TITLE PAGE

Title: Population temporal structure supplements the rate code during sensorimotor transformations

Abbreviated title: Population temporal dynamics in gaze control

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Summary

Sensorimotor transformations are mediated by premotor brain networks where individual neurons represent sensory, cognitive, and movement-related information. Such multiplexing poses a conundrum – how does a decoder know precisely when to initiate a movement if its inputs are active at times when a movement is not desired (e.g., in response to sensory stimulation)? Here, we propose a novel hypothesis: movement is triggered not only by an increase in firing rate, but critically by a reliable temporal pattern in the population response. Laminar recordings in the macaque superior colliculus (SC), a midbrain hub of orienting control, and pseudo-population analyses in SC and cortical frontal eye fields (FEF) corroborated this hypothesis. We also used spatiotemporally patterned microstimulation to causally verify the importance of temporal structure. A spiking neuron model with dendritic integration was able to decode this temporal information. These findings offer an alternative perspective on movement generation and highlight the importance of short-term population history in neuronal communication and behaviour.

Abstract

Sensory-to-motor transformations are critically mediated by neurons in premotor brain networks whose evolving activities represent sensory, cognitive, and movement-related information. However, this multiplexing poses a conundrum: how does a decoder know precisely when to initiate a movement if such neurons are also active at times other than when a movement occurs? Extant models of movement generation that rely on firing rate, including rise-to-threshold, inhibitory gating, and dynamical switches at the population level, leave certain explanatory gaps unfilled. Here, we propose a novel hypothesis: movement is triggered not only by an increase in firing rate, but critically by a reliable temporal pattern in the population response. We show that in brain regions involved in orienting eye movements - the superior colliculus and the frontal eye fields - the temporal dynamics between neurons during visually-driven activity is different from that during pre-movement activation. Specifically, using a measure that captures the fidelity of the population code, we show that the temporal structure fluctuates in the visual response but remains stable during the pre-movement response, thus distinguishing incoming sensory input from motor output. This is an important attribute because SC and FEF "visuomovement" neurons project directly to the brainstem which houses the controller for gaze shifts, and any increase in the incoming drive is poised to trigger a gaze shift. We also demonstrate that a simple firing rate-based network with synaptic facilitation can distinguish between stable and fluctuating population codes, suggesting a putative mechanism for interpreting temporal structure. These findings offer an alternative perspective on the relationship between spatial attention and motor preparation by situating the correlates of movement initiation in the temporal features of activity in shared neural substrates. They also suggest a need to look beyond the instantaneous rate and consider the effects of short-term population history on neuronal communication and behaviour.

In order to successfully interact with the environment, the brain must funnel down the sensory inputs it receives to specific movements at specific times. Such sensory-to-motor transformations are critically mediated by premotor brain networks where evolving activities in individual neurons represent sensory, cognitive, and movement-related information[1-3]. For example, in brain regions involved in the control of gaze, including the SC, so-called visuomovement neurons burst a volley of spikes both in response to a visual stimulus and for generating a gaze shift or saccade to the location of the stimulus[1]. The dual nature of visuomovement neurons is best illustrated by examining their activity in the delayed response paradigm (left panel in Figure 1A), which requires the subject to withhold a saccade to a stimulus in the visual periphery until after the disappearance of a central fixation cue. We recorded population activity from the SC using laminar microelectrode arrays (right panel in Figure 1A) in two monkeys (*Macaca mulatta*). Figures 1B shows responses on individual channels (top row) and population activity averaged across channels (bottom row) aligned on target (left) and saccade (right) onsets for three example trials in one session. The population exhibits a high-frequency visual burst following target onset and a subsequent premotor burst prior to a saccade. The peak magnitude of the visual burst is lower than that of the premotor burst on some trials (light traces in Figure 1B), but it is not uncommon for the peak visual response to match or exceed the premotor activity (medium and dark traces in Figure 1B), especially when accounting for the 10-20 ms efferent delay from neural initiation to movement onset[4-6] (vertical dashed line in bottom panel of Figure 1B), consistent with previous reports that tectoreticular neurons involved in saccade generation show strong visual and premotor transients[7]. Yet, on these trials, the visual burst does not trigger a movement, an observation that casts doubt on thresholding[5,8] as a singular mechanism governing movement initiation. We also tested whether saccade initiation could be controlled solely by "motor" neurons, thought to be active only during saccades and not during the visual epoch. This hypothesis requires motor neurons to exclusively have a high motor potential, i.e., be most correlated with saccade kinematics[9]. While motor neurons indeed have a high motor potential (Supplementary Fig. 1A and B), we found that neurons with strong visual activity also were strong drivers of the saccade (Supplementary Fig. 1C and D), disputing the categorical motor neuron hypothesis. Other mechanisms, primarily based on static weighted linear readouts of population activity, have been proposed for how movement generation unfolds in the skeletomotor system[10-12], but they have certain limitations and explanatory gaps, as we discuss later. Given that visuomovement neurons project directly to the brainstem saccade burst generator that initiates and guides saccadic gaze shifts[7,13,14], we asked how downstream structures are able to differentiate between the two bursts.

Quantification of population temporal structure

We reasoned that if static features of population activity such as the mean firing rate are insufficient to discriminate between visual and premotor bursts, the answer likely resides in the spatiotemporal structure of activity during the two bursts. Indeed, a growing body of work has revealed that precise coordination in the timing of input spikes is more efficient at driving downstream cortical and subcortical neurons[15-17]. Specifically, we hypothesized that a critical criterion for a decoder to generate a movement should be a high level of certainty in the instructed movement and its metrics. Since the exact decoding scheme is unknown, we considered whether certainty is provided by consistency in the population pattern over the course of a burst, under any generalized weighted pooling scheme. To quantify this consistency, we first constructed a population firing rate trajectory as a function of time. Next, we normalized the population vector at each time point, constraining it to a unit hypersphere in

state space (Figure 1C; see Methods for details). This step factors out global changes in firing across the population and focuses on the relative activity pattern. We then computed the dot product between two of these unit vectors separated in time (parametrized by τ) - we call this measure the temporal stability of the population code.

Evolution of population temporal structure during sensorimotor tasks

Figure 1D shows the evolution of temporal stability averaged across all sessions (n = 280 channels/16 sessions, mean +/- s.e.m., coloured traces; also see Supplementary Fig. 2A, top row). The stability of the population pattern decreased relative to baseline during the visual burst and increased during the premotor burst. Moreover, this property was preserved when considering only the subset of trials where the peak visual response matched or exceeded the premotor activity 15 ms before saccade onset (gray trace in Figure 1D), and was significantly different from the trend in the null condition when the saccade was directed to a stimulus in the opposite hemifield (black trace in Figure 1D). Scrambling the population code by either shuffling the activations of individual neurons at each time point or shuffling across time points lowered the stability profile for the entire trial significantly (Supplementary Fig. 2A, bottom row). The anti-phase relationship of stability between the visual and premotor bursts was also present across a range of separation times between the two population vectors used for the dot product (Supplementary Fig. 2B). We also computed temporal stability by realigning activity on the peak population visual response, to discount any effect of visual response onset latency differences across the population, and found similar (if not stronger) effects (Figure 1E, also see Supplementary Fig. 2C). Finally, temporal stability afforded more robust discrimination between the visual and premotor bursts even on individual trials and sessions (Figure 1F), compared to the population firing rate (Figure 1G). Thus, population temporal stability seems to impose a constraint that prevents movement initiation at an undesirable time (visual epoch), allowing the animal to successfully perform the task at hand. Once cued to execute a gaze shift, the activity in the same population rises in a stable manner allowing saccade initiation.

Next, we explored the robustness of the temporal stability hypothesis. We tested whether the properties of stability observed in other populations of neurons or conditions were consistent with its predicted role in movement initiation. For this part of the study we used data obtained from single-unit recordings in SC and the frontal eye fields (FEF), the latter of which plays a major role in the cortical control of saccade initiation[5,18]. Figure 2A shows the average normalized population activity of 57 SC and 22 FEF neurons, affirming the visuomovement pattern of activity discussed above. We then used the trial-averaged activity of individual neurons to construct a pseudo-population, resulting in an “expected neural trajectory” on a given trial (Figure 2B), and used this as the input to the temporal stability computation (for more, see Methods and Supplementary Fig. 3A). Due to averaging across trials, the stability profiles observed here were relatively smoother and closer to unity overall compared to the profiles in the previous section, especially during the delay period (Figure 2C). Importantly, the key observations were in line with those observed with simultaneous population recordings – the dramatic reduction in the stability during the visual burst, and stable activity during the premotor burst – in both SC and FEF, and were consistent across time separations (Supplementary Fig. 3B) and subjects (Supplementary Fig. 3C).

We then tested whether the temporal stability framework was obeyed by SC neurons beyond those that are involved in the generation of large or non-fixational saccades. Neurons in the rostral SC are tonically active during fixation and reduce their activity during larger movements[19] (Figure 2D, middle row). Importantly, they also project to the saccade burst generator[20]. Assuming population stability modulates the input drive to downstream structures, we hypothesized that the temporal structure in rostral SC neurons must decrease during large saccades but remain elevated during fixation, even when a visual burst occurs in other parts of SC and FEF. In other words, we expected the evolution of temporal stability across rostral SC neurons to be the inverse of what occurs in caudal SC - Figure 2D (bottom row) confirms this prediction. In addition to the antiphase relationship with caudal SC during large saccades, rostral SC is also known to play a causal role in the generation of microsaccades[21] during fixation. Therefore, we considered whether the rostral SC population exhibits stable temporal structure during the burst that produces microsaccades. This was indeed the case (Figure 2E). Thus, the population activity of neurons in rostral SC, including its temporal structure, supplements the pattern in other parts of SC in suppressing and initiating movements. Finally, pooling neurons in SC and FEF to form a combined population[22] (since they all project to saccade-generating structures) did not impact the main result (Supplementary Fig. 3C). Note also that the pseudo-population analyses differ from the laminar recording analyses from the previous section in the exact shape of the temporal stability profiles. However, the direction of the main effect remains the same, allowing for further testing of the robustness of temporal stability across brain regions and behaviours using simultaneous recordings.

Causal discrimination of population temporal structure

Thus far, we have shown that population temporal structure is a candidate measure that can be used to discriminate between visual and premotor bursts, using only a correlational analysis. To test whether this measure is actively used by the brain in a causal manner, we performed multi-site patterned microstimulation in SC. We first identified individual contacts of the laminar probe that evoked low-latency saccades with suprathreshold stimulation, to verify their placement in the intermediate layers of SC. We then designed temporally stable and unstable stimulation patterns restricted to these contacts, limiting stimulation parameters for individual sites to the sub-threshold regime and verifying that the overall stimulation was near-threshold (for details, see Methods). Stable patterns were created with a linearly decreasing inter-pulse interval (IPI) sequence for one contact[23] (to simulate a burst) and scaling the IPIs for other contacts by a uniformly spaced factor. For each stable pattern, we also created a *paired* unstable pattern by jittering the pulse times within a window and shuffling spikes between contacts, preserving both the pulse count for each site and the average pulse rate across the "population". An example pair of stable-unstable pulse trains is shown in Figure 3A (top row). The pulse rates determined from these trains (second row) illustrate the scaled rates for the stable pattern and the fluctuating rates for the unstable pattern for individual sites, despite the comparable population rates on individual trials (thick traces; see Supplementary Fig. 4B,C for more examples). Note that the assignment of high and low rates to different contacts was randomized across trials, resulting in similar trial-averaged pulse rates for any given channel, for either type of pattern (third row). The temporal stability for stable and unstable patterns for all trials in the example session (bottom row) confirm the impression provided by the pulse trains and rates, i.e., the scaled patterns are highly stable compared to the relative instability of the jittered patterns.

192 We delivered these stimulation patterns during the "gap period" in a gap saccade task (Supplementary
193 Fig. 4A). Figure 3B shows a scatter plot of the stimulation-aligned saccade latencies observed using
194 stable versus unstable stimulation patterns for all pairs from one session. For the majority of stable-
195 unstable trial pairs, a saccade was evoked with the stable but not the unstable pattern (henceforth
196 referred to as S+US- trial pairs. These are the points in the blue shaded window spanning the stimulation
197 duration in Figure 3B; note that points in the unshaded region refer to trials in which neither stable or
198 unstable pair evoked a saccade, and these trials were assigned the latency relative to stimulation onset
199 of the saccade directed to a target presented after the gap period). The relative likelihood of evoking a
200 movement with the stable stimulation pattern only (as computed in the graphic on the right) is shown as
201 a function of session number in Figures 3C (blue points). For most sessions, the observed relative
202 likelihood values were significantly higher (i.e., biased towards the stable pattern; $p < 0.01$, permutation
203 tests) than the null distribution (gray points) obtained by shuffling trials with randomly assigned stable-
204 unstable identities, reinforcing the observation that the stable pattern was more likely to evoke a
205 movement compared to a *state-matched* unstable pattern. We also analyzed the movement vectors
206 evoked by stable and unstable patterns – both sets of saccades, when they occurred, were similar to
207 each other in both amplitude and direction and to the "fixed vector saccades" evoked by constant
208 frequency multi-channel stimulation, in amplitude (Supplementary Fig. 4D and 4E; $p > 0.01$ for most
209 sessions, Wilcoxon rank-sum tests; for details, see Methods). Additionally, we explored whether
210 differences in pulse rates on subsets of trials could explain the across-sessions range of movement
211 likelihood effects seen in Figure 3C (Supplementary Fig. 5). Sessions in which the stable pattern was
212 more likely to evoke movements were also the ones in which the S+US- trials (Supplementary Fig. 5A)
213 were closest to the intended uniform sampling of pulse rates across channels, as reflected in the low
214 relative dispersion index for those sessions (Supplementary Fig. 5B and 5C). Sessions with no significant
215 (or negative) effect on movement likelihood were the ones which had a high across-channel pulse rate
216 sampling asymmetry, potentially allowing extremes in pulse rates to mask any underlying effect of
217 temporal structure (Supplementary Fig. 5B and 5C; also see Methods).

218

219 **Comparison with other population-based models of movement generation**

220 Having demonstrated the role of population temporal structure in saccade initiation using both
221 correlative and causal approaches, we sought to disambiguate the stability framework from extant
222 models of movement initiation. We earlier argued for the implausibility of threshold-based gating based
223 on the fact that the population activity during the visual burst can sometimes exceed premotor activity
224 (Figure 1B). Could other population activity-based mechanisms, such as weighted linear readout models
225 that seem to govern movement generation in the skeletomotor system (e.g., the optimal or movement-
226 potent subspace frameworks)[10-12], play a role here? To test this, we first used factor analysis (FA) to
227 visualize the low-dimensional neural states[24] in the visual and premotor bursts. An example 3-
228 dimensional FA projection of the two bursts is shown in Figure 4A – the two sets of states are clearly
229 separable, likely an effect of the subtle yet distinct trends in visual versus premotor activity levels along
230 the dorso-ventral extent of the SC (e.g., Figure 1B). Indeed, a linear discriminant analysis (LDA) classifier
231 was able to easily discriminate between the visual and premotor states for most sessions (histogram
232 inset in Figure 4A). The properties of neural activity in SC therefore seem to be consistent with a static
233 state space code as well.

Next, we used data from the patterned microstimulation experiments to disambiguate between the optimal subspace and temporal stability frameworks. Using a representative low-dimensional FA projection to differentially visualize stable and unstable stimulation patterns was infeasible because all the electrode sites contributed equally to the patterns, due to the random assignment of pulse rates across sites on different trials. From the example 3-dimensional projection in Figure 4B, it is evident that the stable and unstable patterns are indiscriminable in state space. Indeed, an LDA classifier failed to discriminate between stable and unstable patterns based on population pulse states alone, never yielding above-chance classification (Figure 4B, orange bar in histogram inset). However, an LDA model that included stability information was able to classify perfectly, reaffirming the difference in temporal structure (by design) between the two sets of patterns (Figure 4B, green bar in inset; also see right matrix in Figure 4C). These results indirectly provide a key piece of evidence in support of the notion that the brain in fact uses temporal information, since the evoked behavior reflected the difference between stable and unstable patterns while a static linear readout of population states did not.

The next set of analyses examined the effect of stimulation pattern on behaviour. We focused on the trial pairs in which only one of stable or unstable pattern evoked a movement (left matrix in Figure 4C), since these are likely to provide insight into the discriminatory role played by temporal structure. We trained another LDA classifier to discriminate between trials in which stimulation evoked a movement and those where no movement was evoked. When using the pulse states alone, the linear decoder was unable to determine whether a movement was evoked on a given trial with above-chance accuracy (orange points in Figure 4D). Since the stable-unstable pairs were matched in terms of whether a movement was evoked or not for this subset, this readout of the population pattern was independent of its temporal structure. Crucially, and in contrast, when the population pulse states were supplemented with stability information (added as a native dimension in the input to the decoder, see green matrix in Figure 4C), classifier performance increased to reflect the broad trend in relative movement likelihood in Figure 3C (green points in Figure 4D). The correlation between performance of the full LDA classifier and the behavioural effects of stimulation is better highlighted in Figure 4E, i.e., the brain's ability to extract temporal structure to generate movements is reflected by a model that utilizes this temporal information. We also independently evaluated whether temporal stability was more informative than each and all pulse count dimensions by performing model selection analysis with a logistic regression fit to the movement occurrence data used for the previous analysis. For every stimulation session, the best model (one with the lowest Bayesian Information Criterion or BIC) was one that only had the temporal stability dimension (blue asterisks indicating minima in BIC curves in Figure 4F). Together with the effect of dispersion seen earlier (Supplementary Fig. 5), these analyses reveal two independent contributors to movement initiation in SC – a static "laminar" code, presumably related to the optimal or potent subspace, that may be a function of the distribution of preferred stimulation sites, and a dynamic "temporal" code, where stability of the population pattern controls movement initiation *even* under matched state space conditions.

We also tested how the temporal stability hypothesis was related to modified threshold-based mechanisms that rely on pooling the activity of a correlated ensemble of neurons[25,26]. In this framework, correlations in the accumulation rates of neurons influence movement initiation (reaction times) under a given pooling scheme, with higher correlations leading to shorter reaction times. Spike count correlations between SC neurons in the visual and premotor epochs (for details, see Methods) were inconsistent with this notion – the correlations during the visual epoch were slightly, but significantly,

higher compared to the premotor epoch (Supplementary Fig. 6A, mean difference between visual and premotor epoch correlations = 0.0167 > 0, p = 2.5E-6, one-tailed t-test). We also computed pulse count correlations for the stable and unstable stimulation patterns and found no difference (Supplementary Fig. 6B, median difference in correlations between conditions = 4.11E-4, not significantly different from 0, p = 0.279, Wilcoxon signed-rank test), despite the significant difference in their effects on behavior. Thus, the temporal stability framework is, to a large extent, independent of extant models of movement initiation.

Biophysical models for decoding population temporal structure

Finally, we sought to identify a mechanism by which downstream neurons could discriminate between stable and unstable population codes. We modelled the decoder as a spiking neuron that receives population inputs through its network of dendrites (Figure 5A). The decoder can be thought to represent neurons in the pons that receive and integrate SC inputs and burst for saccades[20]. To mimic the potent inhibitory gating (and disinhibition during saccades) provided by the omnipause neurons (OPNs) on the burst neurons, we also included a spiking disinhibitor unit with reciprocal inhibitory connections with the decoder. The disinhibitor also received both excitatory[27] and inhibitory[28] inputs from the same population as the decoder, creating a balance between excitation and inhibition that must be overcome in order to produce a saccade. How might the population pattern be converted into a signal that initiates a movement only when the inputs are stable? Conceptually, the decoder should have a mechanism to keep track of the short-term history of population activity, use this history to evaluate temporal structure, and respond selectively when the activity pattern is deemed stable over the time scale of integration. We incorporated these heuristic requirements by using state-dependent modulation of input-evoked excitatory post-synaptic potentials in the decoder, i.e., inputs arriving when the local post-synaptic potential was depolarized caused a higher subsequent change in the potential[29,30] (Figure 5B).

We simulated the model with the stable and unstable patterns from the microstimulation experiments as inputs, since they readily offered mean-matched input sequences differing only in temporal structure. We characterized the efficacy of integration by the decoder as the time of first spike in the burst, a proxy for movement initiation latency. Although there were several pairs of trials for which both or neither the stable and unstable inputs caused the decoder to spike (Figure 5C), there were a number of pairs for which only the stable input pattern was decoded (arrow in Figure 5C). To facilitate visualization and comparison with experimental data (Figure 3B), latency values greater than the stimulation duration were randomly assigned when the decoder wasn't recruited. Figure 5D shows the membrane potential output of the disinhibitor (cyan and magenta traces) and decoder (blue and red traces) units for a pair of stable (top row) and unstable (bottom row) input patterns from this subset of trial pairs. The disinhibitor maintained a tonic firing rate throughout the trial when the inputs were unstable, and sharply reduced its activity at some point during stable stimulation (Figure 5E - magenta and cyan traces, respectively). This latter disinhibition on stable trials was in anti-phase relationship with the bursting exhibited by the decoder, which was absent on unstable trials (Figure 5E - blue and red traces, respectively). See Supplementary Fig. 7 for membrane potential waveforms when both or neither the stable and unstable patterns recruit the decoder unit. The firing rate profiles of the decoder and disinhibitor units share a striking resemblance to medium-lead burst neurons and OPNs, respectively, in the pons[31]. Thus, a

relatively simple, yet biophysically realistic, module seems capable of discriminating between population inputs based solely on their temporal characteristics, offering a putative mechanism by which downstream networks could use temporal information to make decisions about movement generation. The model simulations predict that temporal structure will impact integration near activation threshold, but a surplus of spikes in an unstable input may still be integrated well enough to produce a movement, consistent with the observations in the patterned microstimulation experiment. Another testable prediction is that disinhibition of the gaze control circuitry by silencing the OPNs should diminish the effect of temporal structure in determining movement initiation, producing movements for both stable and unstable inputs. We also found that a firing rate-based accumulator model with short-term synaptic plasticity produces comparable results (Supplementary Fig. 9), demonstrating the flexibility of various biophysical mechanisms in their ability to decode temporal structure and hence, the model-independence of this result.

Perspectives on the role of temporal structure

Neurons in premotor structures are constantly bombarded with information from thousands of presynaptic neurons that are active during sensorimotor processing. It is unclear how activity relevant for movement initiation is discriminated from activity related to other processing. Extant models of movement generation that rely on firing rate, including rise-to-threshold[5], inhibitory gating[31], and dynamical switches at the population level[10,11], leave certain explanatory gaps unfilled. A canonical model of movement initiation, especially in the oculomotor system, is threshold-based gating[5] (Figure 6A-B). Current knowledge points to a role by the OPNs in defining the threshold and controlling saccade initiation[5,32]. However, thresholds vary across behavioural paradigms[8,33], raising the question of how the threshold is set in a particular condition. Furthermore, evidence that the threshold changes during the course of a trial purely based on OPN activity is limited[32]. Critically, the existence of trials in which the population activity during the visual response exceeds premotor activity strongly reduces the likelihood of thresholding operating as a singular mechanism. An extension of simple thresholding is a mechanism based on the pooled activity of neurons with varying degrees of correlation in the population[25]. However, we show that population correlation statistics are not necessarily related to temporal structure or saccade initiation (Supplementary Fig. 6). A related alternative explanation is that a movement is initiated specifically when movement-only neurons are active, but most neurons in sensorimotor structures like SC and FEF span a continuum between visuomovement activity and movement activity[1,34,35]. In fact, antidromically identified tectoreticular neurons that presumably drive saccade generation exhibit both visual and premotor bursts[7]. Moreover, as seen earlier, SC neurons with the highest correlation to movement velocity tend to also have strong visual responses (Supplementary Fig. 1).

Other models, primarily developed in skeletomotor research, posit that muscles are recruited and a movement is initiated when neural activity traverses certain optimal regions of the population state space[10] and is inhibited otherwise, e.g., during movement preparation[11,12] (Figure 6C). While the optimal subspace and nullspace hypotheses certainly seem to be consistent with recorded neural activity in SC (Figure 4A), they cannot readily account for the observation that neck[36] and upper limb[37] muscles are recruited time-locked to the visual target, as proxied through electromyography. We instead show that temporal stability plays an independent role in determining movement initiation, even when the

putative potent subspace is matched in a causal manipulation (Figure 4D, green symbols). We reason that for a decoder downstream, it is important to ensure the stability - or consistency over time - of the input code while processing it in order to influence the motor output. Population activity that creates a high firing rate drive but is unstable is also likely unreliable and must have a reduced efficacy of triggering a movement. This requirement is critical especially in the case of ballistic movements such as saccades, where the ability to reverse the decision once the movement has been initiated is limited. Thus, we present a novel mechanism, wherein both high firing rate and consistent temporal structure are necessary conditions for movement initiation, allowing for population trajectories that traverse away (increasing overall rate) but within hypersectors that fan out (stable temporal pattern) from the state space origin (Figure 6D). Note that this model does not preclude population activity from traversing a localized "optimal" region of state space, possibly due to hardwired network constraints. Crucially moreover, the proposed mechanism is also consistent with classical population vector decoding schemes, since any weighted population vector readout during the sensory and movement epochs will produce decoded movement vectors that are largely similar. This allows for the same physical movement to be planned and executed by a given population of neurons in the labelled line sense, a possibility that is precluded by weighted neural readout mechanisms of movement preparation and generation, such as the potent/nullspace models.

Our findings are closely related to the premotor theory of attention[38] and offer a way to reconcile the attention- intention debate. They could also account for the mirror-like activity recorded during both action observation and execution in neurons known to project directly to motoneurons in the spinal cord[39]. In both cases, it is unclear how the same neuronal population represents two distinct signals that serve different functional roles. The results presented here suggest that this multiplexing ability may be provided by the distinct temporal structures of population activity patterns. Indeed, intracellular recordings have demonstrated that visual stimulation drives cortical networks into an asynchronous state[40], which may be a critical requirement for sensory processing. Additionally, the differential effects of stable and unstable population stimulation patterns are reminiscent of the desynchronizing effects of patterned deep brain stimulation recently developed for the treatment of Parkinson's disease[41]. In this so-called "coordinated reset" approach, sequential, non-overlapping spatiotemporal sequences are more effective at resetting the affected neuronal population from the pathological synchronized state to an asynchronous state, enabling better movement control[42].

Previous studies have looked at the role of precise coordination in the timing of incoming spikes in the transmission of information and the efficacy of driving the recipient neuron[15,16]. However, input firing rates may vary greatly across the population, limiting the ability to compare to spike times. Our study proposes a mean-field equivalent to the spike-based temporal or correlation code[17,43] by looking at the temporal structure of population firing rates, thus tying together the notion of rate, temporal, and population codes. We suggest that temporal structure of population activity is critical to understanding movement generation as well as, more broadly, neuronal communication and its relationship to behaviour.

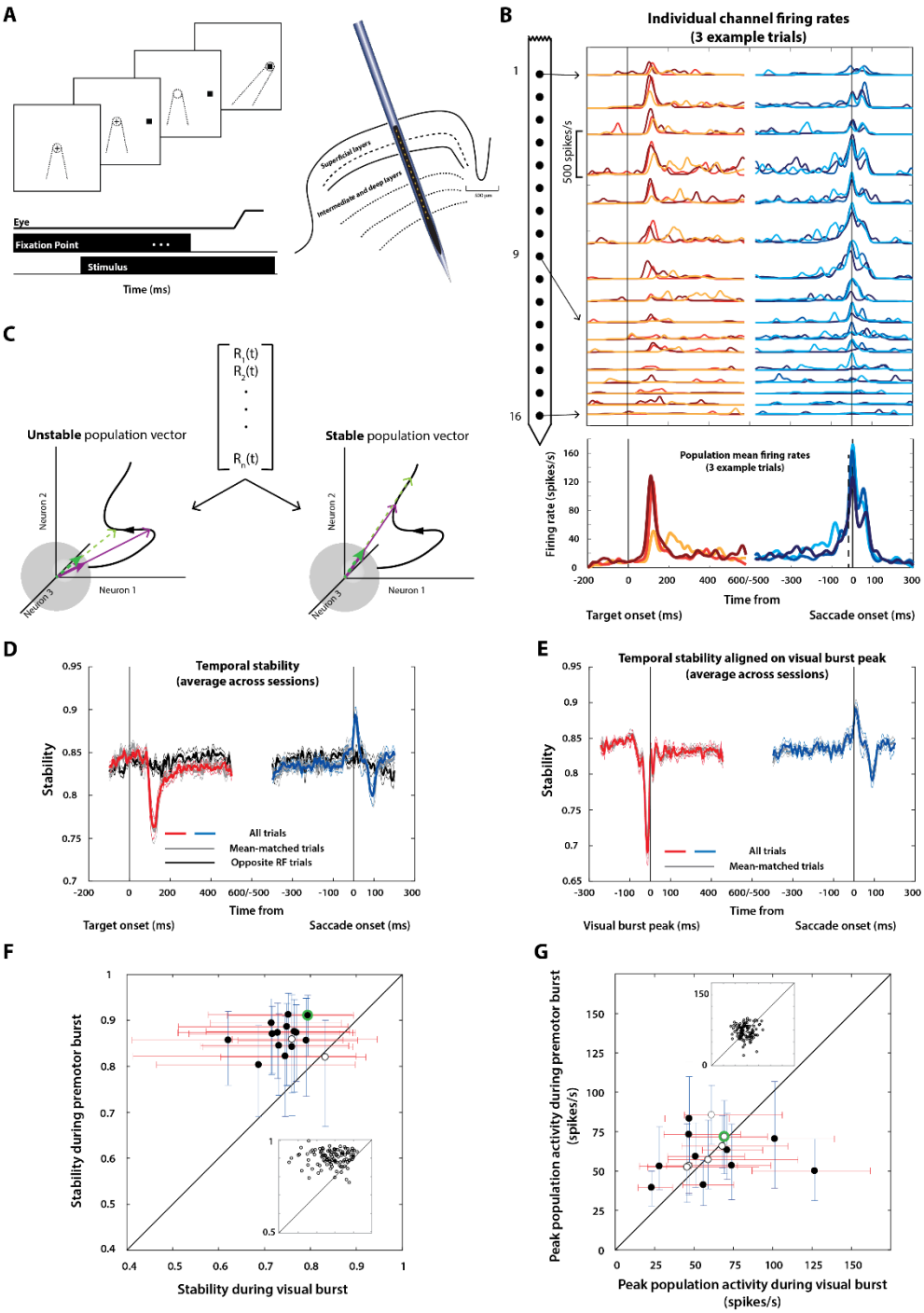

Figure 1. **Temporal structure of population activity during sensorimotor multiplexing. A.** Left - Sequence of events in the delayed saccade task. The top row shows a typical display sequence and the bottom rows show the timeline. The fixation target is shown as a plus symbol for illustration purposes. Dotted lines depict line of sight of the animal. Right – Linear electrode arrays with 16-24 contacts were used to penetrate the SC normal to the surface. Thus, all neurons encountered along the dorso-ventral axis of the SC prefer similar optimal vectors. **B.** Top: Example recording session showing activity from 16 channels aligned on target (left column) and saccade (right column) onsets for 3 different trials (traces with different colour saturations). Bottom: Population activity averaged across the 16 channels for the 3 trials shown in B. Note the considerable variation in the amplitude of the

population visual burst across trials. **C.** Schematic depicting computation of temporal stability. The population vector (centre) was used to construct a single-trial neural trajectory, which was then normalized at each instance to represent a unit length population vector traversing along a hypersphere. The left and right panels highlight unstable and stable parts of a schematic trajectory. Note that in both cases, the two population vectors (thin arrows in green and purple) are separated by a similar length of time. In the unstable case, the normalized vectors (thick arrows) move around on the surface of the hypersphere (green and purple vectors are spatially separate), whereas in the stable case, they stay pointed roughly in the same direction (the two vectors overlap in space). **D.** Temporal stability is computed as a dot product between two normalized population vectors separated by $2\tau = 20\ ms$ aligned on target (left) and saccade (right) onsets. The stability of population activity, averaged across sessions, drastically decreases during the visual burst (red traces, mean +/- s.e.m.; $p < 0.01$ for Wilcoxon signed-rank test with respect to baseline) and increases before and during movement onset (blue traces; $p < 0.01$ for Wilcoxon signed-rank test with respect to baseline). The gray trace is the stability computed only for those trials where the peak visual burst matched or exceeded activity during the premotor burst at saccade initiation (after accounting for an efferent delay of 15 ms). It is effectively identical to the red and blue waveforms. The black trace shows population stability on trials in which the target and saccade were directed to the opposite hemifield, far away from the response field (RF) of these neurons. **E.** Temporal stability aligned to peak visual burst. The peak time was computed on the average population response of each trial, and the peak-aligned trace was averaged across trials and sessions. Note the sharper dip in the stability of the visual response when aligned to the peak. Like in D, the gray trace shows peak-aligned stability for trials in which the peak visual activity matched or exceeded premotor activity at saccade initiation. **F**. Scatter plot of temporal stability in a 20 ms window preceding the peak of visual and premotor bursts for individual sessions. Each point is the median of the stability values computed on individual trials for one session (error bars are +/- 95% confidence intervals). Filled circles indicate significant difference between the visual and premotor stability ($p < 0.01$, Wilcoxon signed-rank test). The inset shows the scatter plot for individual trials for an example session (encircled in green). Thus, temporal stability of visual and premotor epochs on individual trials also showed the same effect. **G**. Similar to F but for the peak population firing rate during the visual and premotor bursts. The inset is for the same example session as in F. For F and G, the premotor burst is truncated at 15 ms before saccade onset, the putative efferent delay between SC and the extraocular muscles.

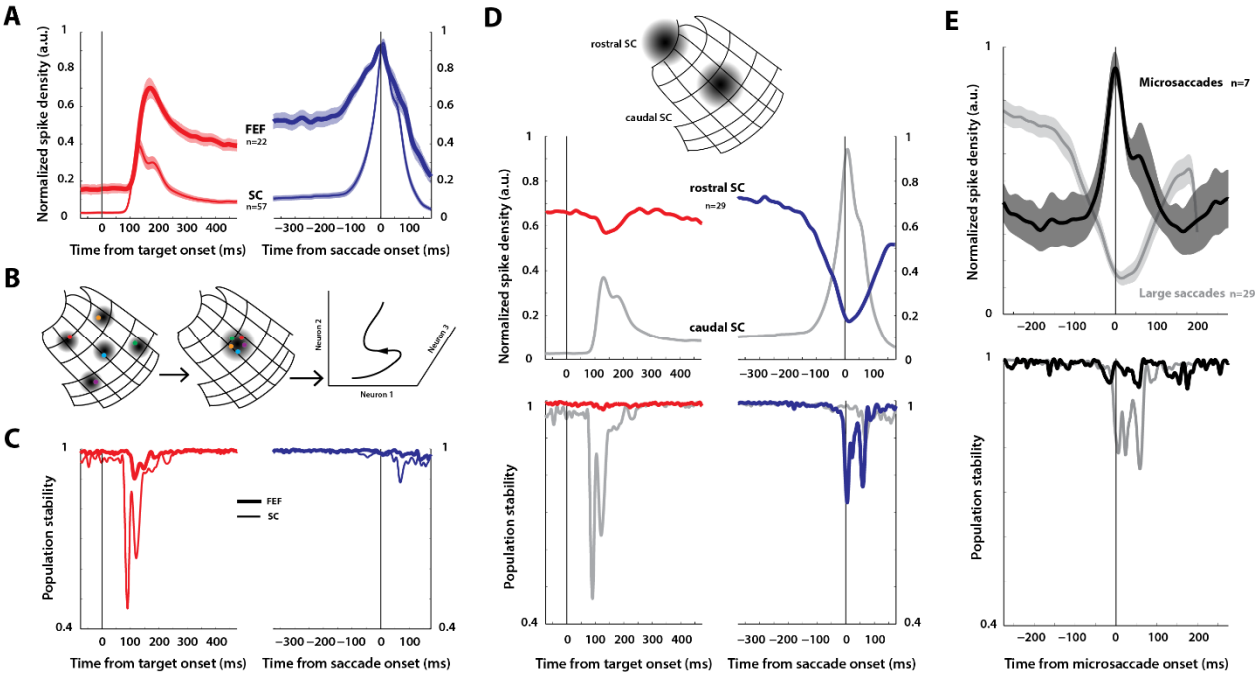

Figure 2. **Temporal stability in sub-populations of SC and FEF. A.** Normalized mean population activity of visuomovement neurons recorded in SC (thin trace) and FEF (thick trace) during the delayed saccade task. The left and right panels show data aligned on target and saccade onsets, respectively. **B.** Inferring population dynamics from single-unit recordings. We combined recordings made in different active populations on the SC map (left) into one pseudo-population (middle) that is active for any saccade, enabling the construction of an expected population trajectory (right) in neural state space (see *Estimating Population Dynamics* in Methods and Supplementary Fig.2 for more details). **C.** Temporal stability for the SC (thin traces) and FEF (thick traces) pseudo-populations. Population stability shows a drastic reduction at the time of the visual burst but is stable before and during the onset of the movement, consistent with the simultaneously recorded population in the previous figure. **D.** Top - Schematic depicting active population regions in the rostral and caudal SC. Middle – Mean normalized activity in rostral SC neurons (coloured traces) during the delayed saccade task. The activity in caudal SC from A is overlaid for comparison (gray trace). Bottom - Temporal stability of the rostral and caudal SC populations (coloured and gray traces, respectively). **E.** Population activity of rostral SC neurons is stable during microsaccades. Top – Normalized population activity of microsaccade-related neurons in rostral SC (black). Note the strong burst compared to the suppression for large saccades in fixation-related neurons in the same region (gray). Bottom – Temporal stability of the rostral SC population for microsaccades(black trace) and large saccades (gray trace). Neurons which burst for microsaccades remain stable during these fixational eye movements, consistent with the hypothesis that both an increase in firing rate and high stability is required for movement generation.

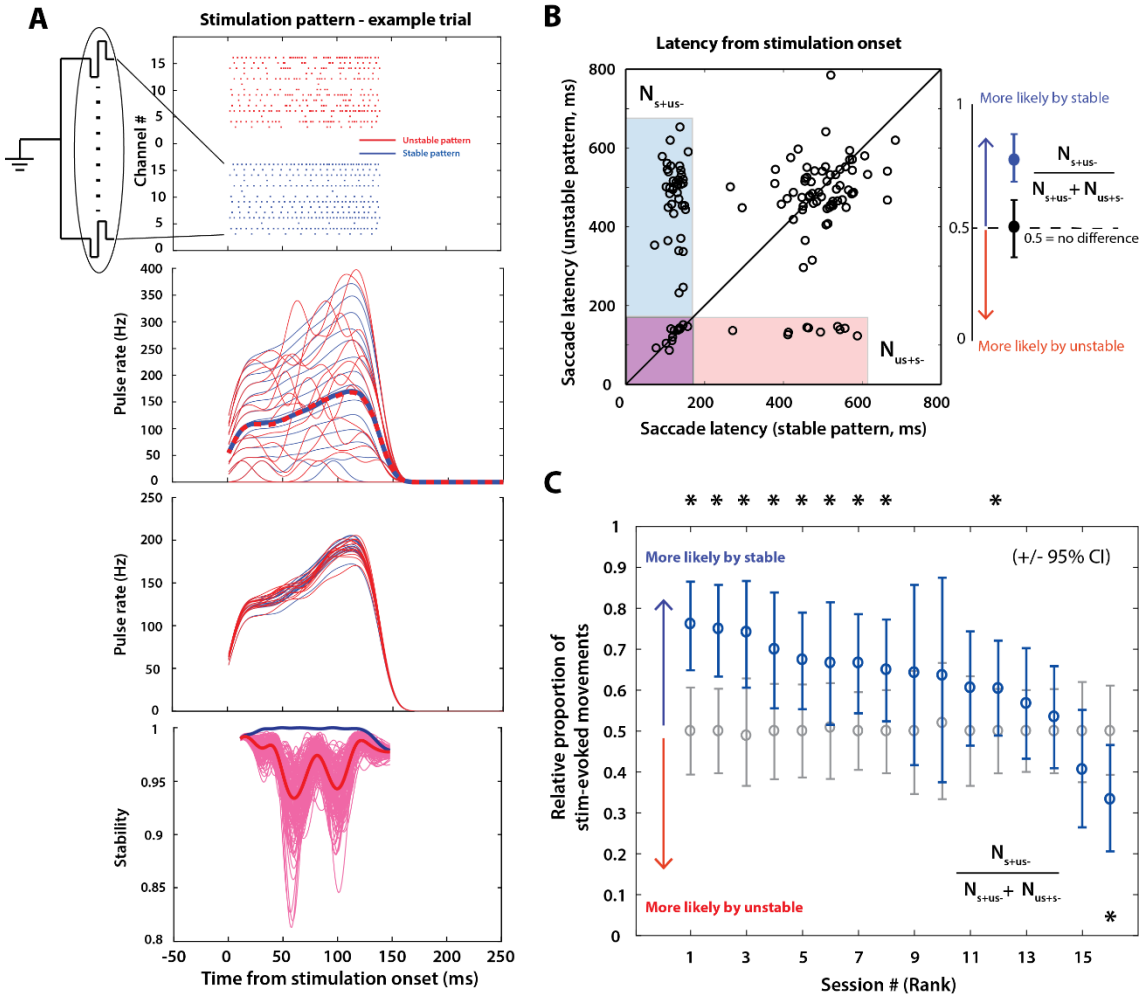

Figure 3. **Patterned microstimulation supports temporal stability as a model of movement initiation. A.** Example pair of stable-unstable stimulation patterns. Top row – Pulse trains for 14 of 16 channels that were stimulation-viable with suprathreshold parameters for this session. Red and blue trains indicate an example pair of unstable and stable patterns, respectively. Second row – Pulse rates for the 14 channels in the stable-unstable pulse patterns, with the population rates averaged across channels overlaid as thick traces. Note that the rates in the unstable pattern are highly fluctuating despite the matched population average. Third row -- Average pulse rates for each channel across all trials for the stable (blue) and unstable (red) patterns used in this session. The clustering of trial-averaged rates in a narrow band is the result of randomization of pulse rate assignment to individual channels on different trials. Bottom row -- Temporal stability of the stable and unstable patterns (blue and pink, respectively) for all trials in the example session. **B.** Scatter plot of saccade latencies (relative to stimulation onset) for the example session. Each point reflects the outcome of stimulation with stable and unstable pulse patterns constituting each pair. The points in shaded regions are stimulation-evoked for at least one condition. N_{s+us-}, points in the light blue shaded box, counts trial pairs for which a stable stimulation pattern evoked a saccade but its unstable counterpart did not. N_{us+s-}, points in the light red shaded box, denotes the trial pairs for which an unstable stimulation pattern evoked a saccade but its stable counterpart did not. Points in the purple box show subset of trials in which both stable and unstable pairs evoked a saccade. Points in the unshaded (white) region refer to trials in which neither stable or unstable pair evoked a saccade. For these pairs, the trial was assigned the latency of the saccade (relative to stimulation onset) directed to a target presented after the gap

period. The graphic on the right shows the calculation of relative likelihood of the stable pattern evoking a stimulation-evoked movement for a given session. **C.** Relative proportions of the stable pattern evoking a movement for each session (blue points, error bars represent 95% CI of the bootstrapped distribution). The sessions are sorted in descending order of proportion for viewing clarity. Note that this sorting order is used in all subsequent figures depicting individual sessions (Figure 4D and Supplementary Fig. 5B). Gray points and error bars are computed from a surrogate dataset in which stable/unstable trial identities are completely shuffled (mean +/- 95% CI). Asterisks denote a significant effect for that session ($p < 0.01$ on the permutation test).

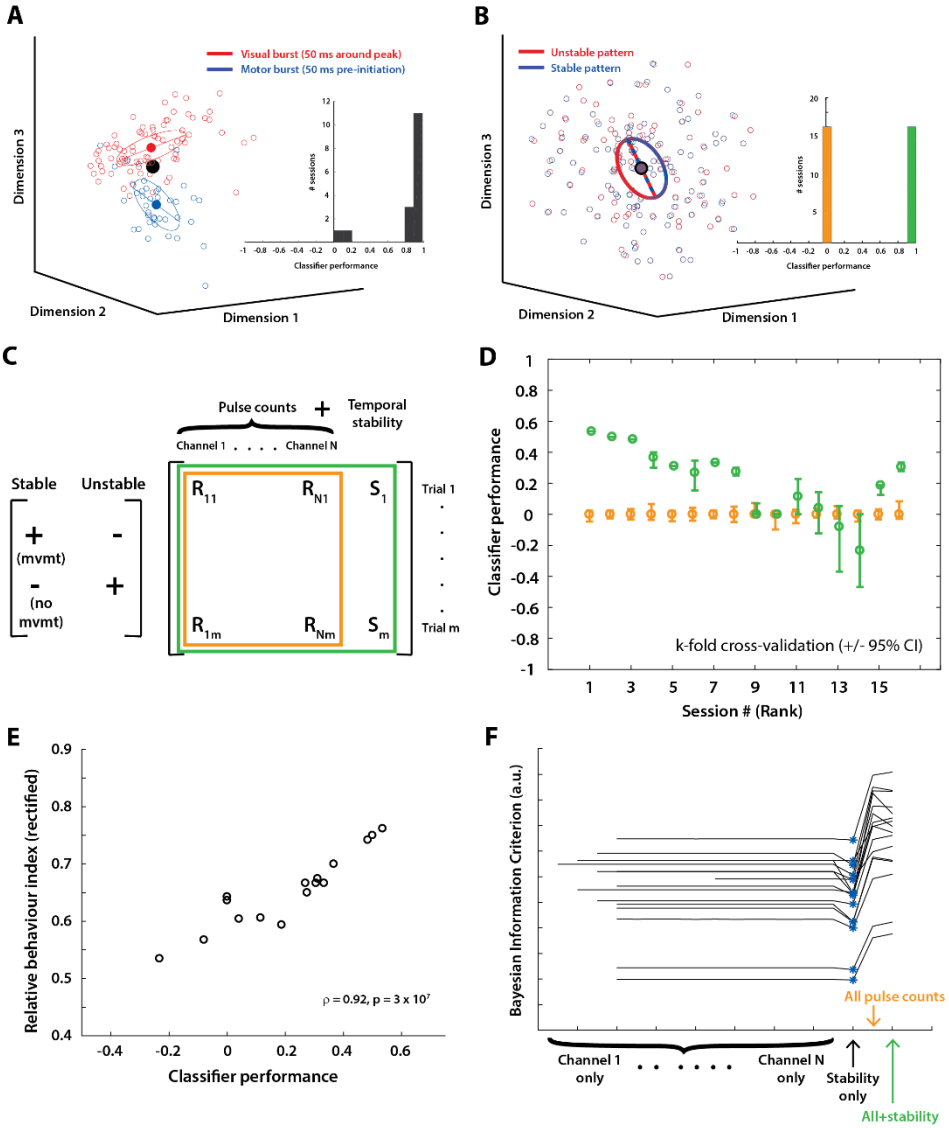

Figure 4. Linear discriminability of population activity and microstimulation patterns. A. Three-dimensional factor analysis (FA) projection of population activity states during the visual and premotor bursts (red and blue points, respectively; 50 ms around peak of visual burst, 50 ms before saccade initiation in premotor burst. The dimensions were chosen arbitrarily to illustrate the separation of the two states. The solid lines and ellipses show the axes of maximum variance and covariance ellipses for each cluster, respectively. The histogram in the inset shows the performance of a linear discriminant analysis (LDA) classifier on labelling visual and premotor states on individual sessions (perfect classification is 1, chance is 0). **B.** FA projection of population pulse states for stable and unstable microstimulation patterns (blue and red points, respectively). The projection dimensions were chosen arbitrarily, but no view showed reasonable separation between the two clusters. The histogram in the inset shows LDA performance on classifying stable and unstable stimulation patterns, based on population pulse states alone (orange bars), or with a combination of population states and temporal stability (green bars). Note that perfect classification is expected by definition in the latter case. **C.** Schematic of the trials and data matrix used for classification of stimulation-evoked movement occurrence. Left - Trial pairs in which only one of the stable or unstable pattern evoked a movement. Right - The classifier was first trained on pulse counts alone (part of the matrix highlighted by the orange boundary – match colour to the next panel). Separately, the classifier was also trained on an additional dimension of temporal stability values (full matrix highlighted by the green boundary). **D.**

LDA classification performance on discriminating trials in which stimulation evoked a movement from those in which it did not. The orange points are with the classifier trained solely on the population pulse states. The green points are with the addition of temporal stability. For most sessions, addition of temporal information increased classification performance ($p < 0.01$, one-tailed t-test of a difference between the cross-validated performance distributions with and without addition of temporal stability). Sessions are sorted by the order determined in Figure 3C based on relative likelihood of evoking a movement. **E.** Scatter plot showing correlation between classifier performance and behaviour (values of blue points in Figure 3D rectified around 0.5). The classifier's discriminative ability predicted the relative behavioural effect size between stable and unstable patterns. **F.** Model selection for discriminating between trials in which a movement occurred versus those in which it did not occur. Bayesian information criterion (BIC) traces as a function of model type for individual stimulation sessions show that the lowest BIC (blue asterisks) was attained for the stability-only model for every session.

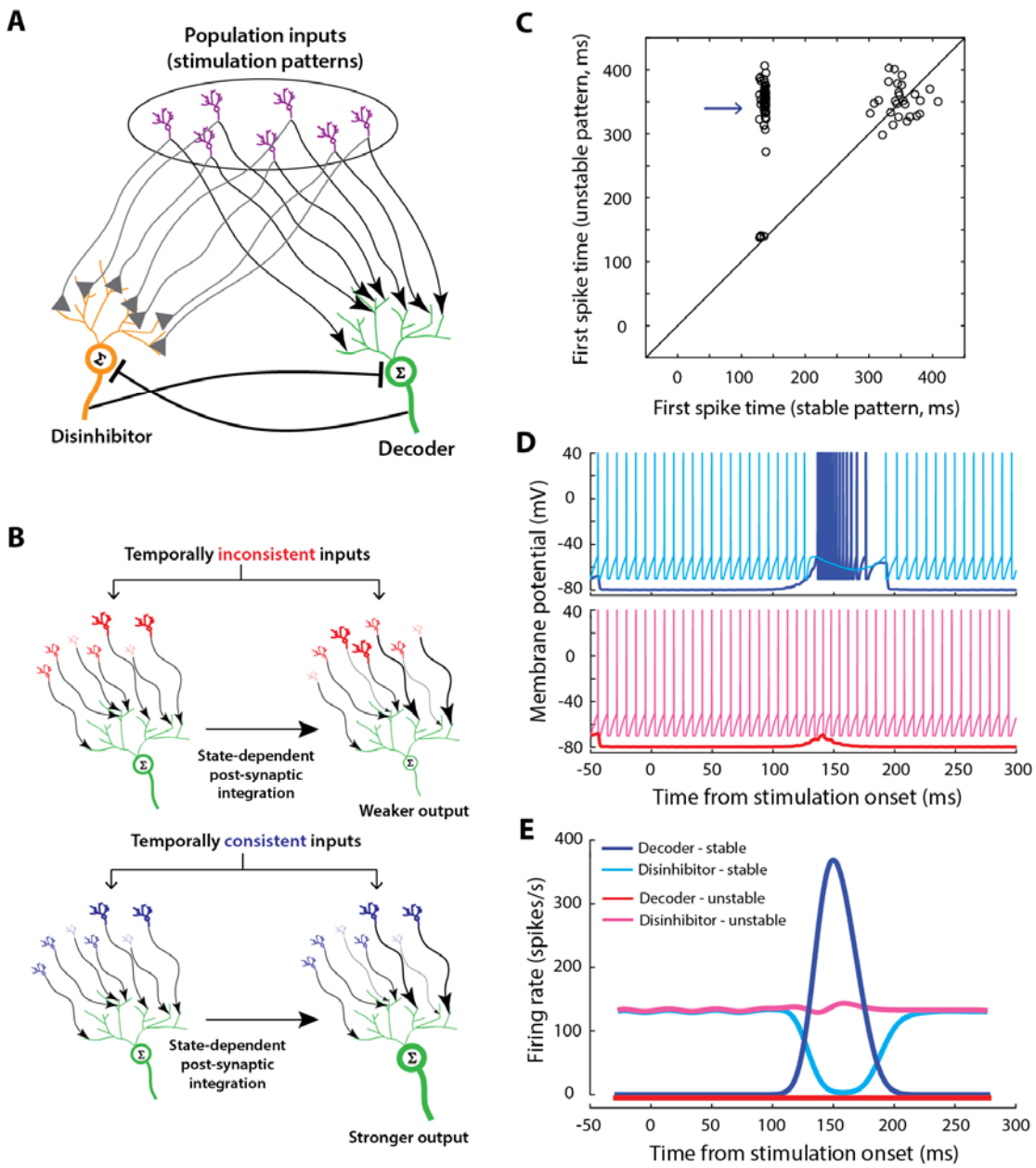

Figure 5. Spiking neuron model with dendritic processes can discriminate population temporal structure. A. Schematic of the model architecture. The decoder (green neuron), representing high frequency burst neurons in the brainstem, receives population inputs (output of purple neurons, or, in this case, microstimulation pulses) through its dendritic network (excitatory inputs, represented by the arrowhead terminals). The disinhibitor (orange neuron), representing pontine omnipause neurons, also receives inputs from the same population (both excitatory and inhibitory[27,28], represented by the triangular terminals), in addition to a constant current that produces tonic firing activity (not shown). The decoder and disinhibitor are both modelled as leaky integrate-and-fire spiking neurons and mutually inhibit each other (flat terminals). **B.** Schematic of the model heuristic. Each input neuron's activation level is represented by its size and thickness. The effect of an input spike at the local dendritic site (i.e., excitatory post-synaptic conductance changes) is represented by the thickness of the arrow. Two time points are shown for illustration (left column – arbitrary initial point, right column – subsequent time point). In the top row,

unstable inputs lead to a scenario where the post-synaptic conductances are no longer aligned to the strong inputs that initially created them, whereas in the bottom, stable inputs lead to matched strong input and post-synaptic conductances, resulting in stronger accumulation and firing. **C.** Scatter plot of first spike latencies in the decoder (putatively representing saccade initiation) for stable versus unstable inputs from matched pairs. The input duration was 150 ms and thus only latency values <150 ms correspond to actual first spikes produced by the decoder. To facilitate comparison with Figure 3B, latency values were assigned randomly for trials in which the decoder did not generate any spikes, sampled from a distribution with an arbitrarily selected mean of 350 ms. Note the occurrence of a number of trial pairs for which only the stable input causes the decoder emit spikes (blue arrow). **D.** Simulated membrane potential of the decoder (blue and red traces) and disinhibitor (cyan and magenta traces) for an example matched trial pair with stable (top row) and unstable (bottom row) input patterns. **E.** Average activity of the disinhibitor (cyan and magenta traces, stable and unstable inputs, respectively) and decoder (blue and red traces, stable and unstable inputs, respectively) for all trial pairs in which only the stable input produced a spike/movement (i.e., trial pairs indicated by the arrow in panel D).

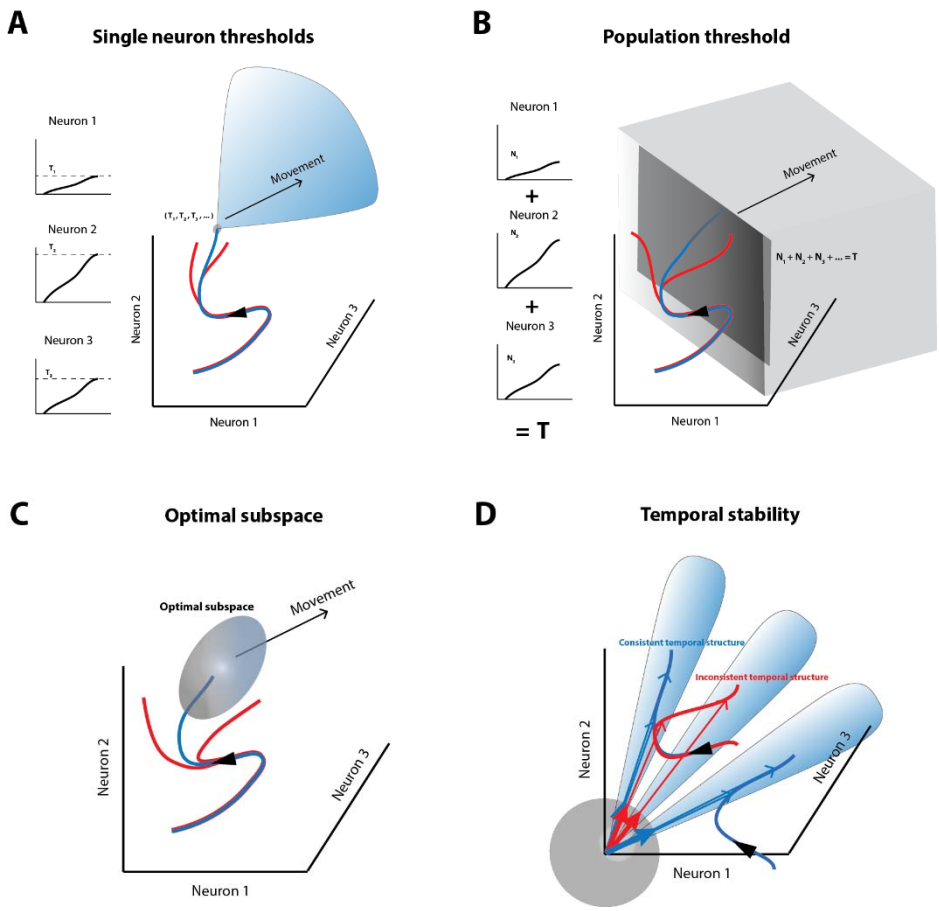

Figure 6. Summary of models of movement preparation in a state space framework. A and **B.** Multi-dimensional representations of the threshold hypotheses. Panel A depicts single neuron thresholds, i.e., the activity of each neuron must rise to a fixed threshold at the same time in order to initiate a movement. Fixed thresholds for each neuron are equivalent to a point (or a small region, represented by the gray sphere) in neural state space. Activity profiles that meet this criterion (e.g., blue trajectory) and beyond (blue region) lead to movement generation while those that don't meet this criterion (red traces) do not result in a movement. Alternatively, activity may need to cross a fixed threshold at the population level (sum of neurons' activities = constant, i.e., an n-1 dimensional hyperplane, dark gray plane), depicted in panel B. **C.** The optimal subspace hypothesis offers more leeway by allowing neuronal activity to reach a relatively larger region of population state space (blue trajectory and gray ellipsoid) over a period of time in order to signal the initiation of a movement. Activity trajectories that evolve outside this "optimal subspace" (red traces) do not lead to a movement. **D.** The temporal stability hypothesis suggests that a burst of neural activity that is consistent over time in state space, i.e., an activity trajectory that points in the same direction (blue trajectories and vectors) is likely to be interpreted as a movement command by a decoder, while high-frequency activity that is inconsistent (fluctuating directions, red trajectories and arrows) is not. It does not matter where in state space the activity happens to evolve – a different subpopulation of neurons could be active, but as long as they are pointing in the same direction (i.e., evolving within one of the blue sectors), it will lead to a movement. The gray sphere around the origin represents a unit hypersphere for visualization of back-projected unit vectors.

565 **Methods**

566 *General and surgical procedures*

567 All experimental and surgical procedures were approved by the Institutional Animal Care and Use
568 Committee at the University of Pittsburgh and were in compliance with the US Public Health Service
569 policy on the humane care and use of laboratory animals. We used three adult rhesus monkeys (*Macaca*
570 *mulatta*, 2 male and 1 female, ages 6 - 12) for our experiments. Both SC and FEF were recorded in
571 monkeys BB and BL whereas only SC was recorded in monkey WM. Under isoflourane anaesthesia,
572 recording chambers were secured to the skull over craniotomies that allowed access to the SC and FEF.
573 In addition, posts for head restraint and scleral search coils to track gaze were implanted. Analgesic and
574 antibiotic treatment protocols were followed after surgery. Post-recovery, the animal was trained to
575 perform standard eye movement tasks for a liquid reward.

576

577 *Visual stimuli and behaviour*

578 Visual stimuli were displayed either by back-projection onto a hemispherical dome or on a LED-backlit
579 flat screen monitor. Stimuli were white squares on a dark grey background, 4x4 pixels in size and
580 subtended approximately 0.5° of visual angle. Eye position was recorded using the scleral search coil
581 technique or using an EyeLink 1000 eye tracker, both sampled at 1 kHz. Stimulus presentation and the
582 animal's behaviour were under real-time control with a Labview-based controller interface[44]. All
583 monkeys were trained to perform standard oculomotor tasks. In the delayed saccade task (Figure 1A),
584 the monkey was required to initiate the trial by aligning gaze on a central fixation target. Next, a target
585 appeared in the periphery, but the fixation point remained illuminated for a variable 500-1200 ms, and
586 the animal was required to delay saccade onset until the fixation point was extinguished (GO cue). The
587 gap task (Supplementary Fig. 4A) was used for the patterned microstimulation experiments. In this task,
588 initial fixation on a central target was followed by a gap period (200-300 ms) during which the fixation
589 point disappeared, while the animal was required to maintain fixation at the now vacant location. On
590 stimulation trials, microstimulation pulses were delivered 100 ms into the gap period and window
591 constraints were relaxed to allow for the stimulation-evoked movements. This was followed by the
592 appearance of a saccade target in the periphery which was also the GO cue for the animal to make a
593 target-directed saccade. All animals performed these tasks with >95% accuracy. Incorrectly performed
594 trials were removed from further analyses. The tasks were occasionally interleaved with visual search
595 paradigms used for a different study.

596

597 *Experimental sessions*

598 We used data from several different types of sessions in this study. Each session was either a laminar
599 recording session (n = 20 sessions), a single-unit recording session (n = 108 sessions), or a patterned
600 microstimulation session (n = 16 sessions). The laminar and single-unit recording sessions employed
601 mostly the delayed saccade task with a few microstimulation trials to verify electrode presence in SC (or
602 FEF) and estimate the location on the topographic map. The patterned microstimulation sessions were
603 restricted to the gap task, with stimulation trials and non-stimulation trials interleaved.

604

605 *Laminar recordings and single-electrode electrophysiology*

606 During each laminar recording session, a linear microelectrode array (LMA, AlphaOmega, Inc.) or a
607 Plexon V-probe (Plexon, Inc.) was inserted into the SC chamber using a hydraulic microdrive. The arrays
608 had either 16 or 24 contacts, with inter-contact spacing of 150 μm or 175 μm, respectively. Neural
609 activity was amplified, digitized and recorded using the Grapevine Neural Interface Processor (Ripple,
610 Inc.) and visualized using the associated Trellis interface. Neural activity was band-pass filtered between
611 500 Hz and 5 kHz to record spiking activity and between 0.1-250 Hz to record local field potentials for
612 another study. Approach towards the SC surface was identified by luminance-based visual modulation of
613 activity in the lowermost channels, after which the electrode was driven down a further 2-3 mm until
614 known hallmarks of SC activity were observed in a majority of the channels. The presence of several
615 contacts in the intermediate layers was further confirmed by the ability to evoke movements with
616 single-channel microstimulation at these contacts. For the initial subset of experiments, a tungsten
617 microelectrode was lowered into the FEF or SC. Neural activity was amplified and band-pass filtered
618 between 200 Hz and 5 kHz and fed to a digital oscilloscope for visualization and spike discrimination. A
619 window discriminator was used to threshold and trigger spikes online, and the corresponding spike
620 times were recorded. Both SC and FEF were confirmed by the presence of visual and movement-related
621 activity as well as the ability to evoke fixed vector saccadic eye movements at low stimulation currents
622 (20-40 μA, 400 Hz, 100 ms). Before beginning data collection for a single or laminar recording site, the
623 neural response field was roughly estimated. Since the electrode track was directed orthogonal to the
624 SC surface, most neurons preferred similar visual response fields and/or movement vectors. In most
625 data collection sessions with either electrode, the saccade target was placed either in the neurons'
626 response field or at the diametrically opposite location in a randomly interleaved manner. In addition,
627 stimulation-evoked saccades were recorded to identify the response field centers (or "hotspots") for the
628 cells recorded during that session. For recordings in rostral SC, stimuli were presented at one of four
629 locations at an eccentricity sufficient to induce a reduction in activity during the large amplitude
630 saccade.

631

632 *Data analysis and pre-processing*

633 Data were analyzed using a combination of in-house software and Matlab. Eye position signals were
634 smoothed with a phase-neutral filter and differentiated to obtain velocity traces. Saccades were
635 detected using standard velocity criteria. The animal was considered to be maintaining fixation if the
636 gaze remained within a 2-3° window around the fixation target. We also detected any microsaccades
637 that occurred during the delay period in each trial by using a velocity criterion based on the noise in the
638 velocity signal for that trial. Only one of the two monkeys (WM) in whom we recorded neural activity in
639 the rostral SC made sufficient number of microsaccades to permit further analysis.

640 Raw voltage signals filtered to spiking frequencies (500 Hz – 5 kHz, see above) were passed through a
641 threshold criterion to obtain spike times corresponding to multi-unit activity (MUA). Spike density
642 waveforms were computed for each neuron (or multi-unit activity cluster) and each trial by convolving
643 the spike trains with the causal portion of a Gaussian kernel (width = 5 ms; in some instances, we used
644 10 ms for display purposes). Data from the patterned microstimulation experiments (n = 16 sessions)

were also subjected to this procedure to compute pulse density waveforms. For the laminar recordings, we analyzed channel activity on single trials independently. Because direct kernel-based estimation of firing rates from binary spike trains on single trials can be noisy, we first computed the inverse of the inter-spike intervals as a measure of the firing rate prior to convolution with the smoothing kernel. All units that met the threshold criterion were considered for further analyses, regardless of their characteristics (so number of neurons/multi-unit clusters matched number of channels for these datasets). Only sessions which had at least 6 channels with typical visuomovement activity patterns were considered for further analysis, resulting in 16 laminar recording sessions (monkey BB – 104 channels/6 sessions, monkey BL – 176 channels/10 sessions). For single-electrode recordings, the spike densities were averaged across condition-matched trials (same target location) following alignment with target or saccade onset. Neurons were classified as visuomovement neurons if the spike density was significantly elevated above baseline during the visual epoch (50-200 ms following target onset) and during the premotor epoch (50 ms before and after saccade onset). This resulted in 57 caudal SC neurons and 22 FEF neurons. In addition, rostral SC neurons were defined as fixation-related if the activity during the premotor epoch of large saccades was significantly reduced below baseline (29 neurons). A subset of these neurons also elevated their discharge around the onset of microsaccades (7 neurons). To minimize the effect of noise in the spike density waveforms due to insufficient number of trials in our analysis, we used only neurons which had at least 10 trials for a given condition. This was not a factor in most cases (we typically had 50-100 trials).

Estimating population dynamics from laminar and single-unit recordings

We define $\mathbf{R}(\mathrm{t})$ as a population activity vector:

$$\mathbf{R}(\mathrm{t}) = \begin{bmatrix} \mathrm{R}_1(\mathrm{t}) \\ \mathrm{R}_2(\mathrm{t}) \\ \dots \\ \mathrm{R}_\mathrm{n}(\mathrm{t}) \end{bmatrix}$$

where $\mathbf{R}(\mathrm{t})$ represents the instantaneous activity at time t as a point in an n-dimensional space, n is the number of neurons, and $\mathrm{R}_\mathrm{i}(\mathrm{t})$ is the spike density function of the ith neuron. The curve connecting successive points over time is the neural trajectory that describes the evolution of population activity. For laminar recording data, a neural trajectory was determined for each trial. Analysis of single electrode data relied on pseudo-population analysis, for which each neuron's firing rate waveform $\mathrm{R}_\mathrm{i}(\mathrm{t})$ is the average across many matched trials (identical stimulus/response conditions). Thus, the neural trajectory is the *expected trajectory* of population activity. Since these neurons have a fairly broad RF, many neurons contribute to the active population for any given visual stimulus or saccade[45]. Our neurons were sampled roughly (but not exactly) around the hotspot of the active population for a given session. Therefore, the pooled data from individual sessions can be thought of as an approximation of the population mound active for an arbitrary location/RF in the visual field on any given trial. Many recent studies have reconstructed such "pseudo-populations" from sequentially recorded neurons and found comparable properties from simultaneous and serial recordings and found comparable properties from simultaneous and serial recordings[11,46,47]. Indeed, this is also expected of our pseudo-population under the assumption of isotropy – that each neuron's contribution to its respective local active population is similar regardless of the locus of the population, and consistency between the results we

683 observed in the laminar dataset and pseudo-population confirms this. To better demonstrate this, we
684 estimated the location of a given neuron in the active pseudo-population as follows (we use SC for
685 illustrative purposes because of its convenient topography). We mapped the target location onto the SC
686 map and used this locus as a representation of the center of the active population for that session, and
687 used the stimulation-evoked saccade vector to identify the location of that neuron on the SC. We
688 referenced the mapped locus of each target location to a single location to create an active pseudo-
689 population and translated the neuron locations relative to this population center (Supplementary Fig.
690 3A). All mathematical equations for transforming between visual and SC tissue coordinates have been
691 defined previously[48]. Inclusion of stimuli/saccades in the anti-preferred RF of the neurons allowed us to
692 also estimate a pseudo-population of neurons in the ipsilateral SC. To complete the representation of
693 activity across the SC topography, we also recorded from and included in our analyses neurons in the
694 rostral portion of SC, which are active during fixation[19], burst during microsaccades[21], and are
695 suppressed during large saccades[19].

696

697 *Temporal stability analysis*

698 To assess temporal stability, we first normalized the population trajectory $\mathbf{R}(\mathrm{t})$ by its Euclidean norm
699 ($\|\mathbf{R}(\mathrm{t})\|$), equivalently its magnitude, at each time point to yield $\hat{\mathbf{R}}(\mathrm{t})$:

$$\hat{\mathbf{R}}(\mathrm{t}) = \frac{\mathbf{R}(\mathrm{t})}{\|\mathbf{R}(\mathrm{t})\|}$$

700 The normalized trajectory can be visualized as a unity length population vector that points in an n-
701 dimensional direction at each instant in time. That is, while $\mathbf{R}(\mathrm{t})$ is free to traverse the n-dimensional
702 activity space, $\hat{\mathbf{R}}(\mathrm{t})$ is constrained to the surface of an n-dimensional hypersphere (Figure 1C). Temporal
703 stability or consistency of the evolving population was then quantified by the dot product of two time-
704 shifted unity length vectors:
705

$$\mathrm{S}(\mathrm{t}) = \hat{\mathbf{R}}(\mathrm{t}-\tau) \cdot \hat{\mathbf{R}}(\mathrm{t}+\tau)$$

706 The stability metric ($\mathrm{S}(\mathrm{t})$) tracks the running similarity of the normalized trajectory separated in time by
707 2τ ms. Crucially, the normalization constrains $\mathrm{S}(\mathrm{t})$ between 0 and 1. Thus, if $\mathrm{S}(\mathrm{t}) \to 1$, the population
708 activity is considered stable since the relative contribution of each neuron is consistent. If $\mathrm{S}(\mathrm{t}) \ll 1$, the
709 population activity is deemed unstable because the relative contribution is variable. If the neural
710 trajectory is not normalized, the dot product quantifies similarity across the vectors' magnitude and
711 direction. It roughly mimics the quadratic of the firing rate (exactly so for $\tau = 0$). When the vector
712 direction remains constant, the dot product yields no additional information than that already present in
713 the firing rate. In contrast, the normalization scales the neural trajectory so it always has unity
714 magnitude. It neither alters the relative contributions of the neurons nor compromises the vector
715 direction. The dot product therefore performs an unbiased evaluation of stability based only on vector
716 direction and is an estimate of the fidelity of the population code modulo a multiplicative gain factor.
717 Intuitively, the stability measure is analogous to the correlation between the neurons' activities at two
718 different time points. We chose the dot product, however, because of its interpretability as a measure
719 of pattern similarity in n-dimensional activity space.

720 We assessed the significance of the stability profiles in two ways. First, we compared the across-trial
721 distribution of stability values in appropriate windows around the visual burst and during the premotor
722 epoch for each session (Figure 1F). For this analysis, the stability values were averaged in a 20 ms
723 window preceding the peak of the visual burst for the visual epoch and in a 20 ms window preceding the
724 saccade initiation time (15 ms before saccade onset) in the premotor burst for the premotor epoch.
725 Second, for each trial, we randomly shuffled the activities of various neurons (channels for laminar
726 recordings) at each time point (dark gray trace, Supplementary Fig. 2A, bottom row), or randomly
727 shuffled the time points at which the population patterns occurred during the trial (light gray trace,
728 Supplementary Fig. 2A, bottom row). The former shuffle retains the average firing rate at each instant
729 and the latter shuffle retains the overall population correlation structure but both shuffles remove any
730 temporal correlation in the firing rate across neurons. We performed multiple such shuffles and re-
731 computed temporal stability for each instance, followed by across-trial averaging, baseline correction,
732 and across-session averaging to obtain the distribution of stability profiles expected to occur by chance
733 if the neurons' activities were uncoordinated.

734 To mitigate the effect of potentially variable visual response onset latencies (on different trials) on the
735 trial- and session-averaged mean temporal stability profiles in the visual epoch, we also performed the
736 averaging after realigning the data to the peak visual response on individual trials (Figure 1E). In order to
737 do this, the time of peak visual burst was identified from the population mean (average across channels)
738 firing rate on individual trials and was used to align the traces across trials before computing the trial
739 average.

740 For the mean-matched control in Figure 1D&E, we performed the temporal stability analysis only on the
741 subset of trials in which the peak of the population visual response was greater than or equal to the
742 population activity at the time of saccade initiation, after accounting for an efferent delay. We chose 15
743 ms before saccade onset as the latest time at which SC activity could influence saccade initiation,
744 because it is consistent with a range of putative efferent delays reported using various approaches[4-6].

745

746 *Patterned microstimulation*

747 The patterned microstimulation experiments allowed us to causally evaluate and compare the temporal
748 stability model to other models of movement initiation. Given the ability to control the delivery of
749 individual stimulation pulses to each contact on the laminar electrode, we used stimulation patterns
750 with specific spatiotemporal features to evaluate their relative efficacy in evoking movements. We
751 designed these patterns as follows. All individual stimulation pulses were biphasic with a leading
752 cathodic phase, monophasic pulse widths of 200-267 µs, and an interphase interval of 100 µs. Our first
753 step was to determine the appropriate range of current intensities and frequencies for each experiment.
754 During each session (i.e., for each electrode penetration into SC, total n = 16 sessions), we first
755 stimulated from individual contacts with standard suprathreshold parameters (40 µA, 400 Hz) to identify
756 the set of contacts that elicited a movement at a sub-50 ms latency. We restricted the experiment to
757 these contacts for the rest of that session. We then stimulated simultaneously across all these contacts
758 at the same current and frequency, starting from 4 µA, 100 Hz, stepping up 1 µA and 50 Hz, to
759 determine the threshold for evoking a movement with multi-channel stimulation. The threshold, defined
760 as the current/frequency combination for which stimulation generated movements on approximately
761 half the trials, ranged from 5-12 µA and 150-200 Hz across sessions. For each session, we used the

metrics of the saccades evoked at these threshold parameters from constant frequency stimulation in lieu of "fixed vector saccades" as a control against which to compare the patterned microstimulation results (Supplementary Fig. 4D&E).

Once we identified the threshold parameters, we designed stimulation patterns at that current intensity but with time-varying frequencies intended to simulate a burst of activity. Each stable pattern was created with a linearly decreasing inter-pulse interval (IPI) sequence for one contact (to simulate a burst) and scaling the IPIs for other contacts by a uniformly spaced factor (see below). The 150 ms duration burst was composed of a flat baseline (40 ms), a rising phase (80 ms), and a falling phase (30 ms). The peak frequency for individual channels ranged uniformly between 20 Hz and 400 Hz with the mean peak frequency across contacts pegged to the threshold frequency determined from the constant frequency multi-channel stimulation in an earlier step. At these parameters, stimulation at no individual channel evoked movements. Each stable stimulation pattern (e.g., blue pulse pattern in Figure 3A, top row) can be envisioned as a $n\ x\ m$ matrix, when n is the contact number and m is stimulation duration. The matrix contains ones and zeros, identifying the time of pulse delivered to each contact. To create additional realizations of the stable stimulation patterns (e.g., blue pulse patterns in Supplementary Fig. 4B & C), the assignment of specific peak frequencies to individual channels was randomly shuffled across trials.

For each stable stimulation pattern, we created a corresponding unstable pattern/pair by jittering stimulation pulses within a 20 ms window for each channel and randomly shuffling pulses across channels (e.g., red pulse patterns in Figure 3A, top row and Supplementary Fig. 4B & C). This step created instability in the population pulse pattern by destroying the relative scaling of pulse rates across neurons while also ensuring that both total pulse counts per channel and the mean instantaneous pulse rates across channels were preserved between the stable and unstable patterns. Thus, all subsequent analyses were performed on pairs of trials with stable and unstable stimulation patterns matched in these aspects. We also ensured that the inter-pulse interval was never less than 2 ms (i.e., the peak frequency never exceeded 500 ms) for any stimulation train. The stimulation patterns were generated offline and the pattern trains corresponding to each trial were introduced 100 ms into the gap period in a gap task. Stable-unstable pairs were randomly interleaved within a block in which roughly 80% of all trials were stimulation trials.

We used the latency of the first saccade after stimulation onset but before stimulation offset as an indicator of the occurrence of a stimulation-evoked saccade (Figure 3B); such saccades exhibited latencies <160 ms. If the microstimulation was ineffective at evoking a saccade, the first movement was typically directed to the target presented after the gap period ended; in such cases, the saccade was produced >400 ms after stimulation onset. We estimated the relative likelihood of evoking a movement by examining trials in which only one of the stable or unstable pulse patterns in a pair yielded a stimulation-evoked saccade (also see Figure 4C and next section). This was quantified based on the number of trials pairs in which only the stable pattern evoked a movement during the window of stimulation ($= \mathrm{N}_{\mathrm{s+us-}}$, number of points in the blue shaded region in Figure 3B) and the number of trial pairs in which only the unstable pattern evoked a movement ($= \mathrm{N}_{\mathrm{us+s-}}$, number of points in the red shaded region in Figure 3B). The relative likelihood of evoking a movement with the stable pattern was defined as

$$\mathrm{RL_s} = \frac{\mathrm{N}_{s+us-}}{\mathrm{N}_{s+us-}+\mathrm{N}_{us+s-}}.$$

RL_S ranges from 0 to 1 and is symmetric with a neutral value of 0.5. To estimate the significance of this estimate, we performed permutation tests with respect to a surrogate dataset in which trials were randomly assigned stable/unstable labels. This lowered the expected estimate of relative likelihood to purely chance levels (Figure 3C).

Discriminability of population patterns – neural activity and microstimulation

To determine whether the visual and premotor bursts are discriminable using static, non-temporal features of population activity, we performed factor analysis (FA) on 50 ms snippets of activity from these two epochs (visual epoch: 50 ms centered around peak response, motor epoch: 50 ms before saccade onset). We used DataHigh[24], a dimensionality reduction and visualization toolbox written in Matlab, to perform FA on the 16- or 24-dimensional laminar recordings and visualize the projections onto the top latent dimensions. The top 3 dimensions accounted for >95% of the variance in neural states for all our datasets (eigenspectrum not shown), and a 3-dimensional projection is shown for an example dataset in Figure 4A, with the visual and premotor snippets coded in different colours. We also performed FA on the microstimulation patterns (the "states" were computed across the entire 150-ms stimulation duration). Almost all dimensions were needed to account for >95% of the variance in the stimulation patterns, owing to the randomized assignment of frequencies across contacts on different trials. Thus, we chose an arbitrary 3-dimensional projection for visualization in Figure 4B; however, note that the qualitative result did not depend on the projection. Since we used this step purely for visualization, we did not perform any subsequent analysis on the estimated FA dimensions.

Next, we used a linear discriminant analysis (Fisher's LDA)[49] to assess a decoder's ability to discern whether its inputs signify a movement command at the population level, based on static population features alone, and how this discriminability relates to temporal stability. We first trained a binary LDA classifier on the visual and premotor 50 ms snippets described above in the native neural space. LDA finds a projection defined by a hyperplane that maximizes the separation between the two classes:

$$\boldsymbol{w} \propto \Sigma^{-1}(\boldsymbol{\mu_1} - \boldsymbol{\mu_0}) \,,$$

where 0 and 1 are the two class labels, the vector $\boldsymbol{w}$ is normal to the hyperplane defining the class boundary, $\Sigma = \frac{n_0\Sigma_0 + n_1\Sigma_1}{n_0 + n_1}$, the pooled covariance matrix derived from the within-class covariance matrices Σ_0 and Σ_1, n_0 and n_1 are class occupancies, and $\boldsymbol{\mu_0}$ and $\boldsymbol{\mu_1}$ are the class means. We subjected the linear scores

$$\boldsymbol{s_i} = \boldsymbol{w}.\,(\boldsymbol{x} - \frac{\boldsymbol{\mu_i}}{2})$$

obtained from the LDA projections to a softmax transformation to compute class probabilities:

$$P(\boldsymbol{x} \in i) = \frac{e^{s_i}}{\sum_i e^{s_i}}$$

In all cases, we used k-fold crossvalidation to test LDA performance (on the classification of visual and premotor population states, and on stimulation patterns described below), with the choice of k dictated by the total number of trials in the dataset such that each fold (test set) had at least 10 trials. We quantified classifier performance using the Matthews Correlation Coefficient (MCC)[50], since accuracy

can be significantly biased and have high variance for classification problems with unequal number of training or test points[51], which was the case with the stimulation patterns below. Instead, MCC takes the complete confusion matrix into account to quantify binary classifier performance as:

$$\mathrm{MCC} = \frac{\mathrm{N}_{00}\mathrm{N}_{11} - \mathrm{N}_{01}\mathrm{N}_{10}}{\sqrt{(N_{00}+N_{01})(N_{00}+N_{10})(N_{11}+N_{01})(N_{11}+N_{10})}},$$

where N_{ij} represents the number of instances where a trial in class *i* is classified to be in class *j* in the classification confusion matrix. Similar to a standard correlation coefficient, MCC values range from -1 to 1 (-1, 0, and 1 respectively indicate poor, average, and perfect classification).

To evaluate the discriminability of microstimulation patterns, we split each dataset in 2 different ways. The first split was based on the predefined stable-unstable pattern pairs and was used to classify pulse patterns as stable or unstable based on their population states alone (inset in Figure 4B). The second split was used to classify stimulation patterns as movement-evoking or non-evoking, in order to identify other features of the stimulation patterns that may have impacted movement occurrence. For this analysis, we focused on stable-unstable trial pairs where only one of the stable-unstable pair evoked a movement (Figure 4C). The rationale was that a classifier trained on this subset may allow for the identification of temporal stability as a predictor because of the differential (i.e., not one-to-one) relationship between stability and movement occurrence. We further evaluated whether a dynamic feature of population activity such as temporal stability can be exploited for this classification by re-training the classifier with explicit addition of temporal stability as an input dimension and comparing it with the performance of one without this addition.

We also performed model selection analysis using nested logistic regression models to identify the predictor variable(s) in the microstimulation patterns that best explained the observed behaviour. Logistic regression models the log odds of an outcome (i.e., movement versus no movement) as a linear function of desired predictors (population pulse states and temporal stability) as

$$\ln\frac{p}{1-p} = \beta_0 + \sum_{i=1}^{n} \boldsymbol{\beta}_i \boldsymbol{x}_i \,,$$

where p is the probability of a movement occurring, i.e., P(stimulation evokes movement), $\boldsymbol{x}$ are the predictors, and $\boldsymbol{\beta}$ are the model coefficients. We used a generalized linear model with a logit link function and obtained the maximum likelihood estimate of the coefficients $\boldsymbol{\beta}$. We did this for models with one or more predictors chosen from the set of population pulse counts and temporal stability. Since the number of samples and/or predictors can have an effect on the log-likelihood of a given model, we used the Bayesian information criterion (BIC) to estimate model performance, which normalizes log-likelihood by a factor related to the number of samples and predictors. This analysis is shown in Figure 4F.

To explain the variability in behavioural effects of stable/unstable microstimulation patterns across sessions, we also considered whether certain sessions had idiosyncratic patterns of activation across channels for trial subsets in which a movement was evoked. That is, we explored whether differences in pulse rates on subsets of trials could explain the across-sessions range of movement likelihood effects seen in Figure 3C. The rationale was that over many trials, individual channel pulse rates should average out to a narrow distribution of rates given the random uniform sampling on individual trials. Thus, discrepancies from this expected narrow distribution may reflect the effect of pulse rates alone for trial

subsets parsed by behavioural effect. We computed relative dispersion for a particular subset of trials as the difference between the dispersion (i.e., pulse count variance across the population) for that subset and dispersion on all trials for that session. That is, $RD_{subset} = var(x_{subset}) - var(x_{all})$, where x is the distribution across channels of trial-averaged pulse counts for a set of trials, and subset refers to S+US- or US+S- trials. The relative dispersion index was then defined as the relative dispersion for S+US- trials divided by the sum of the two RDs:

$$\mathrm{RDI} = \frac{\mathrm{RD}_{s+us-}}{\mathrm{RD}_{s+us-} + \mathrm{RD}_{us+s-}}.$$

Thus, on sessions where the pulse rates for S+US- trials were closer to the distribution of rates on all trials (closer to the intended uniform sampling of pulse rates across channels), more so than the pulse rates for US+S- trials, the RDI is lower than 0.5 and vice versa. This is an indicator of pulse rate bias in one set of trials versus the other, with the unbiased subset (one with lower RDI) more likely to minimize the influence of pulse rates on the behavioural outcome. This analysis is shown in Supplementary Fig.5.

Correlation analysis

In order to compare against pooled accumulator mechanisms[25], we estimated the correlation structure in our population of neurons and microstimulation patterns. We first computed the spike count correlation across trials for every pair of neurons (or multi-unit clusters, n = 1963 pairs) during the visual and motor epochs as defined above. For the microstimulation patterns, we computed the pulse count correlations for every pair of stimulation channels (n = 899 pairs) during the stimulation window for the stable and unstable patterns separately. Note that in this case, pulse count correlation is equivalent to computing the correlation between accumulation rates (and therefore directly comparable to the accumulator mechanism mentioned above), since the duration of stimulation was fixed and the baseline and peak rates were matched between the stable and unstable conditions.

Spiking neuron model

We developed a biophysically realistic computational model with spiking neurons to discriminate and read out temporal structure in population activity. The core component of the model was a recurrently connected module comprising a decoder element and a disinhibitor element, putatively representing pontine high-frequency burst neurons and OPNs, respectively[31]. The decoder and disinhibitor were both modelled as leaky integrate-and-fire (LIF) spiking neurons:

$$\tau_m \frac{dV_{neu}}{dt} = -(V_{neu}(t) - V_{rest}) + R_m I_{neu}(t)$$

where $V_{neu}(t)$ is the membrane potential of the neuron, V_{rest} is the resting potential, τ_m is the membrane time constant, R_m is the membrane resistance, $I_{neu}(t)$ is the net time-varying input to the neuron, and *neu* represents the decoder (*dec*) or disinhibitor (*dis*). The spiking followed standard threshold crossing rules, i.e., if $V_{neu}(t = t^k) > V_{th}$, where V_{th} represents the action potential threshold, the membrane potential was reset to $V_{neu}(t = t^k) \equiv V_{reset}$, and the neuron's spike times $[t^i]$ were updated with the kth spike time t^k.

The current input to both the decoder and disinhibitor was composed of excitatory and inhibitory components:

$$I_{neu}(t) = G_{neu}^{exc}(t)\big(E_{exc} - V_{neu}(t)\big) + G_{neu}^{inh}(t)\big(E_{inh} - V_{neu}(t)\big) + I_{neu}^{0}$$

where $G_{neu}^{exc}(t)$ and $G_{neu}^{inh}(t)$ are the respective net excitatory and inhibitory post-synaptic conductances, and E_{exc} and E_{inh} are the excitatory and inhibitory reversal potentials representing the contribution of AMPA and GABA channels, respectively. I_{neu}^{0} is a constant current term that was set to zero for the decoder and to a fixed value of 4 for the disinhibitor in order to simulate tonic firing without external input.

The decoder received excitatory inputs from the SC in the form of stimulation pulse trains, and inhibitory input from the disinhibitor. The disinhibitor received both excitatory and inhibitory inputs from the SC[27,28] and reciprocal inhibition from the decoder. The net time-varying conductances were modelled as follows:

$$G_{dec}^{exc}(t) = \sum_{i=1}^{N} w_i^{exc-dec} g_i(t) \ , \ \text{and} \ g_i(t) = \sum_{k=1}^{n_i} \epsilon\big(t - t^k\big)\big(1 + g_i\big(t^k\big)\big) \ ,$$

$$G_{dec}^{inh}(t) = w^{dis-dec} \sum_{k=1}^{n_{dis}} \epsilon\big(t - t^k\big) \ ,$$

$$G_{dis}^{exc}(t) = \sum_{i=1}^{N} w_i^{exc-dis} g_i(t) \ , \ \text{and} \ g_i(t) = \sum_{k=1}^{n_i} \epsilon\big(t - t^k\big)\big(1 + g_i\big(t^k\big)\big) \ ,$$

$$G_{dis}^{inh}(t) = w^{dec-dis} \sum_{k=1}^{n_{dec}} \epsilon\big(t - t^k\big) + \sum_{i=1}^{N} w_i^{inh-dis} g_i(t) \ , \ \text{and} \ g_i(t) = \sum_{k=1}^{n_i} \epsilon\big(t - t^k\big)\big(1 + g_i\big(t^k\big)\big).$$

In each equation they appear, N is the number of input units (i.e., number of channels with pulse trains), $w_i^{exc/inh-neu}$ is the excitatory/inhibitory weight from the ith input unit to the spiking neuron, n_i is the number of pulses in the ith input unit, $w^{dis-dec}$ is the weight from the disinhibitor to the decoder, $w^{dec-dis}$ is the weight from the decoder to the disinhibitor, and t^k is the time of the kth input pulse or output spike (depending on which summation term it appears in). The g_i term, when it appears in the sum that produces g_i (as in all but the second conductance equation), represents the state-dependent influence of each incoming pulse input. $\epsilon(t)$ is the post-synaptic conductance kernel defined as:

$$\epsilon\big(t - t^k\big) = \begin{cases} -e^{-\frac{t}{\tau_1}} + e^{-\frac{t}{\tau_2}} \ if \ t > t^k \\ 0 \ if \ t < t^k \end{cases},$$

The conductance and input current terms that were dependent solely on the pulse input patterns were pre-computed and fed into a Eulerian solver (time step = 0.1 ms) for the differential equations governing the membrane potential of the spiking decoder and disinhibitor units. Supplementary Table 1 shows the values of the parameters and constants used for the model simulations.

Reporting Summary

Further information on research design is available in the Research Reporting Summary linked to this article.

Data Availability

The data that support the findings of this study are available from the corresponding author(s) upon reasonable request.

Code Availability

The custom MATLAB code is available from the authors upon reasonable request.

954 **Supplementary Information**

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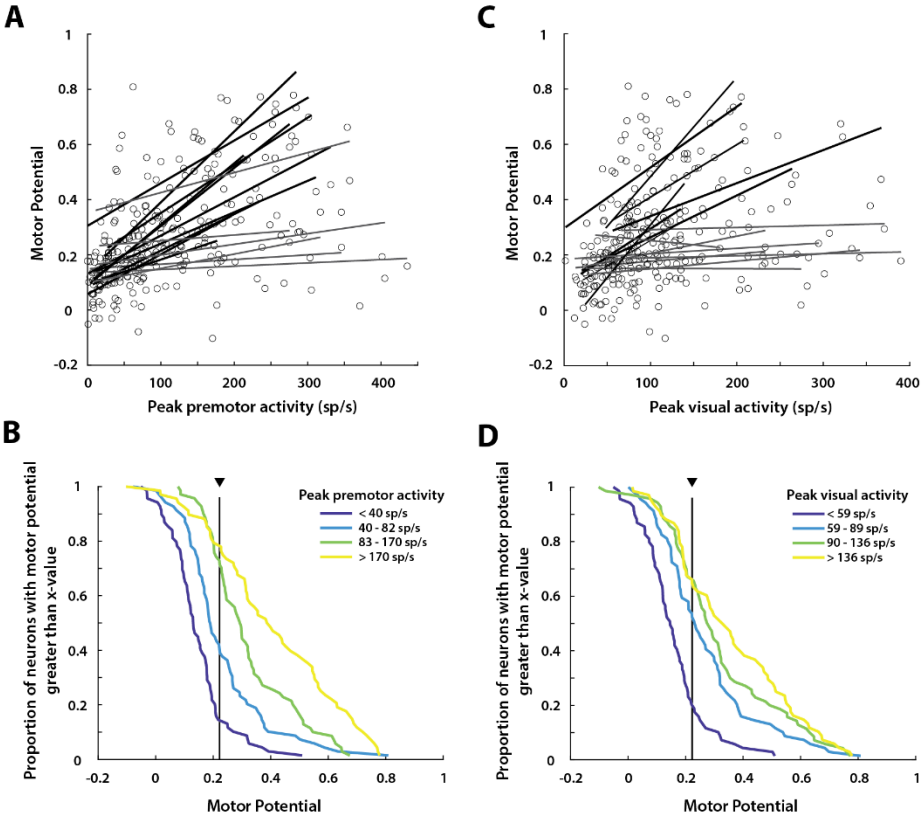
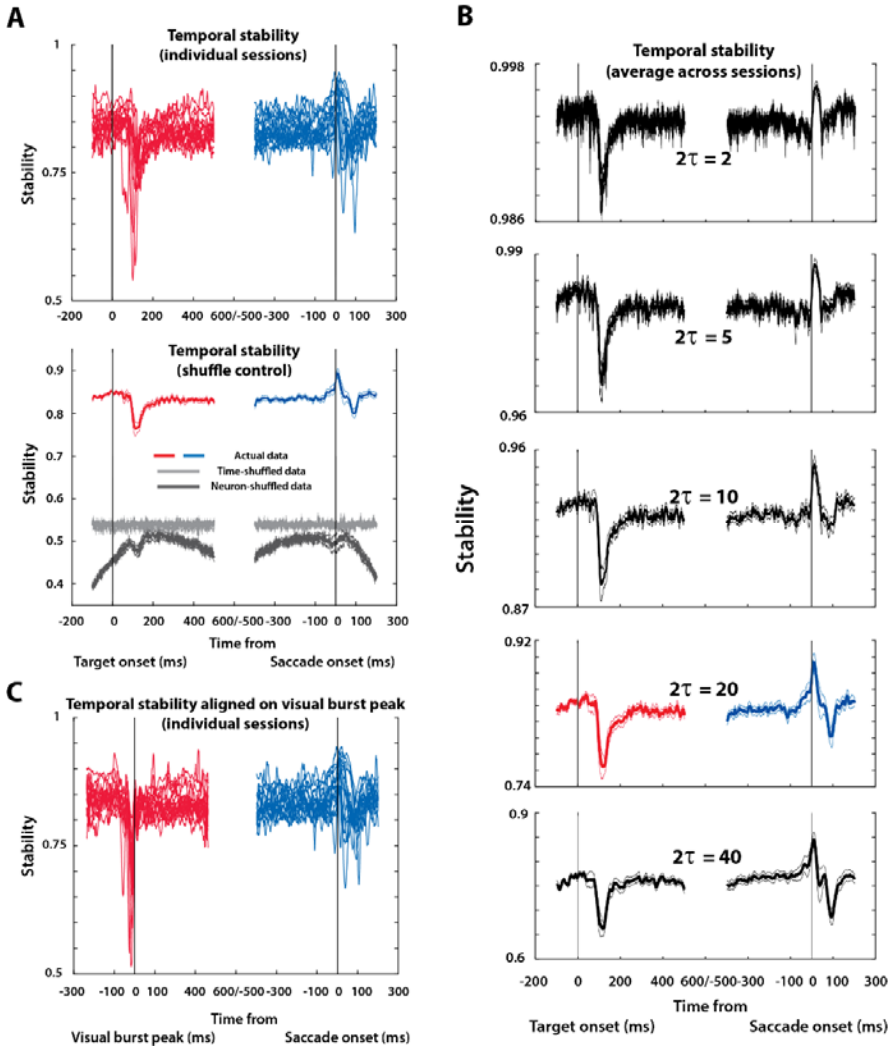


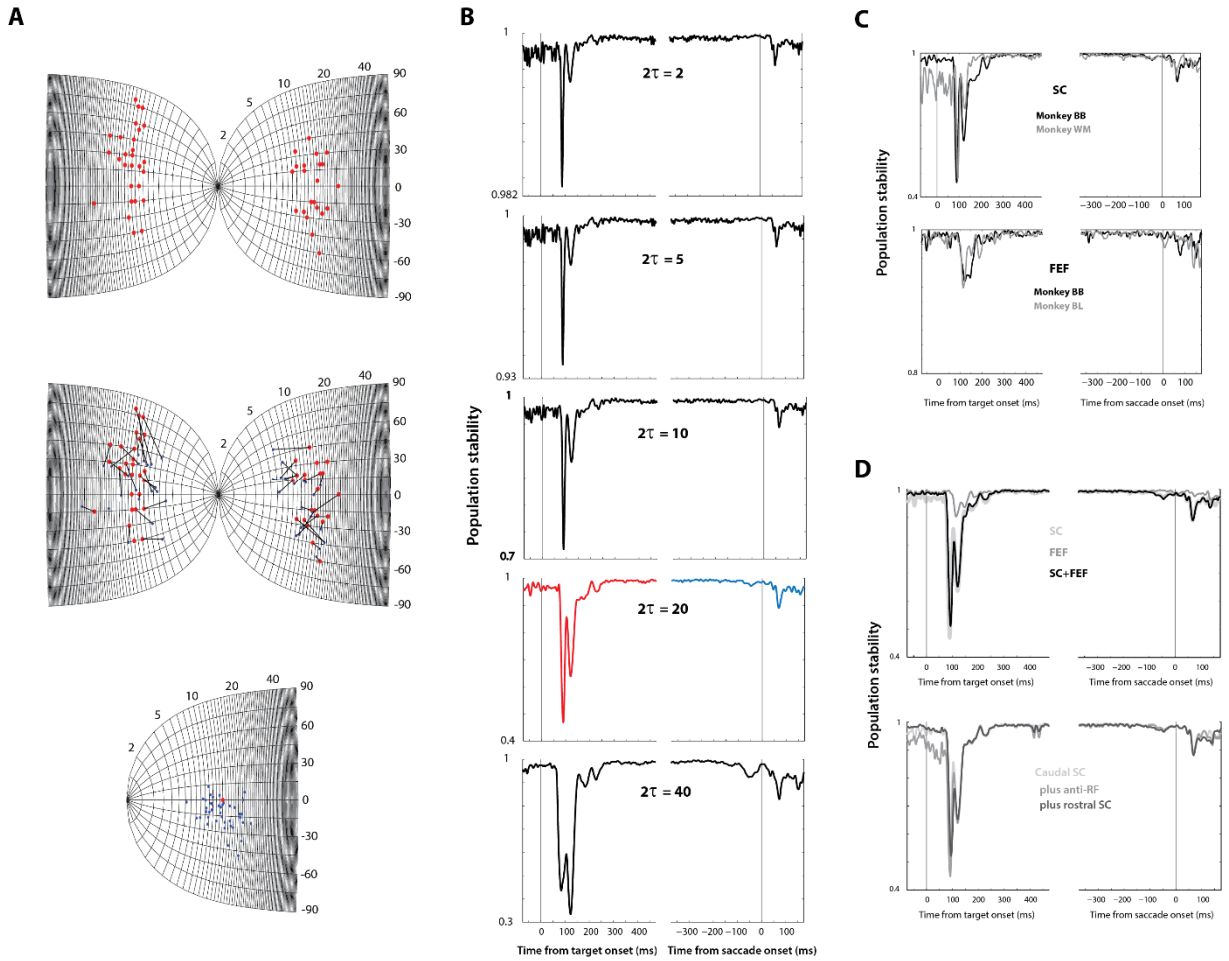
956

957 **Supplementary Figure 1. Strong saccade drivers also have high visual activity. A.** Scatter plot of the motor
958 potential, calculated as the peak correlation between saccade velocity and preceding premotor activity (see
959 Methods), as a function of peak premotor burst for individual neurons. Each point represents a neuron/MUA
960 recorded on an individual channel, and each line is the linear regression fit for the points from an individual,
961 laminar probe recording session (bold lines indicate significant trends, $p < 0.01$). **B.** Neurometric plot of the
962 proportion of neurons in each of 4 quartiles split based on peak premotor activity that have a motor potential (as
963 defined above) higher than the abscissa. The traces are coloured based on their quartile as indicated in the legend.
964 The vertical line and arrowhead indicate the median motor potential. For example, roughly 80% of the neurons in
965 the highest premotor activity quartile (yellow trace) show an activity-velocity correlation above the median and
966 are thus strong saccade drivers. **C.** Scatter plot similar to **A** but for peak visual activity. Note the strong correlation
967 between the neurons' peak visual activity and their influence on saccade kinematics (i.e., motor potential of
968 premotor activity) on several sessions and in the overall distribution. **D.** Neurometric plot similar to **B** of the
969 proportion of neurons in each of 4 quartiles split based on peak *visual* activity that have a motor potential higher
970 than the abscissa. The majority of neurons with high visual activity (>60% in top 2 quartiles, green and yellow
971 traces) exhibit motor potential above the median (vertical line and arrowhead), indicating that neurons with high
972 visual activity also strongly influence saccade kinematics and thus may be causal drivers of the movement.

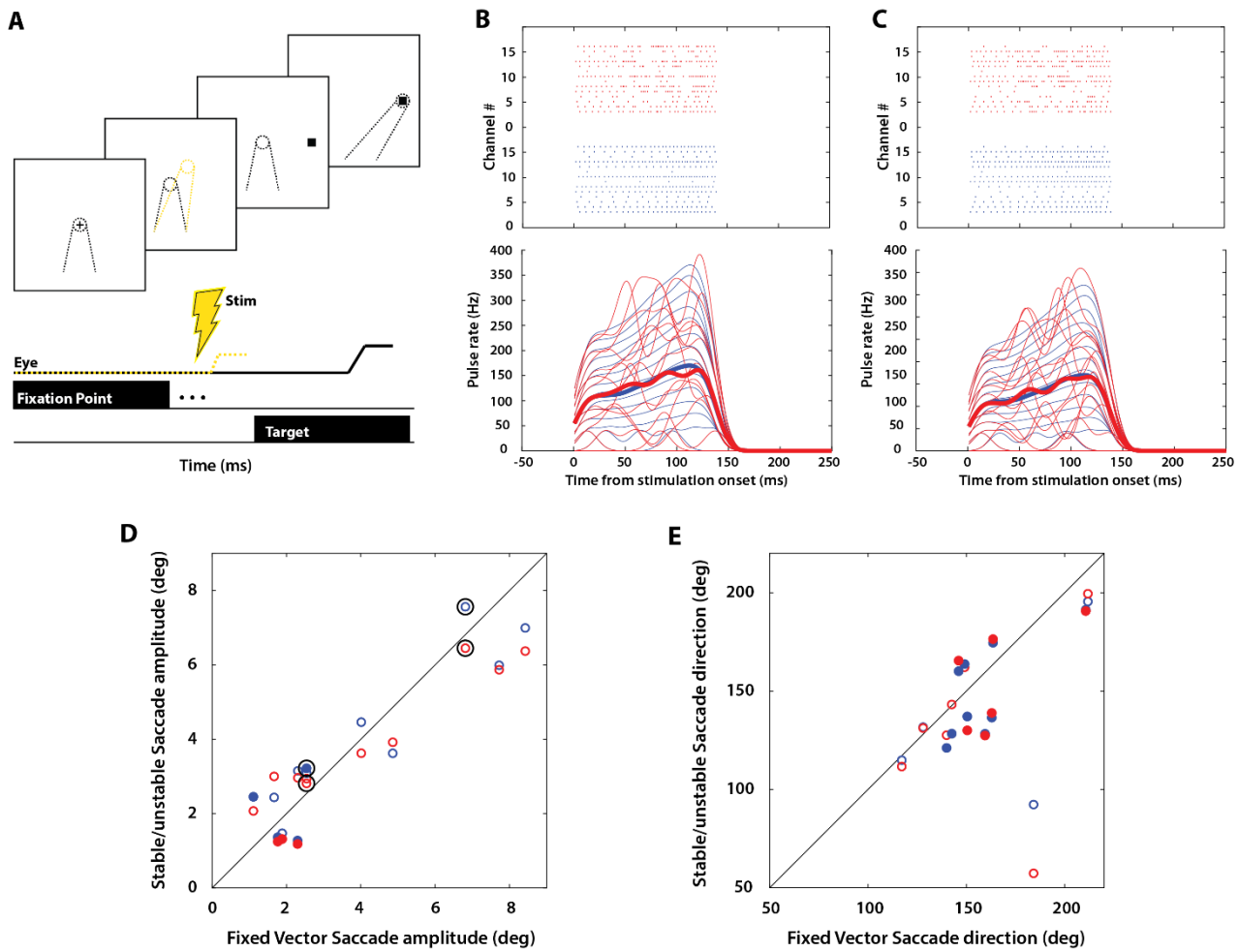
973



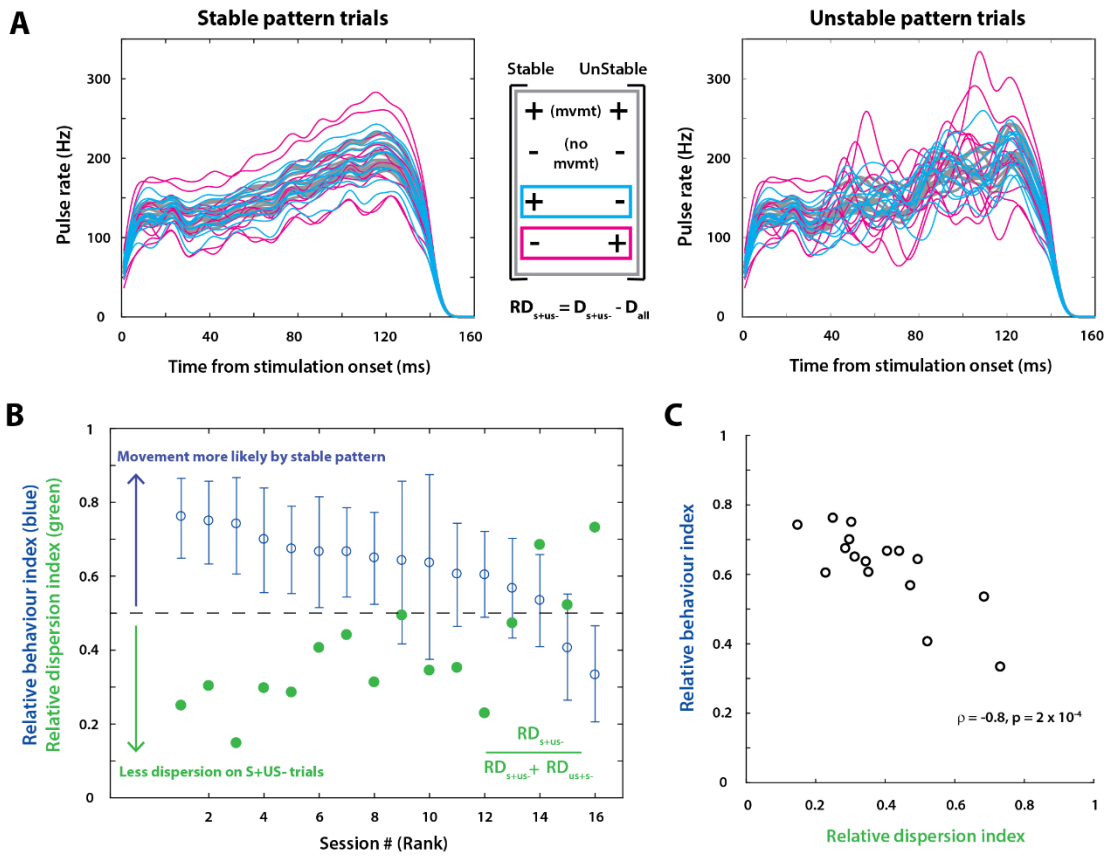
Supplementary Figure 2. Temporal stability profiles within and across sessions collected with laminar probe. A. Top row: Temporal stability averaged across trials for individual sessions (thin traces) have different baselines, possibly due to varying noise levels, spike isolation differences, etc. The baselines were shifted to their mean level before averaging across sessions in Figure 1D. Bottom row: Temporal stability averaged across trials and sessions for two types of shuffled datasets. The light gray traces (mean +/- s.e.m.) are for time-shuffled data where relative activity levels between neurons are preserved but time points during the trial are randomly re-ordered. The dark gray traces are for neuron-shuffled data where the instantaneous population firing rate is preserved but the firing rate distribution is shuffled across neurons at each time point. The coloured traces show the session-averaged temporal stability (as in Figure 1D) for comparison. **B.** In order to ensure that the choice of τ did not have an undue effect on our results, we computed stability for several values of τ. The panels show temporal stability profiles for (from top to bottom), τ = 1, 2.5, 5, 10, and 20, respectively. The coloured traces for τ =10 are the ones shown in the Figure 1D. As evident, the absolute magnitude of stability was inversely related to τ, a consequence of the smooth and continuous nature of the trajectory. In other words, since the state of the neural population evolves smoothly, it must traverse intermediate states in order to move from one state to another, resulting in greater similarity between state vectors close together in time than those further apart. However, the relative shape of stability profile was largely preserved for $\tau > 5$. **C.** Similar to top row of panel A but for temporal stability aligned to peak of visual burst.



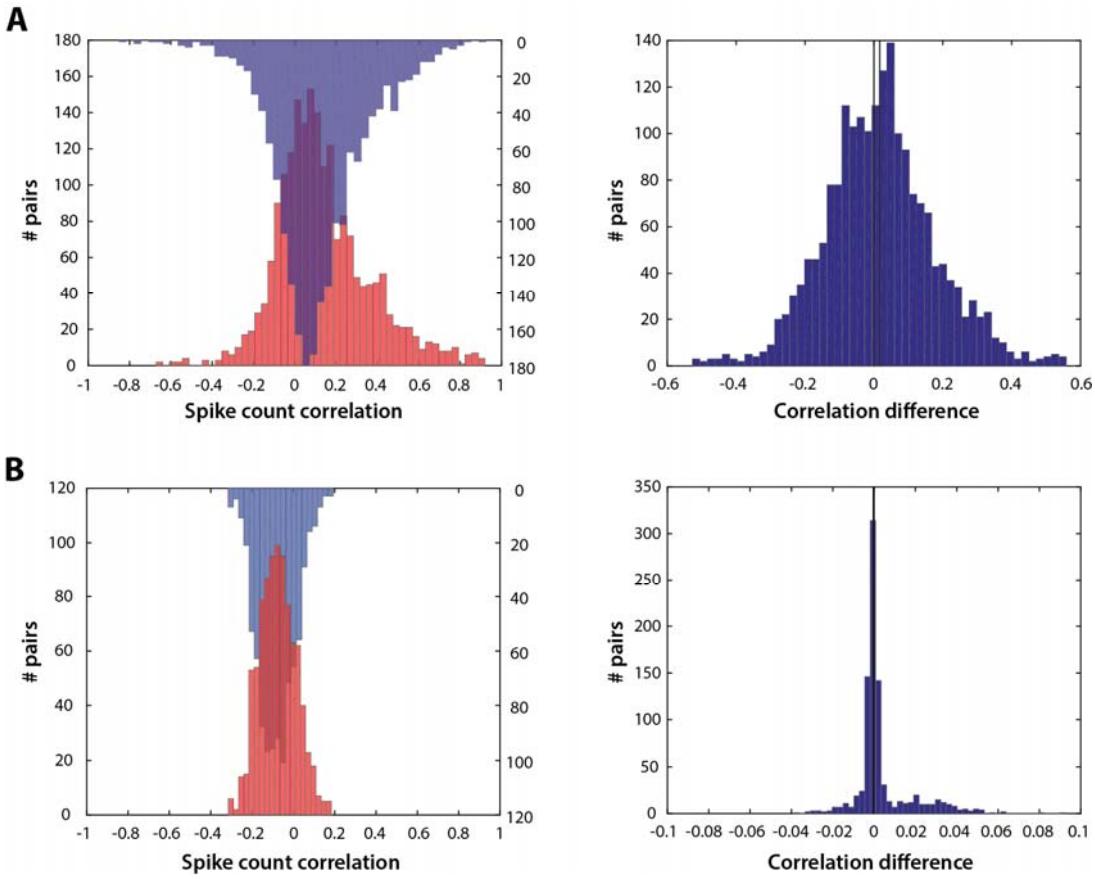
Supplementary Figure 3. Temporal stability for pseudo-population reconstructed from single-unit recordings. A. *Top row* - Target loci (red points) mapped from visual space to SC coordinates across all experimental sessions. The locations on the SC were computed using traditionally established transformations between visual space and SC tissue coordinates (see Methods). *Middle row* - Endpoints of the stimulation-evoked saccade vector at the recording site (blue points) shown with the target loci from above. The stimulation vector provides a proxy for the RF center of the recorded neuron. Neuron-target pairs (blue-red) from individual sessions are connected using black lines (unconnected points did not have the corresponding stimulation/target data). *Bottom row* - The active pseudo-population on the SC map. The red locations from the previous panels were referenced to one arbitrarily selected location on the SC map (here, R=15, theta = 0) and the blue locations were translated accordingly. Points from both colliculi are shown on a single SC for the sake of clarity. **B.** Effect of τ on temporal stability for the pseudo-population data (similar to Supplementary Fig. 2B). **C.** Temporal stability profiles in SC and FEF for individual subjects are qualitatively similar to the combined result in Figure 2C. **D.** Temporal stability profiles of various combinations of pseudo-populations.



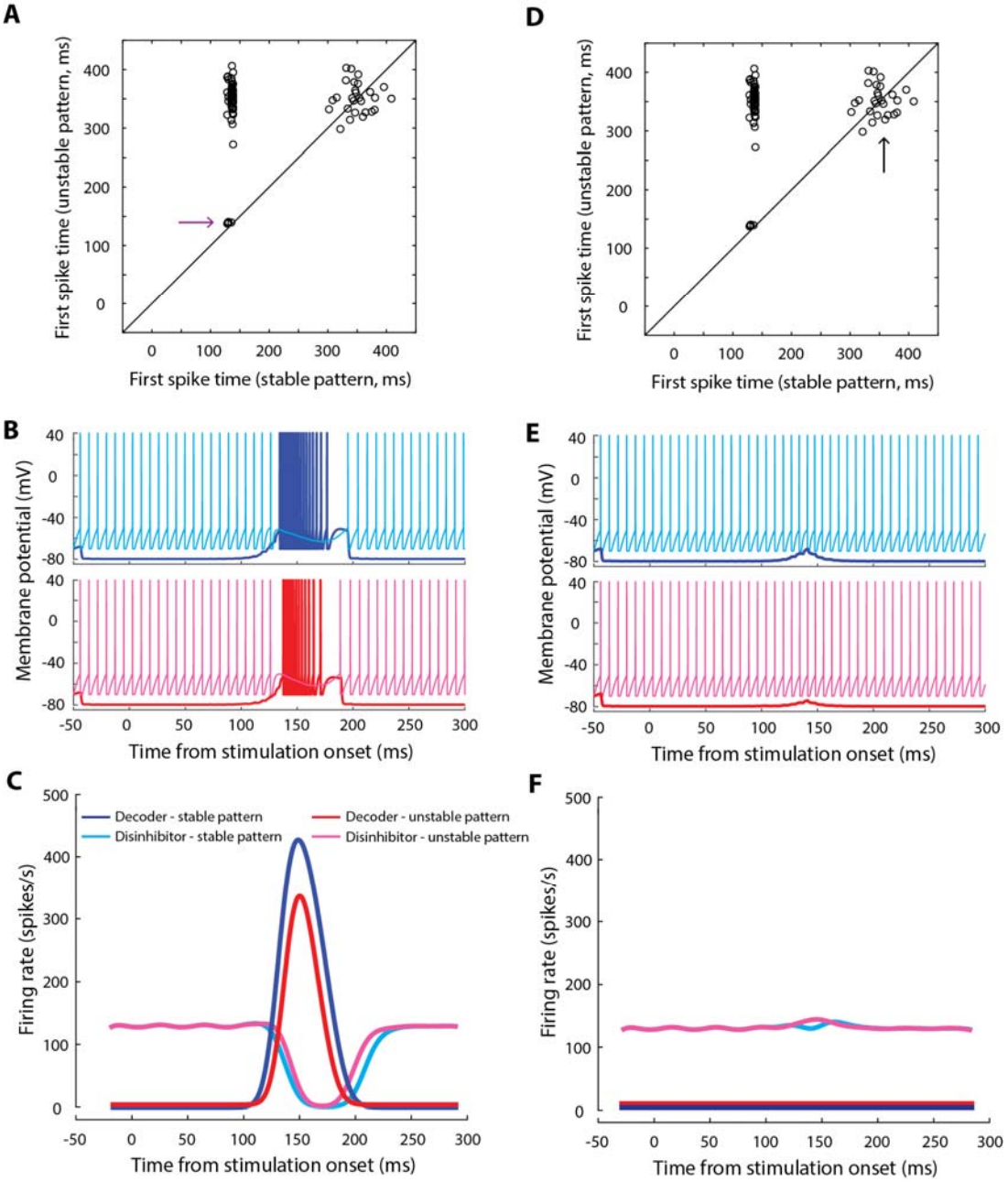
Supplementary Figure 4. Microstimulation experiment - task, examples, and evoked saccade metrics. A. Schematic of the gap task used in the patterned microstimulation experiments. **B** and **C.** Two more examples of pulse rasters and pulse rates for individual channels for stable (blue) and unstable (red) pairs of stimulation patterns (cf. Figure 3A). **D.** Mean stimulation-evoked saccade amplitude for stable (blue points) and unstable (red points) stimulation patterns plotted against the fixed vector saccade amplitude obtained from near-threshold constant frequency stimulation (see Methods). Each point represents one session for that condition. The diagonal represents the unity relationship. Filled circles denote a significant difference of the stable/unstable saccade amplitude from the fixed vector saccade ($p < 0.01$, Wilcoxon rank-sum test). Points circumscribed by black circles denote sessions where the saccade amplitudes on stable and unstable trials were significantly different from each other ($p < 0.01$, Wilcoxon signed-rank test). **E.** Similar to D (including criteria for statistical significance), but for stimulation-evoked saccade direction.



Supplementary Figure 5. Variability in behaviour is partly explained by variability in stimulation pulse rates across subsets of trials. A. Individual channel pulse rates averaged across specific subsets of trials for an example session. *Left* - Average stable pattern for the set of trials in which, only the stable pattern evoked a movement out of the stable-unstable pair (S+US- pairs, cyan traces), only the unstable pattern evoked a movement (S-US+ pairs, magenta traces), and all trials (gray traces). *Middle* - Schematic of which trial pairs are plotted in the left and right columns, highlighted in the appropriate colour. Relative dispersion is calculated as the across-channel dispersion (e.g., variance) of the pulse counts for a particular subset (e.g., S+US-) minus the dispersion of the pulse counts for all trials. *Right* – Average unstable pattern for the three subsets of trials as in the left column. **B.** Relative dispersion index computed as in the formula in the inset, plotted for each session (green points). Values *less than* 0.5 indicate that there was less dispersion in the S+US- trials, and trials with lower dispersion are less dependent on pulse rate effects. The behavioural effect (from Figure 3C) is overlaid for comparison (blue points and error bars). The sessions are ordered by behavioural effect size as in Figure 3C. **C.** Scatter plot showing correlation between behavioural effect size and relative dispersion index. The sessions with negative (ordinate < 0.5) or non-existent effect sizes in behaviour are also the ones with the highest dispersion index, indicating that those sessions were dominated by pulse rate effects and less likely to reveal an effect of temporal structure.



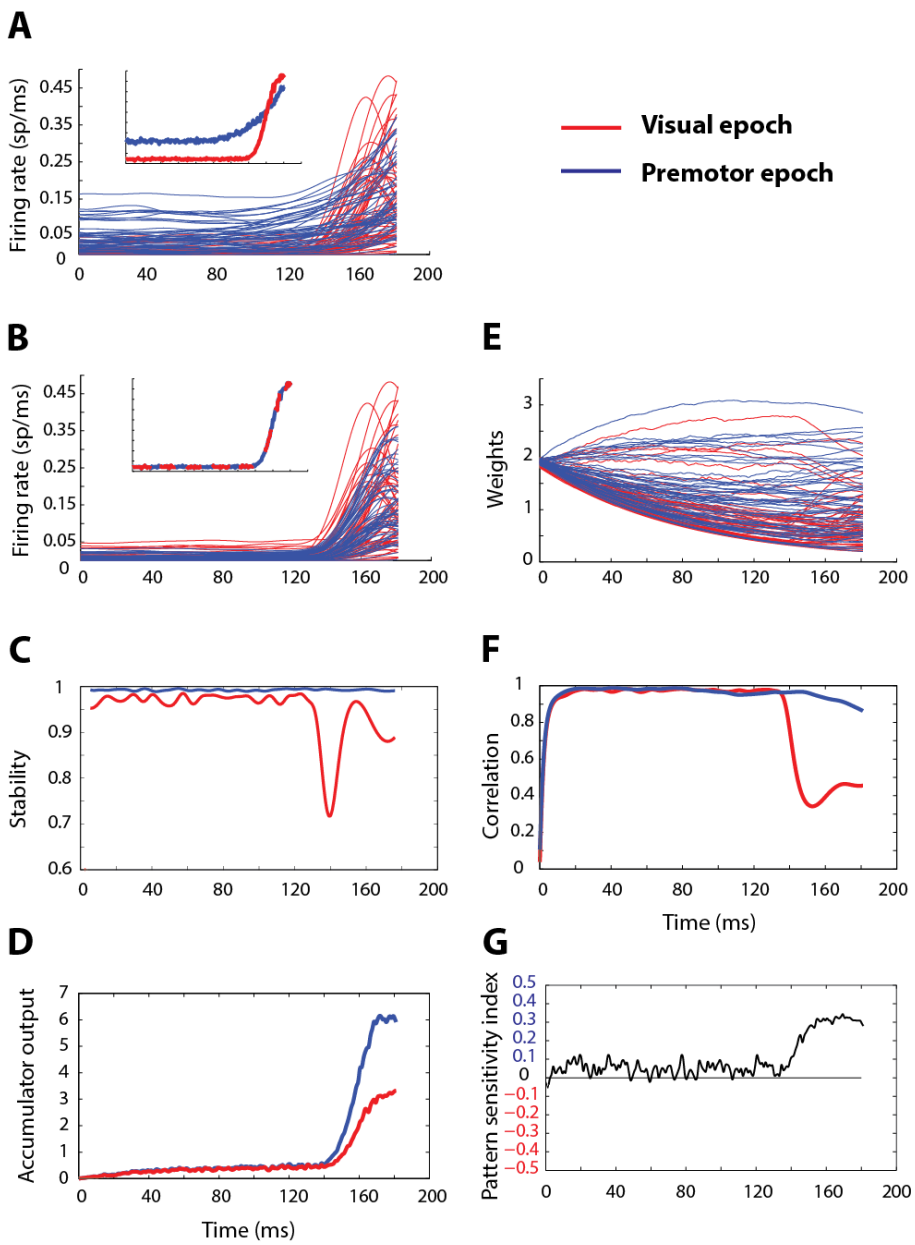
Supplementary Figure 6. Across-trial spike and pulse count correlations. A. Left: Histograms of spike count correlations for all pairs of channels (n = 1963) for the visual and premotor epochs (red and blue histograms, respectively). One of the histograms is shown inverted for the sake of clarity. Right: Distribution of differences between visual and premotor epoch correlations computed for each pair. Positive values indicate larger spike count correlations for spikes in the visual epoch. The two vertical lines represent zero and the mean of the distribution (left and right lines, respectively). **B.** Same as A for pulse counts correlations for all pairs of stimulation channels (n = 899) for the stable (blue) and unstable (red) patterns, with the corresponding difference histogram shown on the right. Positive values indicate higher pulse count correlations in the unstable stimulation pattern.



Supplementary Figure 7. Performance of spiking neuron model for various simulation outcomes with stable and unstable pulse patterns. A. Scatter plot of first spike latencies in the decoder (putatively representing saccade initiation) for stable versus unstable inputs from matched pairs (same as Figure 5C). The next two panels are based on the trial pairs highlighted by the arrow (in which both stable and unstable patterns produced a saccade). **B.** Simulated membrane potential of the decoder (blue and red traces) and disinhibitor (cyan and magenta traces) for an example matched trial pair from the subset in panel A, for stable (top row) and unstable (bottom row) input patterns. **E.** Average activity of the disinhibitor (cyan and magenta traces, stable and unstable inputs, respectively) and decoder (blue and red traces, stable and unstable inputs, respectively) for all trial pairs in which both stable and unstable input patterns produced a movement. **D.** Same as panel A, except for the focus on trial pairs (arrow). The next two panels are based on the trial pairs in which neither stable nor unstable patterns produced a saccade. **E.** Simulated membrane potential of the decoder and disinhibitor for an example matched trial pair from the

1061 subset in panel D. Layout and colour scheme as in panel B. **F.** Average activity of the disinhibitor and decoder for all
1062 trial pairs in which neither stable nor unstable input patterns produced a movement. Colour scheme as in panel C.
1063 Note the small increase in disinhibitor activity around the time when a movement would have normally occurred,
1064 reminiscent of the slight increase in OPN activity during visual input[32].

1065



Supplementary Figure 8. Leaky accumulator with facilitation (LAF) model can discriminate population temporal structure. A. Inputs to the model from SC visuomovement neurons. Raw unstable (red) and stable (blue) input profiles (inset – population means). The two sets of inputs are 180 ms snippets taken from the visual and premotor bursts, respectively, in the spike density profiles shown in Figure 2A. **B.** Mean-matched input profiles and population means. **C.** Temporal stability of the two mean-matched populations. **D.** Output of the LAF accumulator in response to the stable and unstable model inputs. **E.** Evolution of synaptic weights for the two conditions. **F.** Correlation between instantaneous weights and input rates for the two conditions. **G.** Pattern sensitivity index of the model's ability to discriminate between the two types of inputs. Values in the top half of the plot indicate higher sensitivity (faster accumulation) to stable population input.

Supplementary Table 1. Values of the constants and parameters used for the spiking neuron model.

Biophysical constants	**Values**
τ_m	10 ms
R_m	10 Mohms
V_{th}	-50 mV
V_{rest}	-65 mV
V_{reset}	-70 mV
E_{exc}	50 mV
E_{inh}	-80 mV
Model parameters	
τ_1	2 ms
τ_2	10 ms
$\boldsymbol{w}^{exc-dec}$	5 x 10^{-6} $uniform[0,2]$
$w^{dis-dec}$	5
$\boldsymbol{w}^{exc-dis}$	0.2 $\boldsymbol{w}^{exc-dec}$
$\boldsymbol{w}^{inh-dis}$	0.8 $\boldsymbol{w}^{exc-dec}$
$w^{dec-dis}$	0.1
Numerical parameters	
dt (time step)	0.05

1079 **S1. Inferring population dynamics from single-unit recordings**

1080 The main text and methods describe how we reconstructed a pseudo-population from unit recordings.
1081 Using knowledge of the RF centre of a given session's local population obtained from microstimulation,
1082 and known transformation from visual space to SC tissue coordinates, here we reconstruct the pseudo-
1083 population on the SC map.

1084 We first transferred target locations (R_T, θ_T) inside the RF for each neuron onto the SC map using the
1085 following transformations[48] –

1086 $x_T = \frac{B_x}{2} \ln \frac{(H+A)^2+V^2}{A^2}$, $y_T = B_y \tan^{-1} \frac{V}{H+A}$, where,

1087 $H = R_T \cos\theta_T$, $= R_T \sin\theta_T$, and $A = 3$, $B_x = 1.4$, $B_y = 1.8$.

1088 The transformed locations (x_T, y_T) on the bilateral SC map are shown in Supplementary Fig. 3A, top row.
1089 In order to move these target locations to one pseudo-population, we need to identify where these
1090 points reside in the RF of each neuron or local population. We used the endpoints of the site-specific
1091 microstimulation-evoked saccades as a proxy for the respective RF centres. The transformed endpoints,
1092 with their locations relative to the corresponding target locations, are shown in Supplementary Fig. 3A,
1093 middle row. We picked an arbitrary location in the visual field as the RF centre of the pseudo-
1094 population, $(R_c, \theta_c) = (15,0)$. We used the fact that the size of the active SC population is invariant
1095 regardless of the encoded saccade to preserve relative distances in tissue space between a site's target
1096 location and RF centre, and translated the transformed microstimulation endpoints to the common
1097 pseudo-population centre, along with the respective target locations. To construct one active population
1098 from sites gleaned from both hemifields (and therefore both colliculi), we reflected the coordinates
1099 from one colliculus onto the other. The resulting pseudo-population (Supplementary Fig. 3A, bottom
1100 row) shows a fairly representative sampling of neurons from the pseudo-population, with its extent
1101 consistent with a large (25% of SC tissue) active population, albeit one that is biased to one side of the
1102 population.

1103

S2. Leaky accumulator with facilitation (LAF) model

We developed an alternative computational model to demonstrate how the temporal structure of population activity could be used by neural circuits to gate decisions such as movement initiation. Similar to the spiking neuron model presented in the main text, a core principle behind this model is the hypothesis that signal integration is stronger when the temporal structure in input activity is stable, which allows the decoder neuron to reach threshold during the high frequency burst that triggers the movement. We constructed an accumulator as an abstraction of a neuron receiving population inputs through its network of dendrites. The total synaptic current $I(t)$ and the firing rate $v(t)$ of the accumulator were defined as

$$\tau_s \dot{I} = -I + \sum_1^n w_i u_i$$

and

$$v = F(I)$$

where u_i and w_i are the instantaneous firing rate and synaptic gain of the ith input neuron, and τ_s is the time constant of the synaptic current. The output firing rate of the single decoder neuron $v(t)$ can be described by a standard monotonic function (e.g., linear or sigmoid) applied to the net current[52]. The family of stochastic, leaky accumulator models that integrate the firing rate of neurons toward a threshold criterion has been commonly used to explain reaction times, decision making, and perception[25,53-55]. We used the following heuristic in order to extend this framework to incorporate temporal structure. In order to assess stability, the decoder neuron must keep track of the short term history of the population activity, use this "memory" to evaluate stability, and respond selectively when the activity pattern is deemed stable over some time scale. We implemented these requirements by introducing short-term plasticity in the form of facilitatory connections[56,57] from the input population onto the output unit (accumulator). The change in connection strength or gain of each neuron on the decoder neuron w_i can be defined by a differential equation that incorporates a Hebbian-like learning rule and leak current:

$$\tau_w \dot{w}_i = -w_i + \frac{u_i v}{wnf_i}$$

The Hebbian-learning component, $u_i v$ describes the change in weight coupled to the firing rates of the ith pre-synaptic neuron and the post-synaptic accumulator neuron. τ_w is the time constant of the weight parameter. Since this version of the model contains only excitatory connections, the weight parameter can exhibit unbounded accumulation, which can be controlled by incorporating normalization. We normalized the Hebbian-learning component $u_i v$ with the contribution of that neuron to the total resource pool. The resource pool available for facilitation at any given time was defined as the sum of the Hebbian-learning component across all input units $\sum_1^n u_i v$. The contribution of a neuron to the output rate $v(t)$ then determines its contribution to the overall pool, giving rise to the weight normalization factor:

$$wnf_i = \sum_1^n u_i w_i u_i$$

For this model simulation, we used visuomovement neuron activity drawn from the SC pseudo-population as inputs (Supplementary Fig. 8A). We created two sets of input snippets from the visual and premotor bursts, each 180 ms in length. For the visual burst, we used the activity upto the peak in the population response. For the premotor burst, we used activity upto 35 ms before saccade onset (which was the time when the response magnitude reached the same level as the peak of the visual burst). In order to control for the effect of average firing rate on the accumulation, we mean-matched the input profiles as follows. We divided the activations in the premotor input set at each instant by the mean activation of the visual inputs at the corresponding instant. That is,

$$u_i^{pre}(t)_{mm} = \frac{u_i^{pre}(t)}{\frac{1}{n}\sum_1^n u_i^{vis}(t)}$$

where $u_i^{vis}(t)$ and $u_i^{pre}(t)$ are the activity of neuron *i* at time *t* in the visual and premotor input sets, respectively, and $u_i^{pre}(t)_{mm}$ is the premotor input instantaneously rescaled to match the mean of the visual input (Supplementary Fig. 8B). This ensured that we isolated the effect of temporal structure (Supplementary Fig. 8C), independent of firing rate, on the model's response.

The accumulator increased its activity at a faster rate in response to the stable pattern compared to the unstable pattern (Supplementary Fig. 8D), suggesting that the network was able to discriminate between two types of population patterns even though the net input drive was identical. How critical is facilitation to this function? Like the inputs themselves, the weights also showed greater fluctuation during the visual burst (Supplementary Fig. 8E). Consistent with our heuristic, the weights tracked the input rates when the input was stable, but this correlation dropped away when the input was unstable (Supplementary Fig. 8F). Note that the shape of the correlation profile is not unlike the stability profile in Supplementary Fig. 8C. Therefore, facilitation allows the weights to retain the memory of a pattern over the time scale of tens of milliseconds, but the memory can be scrambled by a fluctuating input pattern.

We also quantified the ability of the synaptic weights to track the inputs by computing the Pearson's correlation between the weight and input vectors at each time point (Supplementary Fig. 8G). To quantify the accumulator's ability to discriminate temporal pattern in population input, we computed a pattern sensitivity index (*psi*) as

$$psi(t) = \frac{v^{pre}(t) - v^{vis}(t)}{v^{pre}(t) + v^{vis}(t)}$$

where $v(t)$ is the output of the accumulation for the corresponding inputs.

The results here suggest that the accumulator is driven more strongly by the stable premotor burst, even when other features of population activity remain the same, providing yet another biophysical mechanism by which temporal structure could be read out.

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