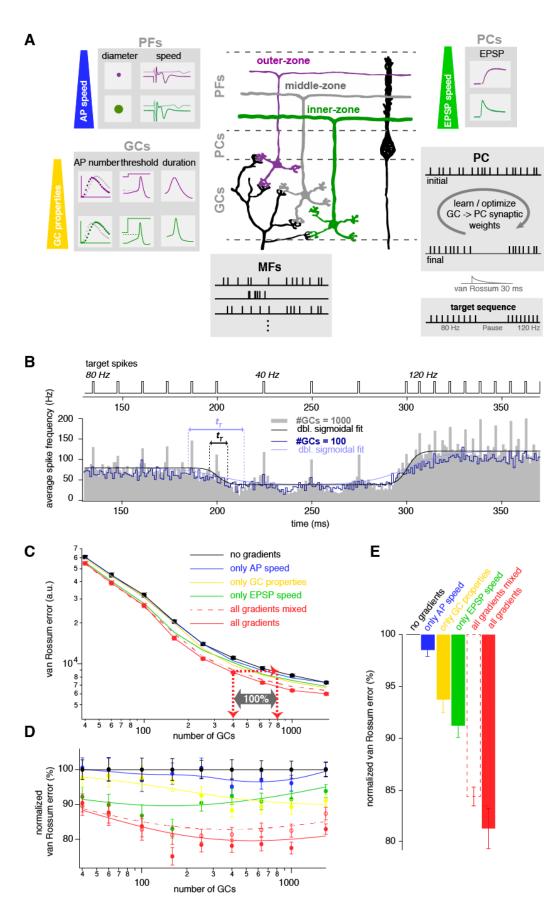
and *b* represent parameters related to the width and the skewness, respectively.

- 1138 The peak is indicated by a vertical line.
- 1139 1140



### 1142 Figure 7: PCs process inner-, middle-, and outer-zone PF inputs 1143 differentially

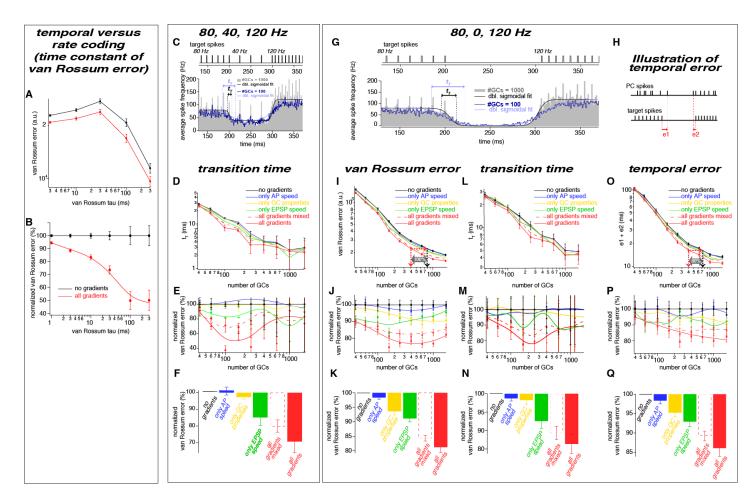
- 1144A.DIC image of the molecular layer superimposed with a schematic1145illustration of PC recordings while stimulating inner (top) and outer-1146zone PFs (bottom). Shown are the GC layer (GL), PC layer (PC) and1147molecular layer (ML).
- 1148B.EPSPs measured at the PC soma after stimulation (1 Hz) of inner-1149(green), middle- (grey), and outer-zone PFs (magenta).
- 1150C.Average 20% to 80% rise time, time to peak and weighted time-1151constant of PC EPSPs after stimulation of inner- (green; n = 12),1152middle- (grey; n = 4) and outer-zone PFs (magenta; n = 12) as shown1153in B ( $P_{Tukey} = 0.001$ ;  $P_{Tukey} = 0.0001$ ;  $P_{Tukey} = 0.0004$  for inner- vs outer-1154zone GCs, respectively).
- 1155D-E.Example traces of EPSPs from a PC after five impulses to inner-1156(green) and outer-zone PFs (magenta) at 100 Hz (D) and 500 Hz (E).
- 1157F.Average paired-pulse ratio measured in PCs after five 100-Hz stimuli1158at inner- (green; n = 11), middle- (grey, n = 3) and outer- zone PFs1159(magenta, n = 8) ( $P_{Tukey}$  = 0.054 for inner- vs outer-zone GCs).
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## 1162Figure 8: The observed neuronal gradients increase storing capacity and1163improve temporal precision of PC spiking

- 1164A.Schematic illustration of the network model of the cerebellar cortex as1165explained in the main text.
- 1166B.Average spiking histogram for models consisting of 100 and 10001167GCs, superimposed with double sigmoidal fits constrained to 80, 401168and 120 Hz. Above the target spiking sequence is indicated.  $t_T$ 1169indicates the transition time of the sigmoidal fit for the respective1170number of GCs.
- 1171 C. Double logarithmic plot of the average minimal van Rossum error 1172 plotted against the number of GCs for a model with no gradients 1173 (black), a model with only gradually varied GC parameters (vellow), PF 1174 propagation speed (blue), EPSP kinetics (green), and all gradients 1175 (red). Furthermore, all parameters were gradually varied but the connectivity between GC, PF and EPSPs was random (all gradients 1176 1177 mixed; dashed red). Red dashed lines with arrows indicate the number 1178 of GCs needed to obtain the same van Rossum error with all gradients 1179 compared to no gradients. With no gradients 100% more GCs are needed to obtain the same van Rossum error. 1180
- 1181D.Average van Rossum errors as shown in panel C but normalized to the1182value of the model without gradients, superimposed with a smoothing1183spline interpolation.
- 1184 E. Error bar indicate average of the relative differences shown in panel D.



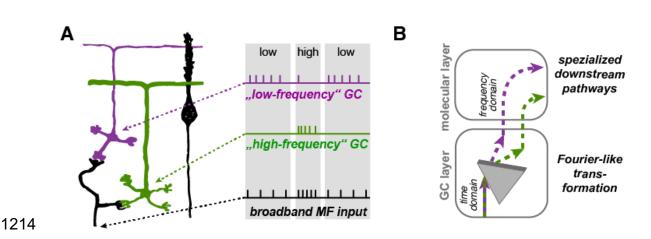
### 1187 Figure 8—figure supplement 1: The observed neuronal gradients reduce 1188 the temporal error and improve rate coding of PC spikes.

- 1189A.Double logarithmic plot of the van Rossum error of model with 3001190GCs without (black) and with all gradients (red) plotted versus the time1191constant of the van Rossum kernel ranging from 2 to 300 ms.
- B. Data as in panel A normalized to the model without gradients.
- 1193C.Average spiking histogram for models consisting of 100 and 10001194GCs, superimposed with double sigmoidal fits constrained to 80, 401195and 120 Hz. Above the target spiking sequence is indicated.
- 1196D.Double logarithmic plot of the transition time  $(t_T)$  of the double1197exponential fits as illustrated in panel C. Error bars represent 95%1198confidence intervals.
- 1199E.Transition time  $(t_7)$  as shown in panel D but normalized to the value of1200the model without gradients, superimposed with a smoothing spline1201interpolation.
- 1202 F. Average of the relative differences shown in panel E.
- 1203G.Average spiking histogram for models consisting of 100 and 10001204GCs, superimposed with double sigmoidal fits constrained to 80, 0 and

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- 1205 120 Hz. Above the target spiking sequence with 80, 0, and 120 Hz is 1206 indicated.
- H. Illustration of the temporal error (e1 and e2) of the spikes defining the beginning and the end of the pause.
- 1209 I-K, L-N, and O-Q. Same plots as D-F but for the 80, 0, 120 Hz target 1210 sequence and the van Rossum error (I-K), the transition time ( $t_T$ ) (L-N) and
- 1211 the temporal errot (O-Q).
- 1212

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1215 Figure 9: Illustration of the concept of Fourier-like transformation in the 1216 cerebellar cortex

- 1217A.Illustration of a broadband MF inputs conveying a sequence of low,1218high, and low firing frequency. Inner-zone GCs will preferentially fire1219during high-frequency inputs ('high-frequency' GC) and outer-zone1220GCs during low-frequency inputs ('low-frequency' GC).
- 1221B.Schematic illustration of the signal flow through the cerebellar cortex.1222The Fourier-like transformation in the GC layer is illustrated as an1223optical prism separating the spectral components on the MF input.1224Thereby the MF signal in the time domain is transformed to the1225frequency domain and sent via specialized signaling pathways in the1226molecular layer to the PC.

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