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Short-Term Influence of Recent Trial History on Perceptual Choice Changes with Stimulus Strength

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Abstract—Perceptual decisions, especially for difficult stimuli, can be influenced by choices and outcomes in previous trials. However, it is not well understood how stimulus strength modulates the temporal characteristics as well as the magnitude of trial history influence. We addressed this question using a contrast detection task in freely moving mice. We found that, at lower as compared to higher stimulus contrast, the current choice of the mice was more influenced by choices and outcomes in the past trials and the influence emerged from a longer history. To examine the neural basis of stimulus strength-dependent history influence, we recorded from the secondary motor cortex (M2), a prefrontal region that plays an important role in cue-guided actions and memory-guided behaviors. We found that more M2 neurons conveyed information about choices on the past two trials at lower than at higher contrast. Furthermore, history-trial activity in M2 was important for decoding upcoming choice at low contrast. Thus, trial history influence of perceptual choice is adaptive to the strength of sensory evidence, which may be important for action selection in a dynamic environment.

Key words: choice history, contrast, decision making, rodent, secondary motor cortex.

INTRODUCTION

Humans and other animals integrate sensory inputs, internal state, and past experience to select action in changing environments. Behavioral performance in this process is often influenced by trial history. For example, in sensory delayed comparison task, sensory perception is affected by previous history of sensory stimuli (Ashourian and Loewenstein, 2011; Karim et al., 2013; Akrami et al., 2018) and the effect can be explained in the context of Bayesian inference (Körding and Wolpert, 2006; Raviv et al., 2012). In dynamic foraging task with probabilistic reward schedule, the choice of decision maker is influenced by the history of choice and reward (Sugrue et al., 2004; Corrado et al., 2005; Lau and Glimcher, 2005; Sugrue et al., 2005; Sul et al., 2011), which reflects rational strategies and can be understood in the framework of reinforcement learning (RL) theory (Sutton and Barto, 1998). According to RL theory, the feedback based on trial history is important for the update of value function in value-based decision making (Sugrue et al., 2005; Daw and Doya, 2006; Lee et al., 2012). In competitive games in which the optimal strategy is to behave randomly, the decisions of humans and other animals are also influenced by the local history of choices and rewards as in RL (Barraclough et al., 2004; Forder and Dyson, 2016). Choice history biases still exist without the information of feedback about choice outcome (Akaishi et al., 2014; Braun et al., 2018). Thus, trial history influence is prevalent and may be a fundamental aspect in sensory perception, decision making, and action selection.

In perceptual decision task, the optimal strategy should be based on sensory factor, yet the choices of humans and other animals are influenced not only by sensory stimulus but also by previous choices and outcomes. For instance, in monkeys performing a direction-discrimination task, the choices exhibit dependencies across trials, and the effect of such sequential dependencies on behavior is stronger when the stimulus information is weaker (Gold et al., 2008). In human perceptual decision task, the choices of subjects are biased by the choice history (Fernberger, 1920; Abrahamyan et al., 2016; St John-Saaltink et al., 2016; Braun et al., 2018), especially when the stimulus is ambiguous (Fründ et al., 2014; Abrahamyan et al., 2016). Similarly, the choices of rodents performing a sensory-guided choice task are influenced by the successes and

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Abbreviations: M2, secondary motor cortex; PPTg, pedunculopontine tegmental nucleus; PR, prediction rate; PSTH, peristimulus time histogram; RL, reinforcement learning; ROC, receiver operating characteristic; SVM, support vector machine; 2AFC, two-alternative forced choice.

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failures in previous trials (Busse et al., 2011; Scott et al., 2015; Thompson et al., 2016; Akrami et al., 2018). However, it is unclear how the integration of trial history and sensory input is dynamically modulated by the strength of sensory evidence.

Neural signals related to the previous choices or outcomes of the animal have been found in many brain regions, including prefrontal cortex, parietal cortex, premotor cortex, and striatum (Barraclough et al., 2004; Genovesio et al., 2006; Kim et al., 2007; Seo and Lee, 2007; Seo et al., 2009; Sul et al., 2010; Sul et al., 2011; Kim et al., 2013; Yuan et al., 2015; Murakami et al., 2017; Scott et al., 2017; Abzug and Sommer, 2018). For example, neurons in rodent M2 region have been found to exhibit the earliest choice-related signal among several frontal and striatal regions, and M2 responses reflect the past choice or outcome in both value-based and perceptual decision-making tasks (Sul et al., 2011; Yuan et al., 2015; Scott et al., 2017; Siniscalchi et al., 2019). However, it is unclear how history-related activity in M2 is modulated by stimulus strength.

We addressed these questions using a contrast detection task in mice. We found that the influence of trial history on the current choice was stronger and arrived from a longer past when the stimulus strength was weaker. In behaving mice, the signatures of such stimulus-strength dependent trial history influence were present in the neural activities in M2. Our results indicate that the length of recent trial history integrated with sensory evidence is dynamically modulated by stimulus strength at both behavioral and neuronal level.

EXPERIMENTAL PROCEDURES

Animals

All procedures were approved by the Animal Care and Use Committee at the Institute of Neuroscience, Chinese Academy of Sciences, and were in accordance with the guidelines of the Animal Advisory Committee at the Shanghai Institutes for Biological Sciences. Data were collected from a total of 39 male adult C57BL/6 mice (2–10 months old), in which 8 were used for the experiments with electrophysiological recordings.

Behavior and visual stimuli

Behavioral training began after the mice were water-deprived for 2 days. In the custom-design behavioral chamber (36 × 17 × 29 cm, L × W × H), three ports were positioned along the transparent front wall and two spouts were positioned in the left and right ports, respectively (Long et al., 2015; Zhang et al., 2017). The behavioral chamber was divided into three connected areas using two dividers (Busse et al., 2011). The dividers were removed in sessions with electrophysiological recordings or in some sessions of the behavioral experiments. Visual stimuli were presented on a 17" LCD monitor (Dell E1714S, mean luminance 39.5 cd/m^2) placed 12 cm away from the front wall of the chamber. Gamma correction was used to calibrate the monitor. The monitor subtended 109.6° × 96.7° of visual space, assuming that the mouse's head was at the central port facing the stimulus. Sound speakers were placed inside the chamber to provide auditory go signal and feedback signals.

The mice were trained to perform a two-alternative forced choice (2AFC) contrast detection task using the following steps (Felsen and Mainen, 2008; Stubblefield et al., 2013; Long et al., 2015). In step 1, with the central port blocked, the mouse nose-poked into the two side ports in an alternating sequence to receive water reward (4–5 μl). In step 2, the central port was open and the left port was blocked. The mouse initiated a trial by nose-poking into the central port. After the mouse held its head for 150 ms, a vertically oriented light bar (luminance = 149 cd/m^2, 34.7° × 96.7°) was presented on the right side of the screen over a background of mean luminance. After a minimum hold time of 300 ms following stimulus onset, an auditory go signal (a 100-ms, 8 kHz pure tone) appeared, and the mouse was allowed to exit the central port to choose the right port for water reward. If the hold time following stimulus onset was less than 300 ms, the trial was invalid and no water was given. The required hold time following stimulus onset was gradually increased to 600 ms. After the mouse's performance reached 60%, the right port was blocked and the left port was open, and the mouse was trained to perform similar task to obtain water reward from the left port. In step 3, all three ports were open, and the mouse initiated a trial by nose-poking into the central port. After the mouse held its head for 150 ms, a vertically oriented light bar (luminance = 149 cd/m^2, 34.7° × 96.7°) was presented randomly on the left or right side of the monitor. In a valid trial, the required hold time following stimulus onset was 600 ms, and the mouse was allowed to leave the central port after the go signal. If the mouse chose the port corresponding to the side of the stimulus, it was rewarded by 4–5 μl of water. If the mouse chose the opposite side, no water was delivered, the screen was turned black, and an auditory white noise was played for 1 s during the 4 s timeout period. The stimulus disappeared after the mouse chose the side port. If the hold time following stimulus onset was <600 ms, the trial was invalid, and the stimulus disappeared after the mouse exited the central port, with an auditory white noise played for 1 s during the timeout period. In step 4, the mouse was trained to detect the position of the light bar using a procedure similar to that in step 3, except that the stimulus disappeared once the mouse exited the central port. The mouse advanced to the next step after the performance reached 85% for 3 consecutive sessions. In step 5, light bar with lower luminance was gradually introduced until a session contained five blocks of contrasts (80 trials/block). The contrast of the light bar was defined as $(L - L_b)/(L + L_b)$, in which L and L_b were the luminance of the light bar and the background, respectively. The five blocks of contrasts were presented in a descending sequence ([58%, 53%, 41%, 29%, 16%]). Once the performance was stable across multiple sessions, the training was over and the mouse was used in the final form of behavioral experiment.

Because random sequence of stimulus contrast across trials may cause contrast adaptation (Ohzawa et al., 1982; Sclar et al., 1989; Long et al., 2015), the contrast detection

task was conducted in a block design manner, so that the effect of past choice and outcome was not confounded by the effect of contrast adaptation. Each session contained five blocks of contrast (16%, 29%, 41%, 53%, and 58%, 80 trials/block). In each block, the light bar was presented randomly on the left or right side, except that we did not allow the bar to appear on the same side for more than three consecutive trials or the bar to alternate between sides in consecutive trials for more than three times (Busse et al., 2011). The sequence of contrast blocks in each session was chosen from the following: [58%, 53%, 41%, 29%, 16%], [58%, 16%, 53%, 41%, 29%], [41%, 29%, 58%, 53%, 16%], [29%, 58%, 16%, 41%, 53%], [58%, 53%, 41%, 16%, 29%], [41%, 29%, 16%, 58%, 53%], and [16%, 53%, 41%, 58%, 29%]. To analyze whether stimulus-strength dependent trial history influence is affected by block sequence, we required that a specific block sequence was measured for at least 25 sessions. The mouse was required to hold its head in the central port for 450 ms in some sessions, and above or below 450 ms in other sessions. For all conditions, the stimulus disappeared after the mouse exited the central port. The behavior of each mouse was measured for 18.2 ± 12.5 (mean ± SD) sessions.

To examine whether the trial history influence depends on trial duration, we fixed the sequence of contrast blocks at [58%, 53%, 41%, 29%, 16%], and manipulated trial duration by varying the hold time required for a valid trial and the timeout period following a wrong choice, or by adding or removing the two dividers. There were four types of trial duration manipulation. The two dividers were in the behavioral chamber for the following three types: (1) hold time = 750 ms and timeout = 4 s; (2) hold time = 450 ms and timeout = 2 s; (3) hold time = 0 ms and timeout = 1 s. For the fourth type, hold time = 0 ms, timeout = 1 s, and the two dividers were removed from the chamber.

For mice used in the above experiments, the sequence of stimulus position across trials was not completely random. For another group of mice (n = 7), we also used a behavioral paradigm in which the sequence of stimulus position was completely random (the sequence of contrast blocks was [58%, 53%, 41%, 29%, 16%], 60 trials/block). For this experiment, the behavior of each mouse was measured for 7.4 ± 3.9 (mean ± SD) sessions.

For behavioral experiments used for electrophysiological recordings, each session contained two blocks of contrast (110 trials of 16% contrast and 220 trials of 53% contrast) and started with the high contrast block. We used more trials for 53% contrast in order to collect enough number of wrong trials for the analysis of outcome preference index. The hold time required for a valid trial was 450 ms, the timeout period following a wrong choice was 2 s, and the two dividers were removed from the chamber. The sequence of stimulus position across trials was completely random.

Surgery

For mice used in the electrophysiological recordings, electrodes (A2 × 2-tet-3 mm-150-150-121-H16_21mm, dDrive mounted, NeuroNexus Technologies, Ann Arbor, MI, USA) were implanted after behavioral training. The mouse was injected intraperitoneally with a mixture of midazolam (5 mg/kg), fentanyl (0.05 mg/kg), and medetomidine (0.5 mg/kg). After the mouse was fully unresponsive to toe-pinch, it was head-fixed in a stereotaxic apparatus. The body temperature was maintained at 37 °C through a heating blanket (FHC Inc., Bowdoin, ME, USA). A craniotomy (~ 1 mm diameter) was made above left M2 (AP 2.1 mm, ML 0.75 mm), and the dura was removed. The micro-drive/electrode/rod package was mounted on a stereotaxic manipulator and moved above the craniotomy under the supervision of a binocular microscope. The electrode was inserted into the cortex and the micro-drive was fixed to the skull using dental cement. The micro-drive was detached from the manipulator and protected with a cap. The ground and reference wires of the electrode were connected with a screw driven into the bone. The mouse was injected with ceftriaxone sodium (2 mg/kg) subcutaneously after the surgery.

Electrophysiology

Recordings in M2 were made with silicon probes with 2 × 2 tetrode-like arrangements on 2 shanks (A2 × 2-tet-3 mm-150-150-121-H16_21mm, NeuroNexus Technologies). The depth of the electrode was estimated by the number of rotations of the screw on the micro-drive (one turn = 150 μm), and was advanced by ~50 μm after 3–5 recording sessions. The neural signals were amplified and filtered using a Cerebus 32-channel system (Blackrock microsystems, Salt Lake City, UT, USA). Spiking signals were sampled at 30 kHz. Signals collected over different sessions at the same depth were combined into a single file before spike sorting. Single units were isolated offline, by manually clustering spike features derived from the two-dimensional projections of spike waveform parameters using MClust software (MClust-3.5, A. D. Redish, University of Minnesota, Minneapolis, MN, USA) in Matlab (MathWorks).

Analysis of behavior

To compute the correct rate for each stimulus, we calculated the percentage of left (or right) choices for those trials in which the light bar was presented on the left (or right) side, and averaged the two percentages.

Trial duration was defined as the interval between the times of central port entry in two consecutive valid trials. Note that the trial duration averaged across all valid trials in a session could be larger than 20 s because there could be invalid trials between two consecutive valid trials. To examine whether the trial history influence depends on trial duration, only those sessions in which the mean trial duration was <20 s were included in the analysis.

We used a logistic regression analysis to quantify the influence of current stimulus contrast and previous trial outcome on the choice of current trial (Lau and Glimcher, 2005; Busse et al., 2011). For each contrast block in each session, the choice of a given trial was modeled with a logistic function: $p = \frac{1}{1+e^{-z}}$, where p is the probability of choosing

right and z is a decision variable. In each trial *t*, the variable z is a linear function of the sensory and history terms:

$$z(t) = b_0 + v[c(t)] + \sum_i \left[b_s(i)s(t-i) + b_f(i)f(t-i)\right],$$

where *c* is the contrast in current trial, *v* weights the stimulus contrast, *i* indicates *i* trial back (*i* ranges from 1 to 5), $b_s(i)$ and $b_f(i)$ are the weights for the successes and failures in *i* trial back, and b_0 is the weight for a general bias. The bias term b_0 is negative (positive) for leftward (rightward) bias. The dummy variables $s(t-i)$ and $f(t-i)$ have three possible values: 1, −1, and 0. If the outcome in *i* trial back is a success, $s(t-i)$ is set to 1 (or −1) if the stimulus is on the right (or left), and $f(t-i)$ is set to 0. If the outcome in *i* trial back is a failure, $f(t-i)$ is set to 1 (−1) if the stimulus is on the right (left), and $s(t-i)$ is set to 0.

For each session, we used the Matlab function glmfit to apply the logistic regression model separately for each contrast block. The predictor matrix was defined as the following. The first row was a constant to estimate b_0. The next *i* (*i* ranges from 1 to 5) row/rows were used to estimate the weight of success in past trials. For example, if the model included history influence of only one trial back ($i = 1$), the second row of the matrix was $s(t-1)$. If the model included history influence of three trials back ($i = 3$), the second row of the matrix was $s(t-1)$, the third row was $s(t-2)$, and the fourth row was $s(t-3)$. Following the row/rows for estimating the weight of success, there were another *i* (*i* ranges from 1 to 5) row/rows organized in a similar manner to estimate the weight of failure in past trials. The last row of the matrix was used to estimate the weight of visual stimulus, with $c(t)$ set to 1 (or −1) for stimulus presented on the right (or left) (Busse et al., 2011).

For each contrast block, we fitted the model to the choices and predicted the choices by applying a cross validation procedure. We randomly divided the trials into training dataset and test dataset, which contained equal number of trials. The logistic regression was fitted using the training dataset and the choices were predicted using the test dataset. The prediction rate (PR) was computed as the percentage of correctly predicted trials. The process of training and prediction was repeated 1000 times, and the PR was averaged across repeats. We used five different models, in which the number of history trials varied from one to five, and computed five PRs, respectively. Specifically, the model included history terms in *t*-1 trial when we modeled the effect of one trial back, and the model included history terms in *t*-1, *t*-2, and *t*-3 trials when we modeled the effect of three trials back. We also used a simple model including only the visual term $v(c)$ and the general bias term b_0 to fit the choices. For each history model with a specific number of history trials, we computed a difference in prediction rate (ΔPR), which was defined as the PR of the history model subtracted by that of the simple model. We repeated the same procedure for the other four contrast blocks in the same session except that no history effect was considered in the model, resulting in four baseline ΔPR values. The process of calculating baseline ΔPR was repeated five times, resulting in a total of 20 baseline ΔPRs. We defined a threshold ΔPR as 3 SD above the mean of baseline ΔPRs.

For each contrast block in each session, if the ΔPR for at least one *i* trial back (from one trial back to five trials back) was above the threshold ΔPR, the optimal number of history trials that could influence current choice was defined as the one at which the ΔPR was maximum. If the ΔPR was lower than the threshold ΔPR for any *i* trial back, the optimal number of history trials was set to zero. We used a one-way repeated measures ANOVA with the Greenhouse–Geisser correction to test the effect of stimulus contrast on the optimal number of history trials.

For each contrast block in each session, we predicted the choices of each mouse using the model containing history terms for the optimal length of history trial, and computed a ΔPR relative to the PR of a simple model without history terms. For each mouse, we used Wilcoxon signed rank test to determine whether ΔPR is significant.

To compute a history strategy index for each session, we used the logistic regression model including only the history terms at the optimal number of history trials. The model was used to generate choices to a set of visual stimuli in the behavioral experiments, and the history strategy index was calculated as the fraction of trials correctly predicted by the model (Hwang et al., 2017). Only those sessions in which the optimal number of history trials was non-zero were used for this analysis. We used ANOVA to determine whether history strategy index exhibits significant difference across different contrasts, and whether behavioral performance differs among sessions with low (< 0.55), middle (> 0.55 and ≤ 0.65), and high (> 0.65) history strategy index. We used F test to determine whether the variability of performance is significantly different between sessions with high and low (or between sessions with high and middle) history strategy index.

Analysis of neuronal responses

For mice used in the electrophysiological experiments, hold time was 0.71 ± 0.1 s (mean ± SD). We analyzed the neuronal responses during the 1 s period before the mouse exited the central port. Spikes within this 1 s period were 95.5% ± 6.2% (mean ± SD) of all the spikes occurred during the hold time across trials. To quantify the selectivity of each neuron for choice or outcome, we used an algorithm based on the receiver operating characteristic (ROC) analysis (Green and Swets, 1966) that measures the probability of an ideal observer to correctly classify whether a given response was recorded in one of two conditions (e.g., left or right choice). A preference index was defined as $2(ROC_{area} - 0.5)$, which ranged from −1 to 1 (Felsen and Mainen, 2008; Thompson et al., 2016). To compute choice (or outcome) preference index for current or previous trial, we grouped the responses by the choice (or outcome) on the current trial, one trial back, two trials back, or three trials back. The magnitude of the preference index indicates the degree of selectivity, and the sign of the index denotes preference for contralateral (+) or ipsilateral (−) choice, or preference for correct (−) or wrong (+) choice. Cells had to satisfy two criteria to be included

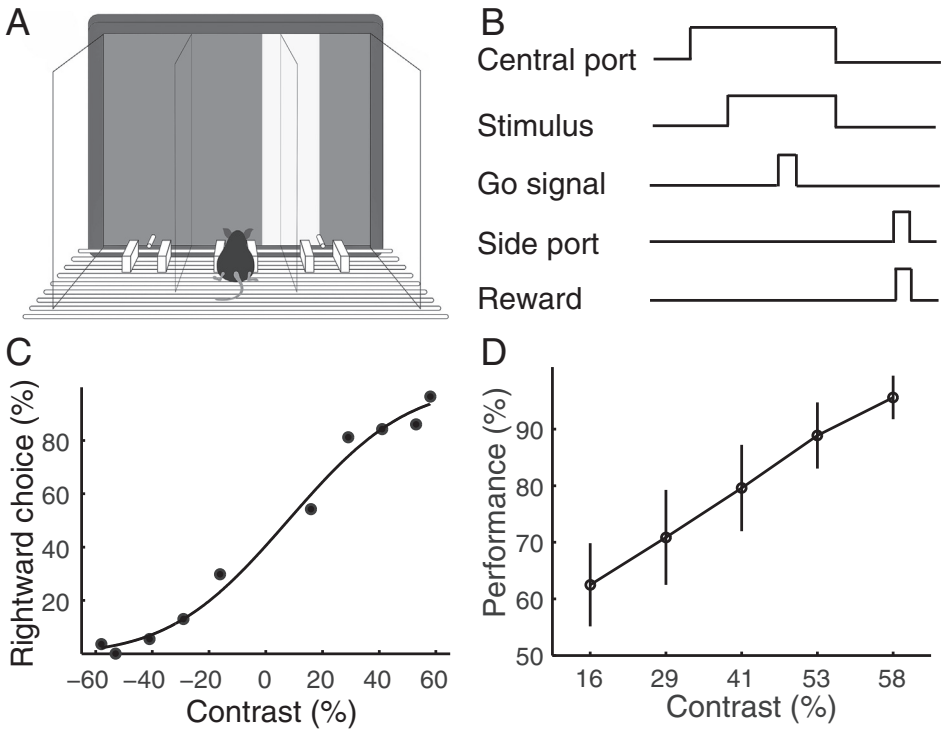


Fig. 1. Contrast detection task and behavioral performance. (A) Schematic illustration of the behavioral apparatus. (B) Timing of task events. (C) Performance of an example mouse. Negative (positive) contrasts indicate that the stimulus was presented on the left (right) side. The line is the psychometric function fitted with a cumulative Gaussian. (D) Correct rates for stimuli at different contrasts for a population of mice ($P < 1 \times 10^{-15}$, one-way repeated measures ANOVA, 131 sessions from 9 mice, in which hold time = 450 ms and timeout period = 2 s). Error bar, ±SEM.

in the analyses: 1) more than 20 trials for each condition; 2) firing rate above 0.5 spikes/s. Among 100 neurons recorded, 88 neurons satisfied the criteria.

We used a Monte Carlo permutation test to determine the statistical significance of preference index. We randomly reassigned the responses to one of the two conditions and repeated the same analysis to calculate a preference index. This procedure was repeated 1000 times. The *P* value was determined by the fraction of randomly generated preference indexes exceeding the actual preference index. Statistical significance was tested at $\alpha = 0.05$. We used χ^2 test to determine whether the fraction of significant neurons is above chance level or the fractions of significant neurons differ between 16% and 53% contrasts.

We also examined whether trial duration affects the trial history-related activity in M2 at 16% contrast. For the responses of each neuron grouped by choice at one trial back, we separated the trials into two subsets, with trial duration shorter and longer than the mean duration, respectively. We used χ^2 test to determine whether the fractions of neurons with significant choice preference at one trial back differ between trials with short and long duration.

A support vector machine (SVM) classifier with a nonlinear kernel (Gaussian kernel) (Chang and Lin, 2011; Astrand et al., 2014) was used to decode the animal's choice (or outcome) in current or previous trials from the activities of M2 neurons. For each trial, we used the neuronal responses (bin size = 0.1 s) during the 1 s period before the mouse exited the central port. By applying the decoder derived from the training dataset to the test dataset, we performed the classification using a 10-fold cross validation procedure. The training and test dataset were data from 90% and 10% of the trials, respectively. During training, the classifier separated the data into two classes according to choice (or outcome) on the current trial, one trial back, or two trials back. During testing, the decoder was presented with neuronal responses in the test dataset and produced prediction about choice (or outcome) on the current trial, one trial back, or two trials back. The classification performance was calculated as the percentage of correctly classified trials. The two key parameters (box constraint and scaling factor sigma of the Gaussian kernel function) were calculated through a nonlinear optimization process using the Matlab function fminsearch. The 10-fold cross validation was repeated 10 times. To compare the classification performance between choice (or outcome) on the current trial and that on one trial back (or two trials back), we used a one-way repeated measures ANOVA followed by Tukey's multiple comparisons test.

SVM classifier was also used to decode the animal's upcoming choice from neuronal responses. The decoding was performed using a 10-fold cross validation procedure. We compared the decoding accuracy between the model using neuronal responses in current trial only (trial *t*) and that using responses in both current and previous two trials (trial *t*, *t*-1, and *t*-2). The decoding accuracy was quantified by the PR, which was the percentage of trials correctly predicted by the decoder. For 16% and 53% contrast, the total number of trials used in this decoding analysis was 1239 and 1289, respectively. Note that the number of trials for this analysis was smaller than that in the classification analysis, because here we required that spikes also occurred in trials *t*-1 and *t*-2 for trial *t*. The decoding analysis was repeated 10 times. To compare the decoding accuracy between the model using neuronal responses in current trial only and that using responses in both current and previous two trials, we used Wilcoxon signed rank test.

RESULTS

Stimulus contrast modulates the trial history influence on perceptual choice

We trained freely moving mice to perform a 2AFC contrast detection task (Busse et al., 2011; Long et al., 2015; Zhang et al., 2017). The mouse poked its nose in the central port of

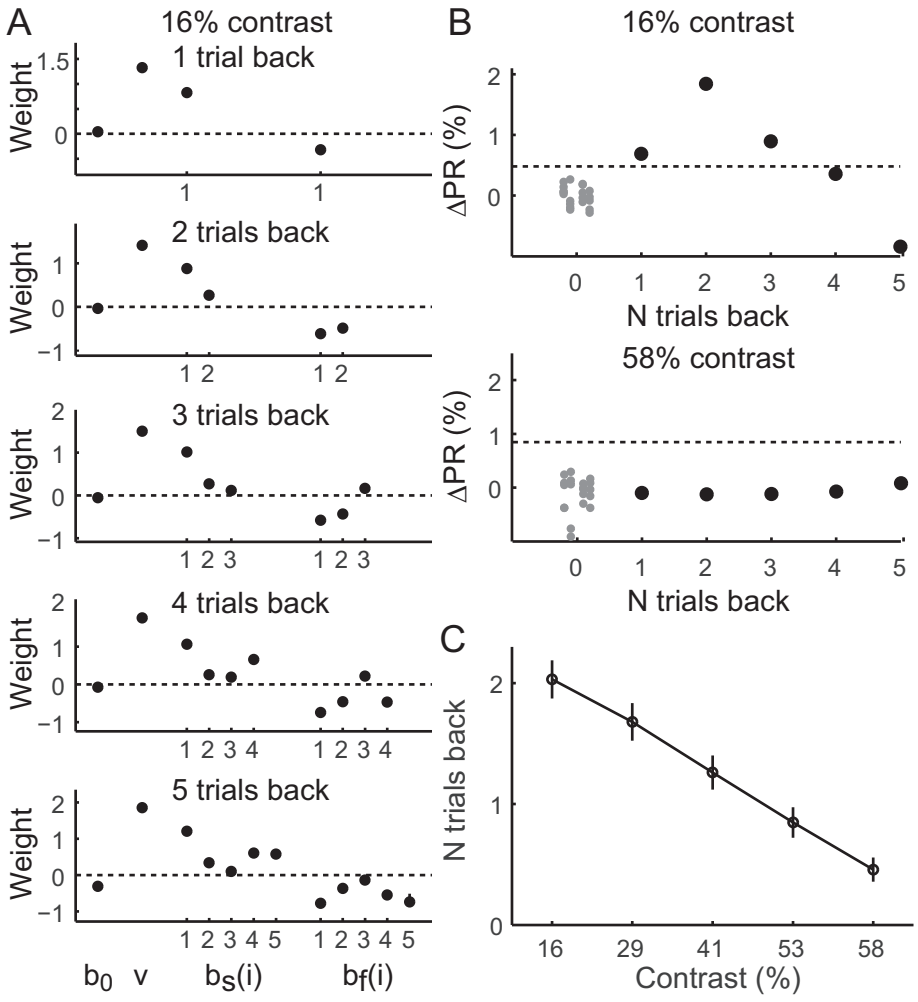


Fig. 2. The influence of trial history on perceptual choice comes from a longer past when the stimulus contrast is lower. (A) The weights for five different models, in which the number of history trials varied from one to five, for a 16% contrast block in an example session. (B) ΔPR versus N trials back for two example sessions in 16% and 58% contrast blocks, respectively. Data points around 0 trial back were baseline ΔPRs. The horizontal dashed line represents 3 SD above the mean of these baseline ΔPRs. (C) The number of history trials that could influence current choice was significantly different at different stimulus contrasts, with a larger number of history trials at lower contrast (Spearman's rank correlation coefficient r = −1, $P = 0.017$). $F_{(3.7,\ 481.4)} = 21$, $P = 5 \times 10^{-15}$, one-way repeated measures ANOVA with the Greenhouse–Geisser correction. The data were from 131 sessions from 9 mice, in which hold time = 450 ms and timeout period = 2 s. Error bar, ±SEM.

the behavioral chamber to trigger stimulus presentation. Visual stimulus was a vertical light bar presented randomly on the left or right side of the monitor (Fig. 1A). The mouse held its head in the central port until a go signal was presented, and the stimulus disappeared once the mouse exited the central port to make a choice (Fig. 1B). Choosing the port corresponding to the side the light bar was presented was counted as a correct choice, which was followed by water reward. Choosing the other port was counted as a wrong response, which was followed by a timeout period. The contrasts of the light bar relative to the background (mean luminance) ranged from 16% to 58% (Fig. 1C) and were presented in a block-design manner. Each contrast block consisted of 80 trials, and the sequence of different contrast blocks was changed in different sessions. The performance increased with stimulus contrast (Fig. 1D, 131 sessions from 9 mice), consistent with previous reports (Busse et al., 2011; Histed et al., 2012; Long et al., 2015; Burgess et al., 2017).

To examine the effect of trial history on behavioral choice, we used a logistic regression model to fit the choice on individual trials in each session for each mouse (Lau and Glimcher, 2005; Busse et al., 2011; Abrahamyan et al., 2016; Hwang et al., 2017). In the model, the mouse flipped a coin to decide which side to choose in each trial t, with a probability P of choosing right. The probability P is a logistic function of a decision variable z that depends on the sum of a sensory term (v), a general bias (b_0), and the history terms (b_s and b_f), which are the outcomes (success or failure) of the previous trials (t-i trials).

To compare the history influence across different stimulus strength, the model was applied to fit the choices in different contrast blocks separately. For each contrast block in each session, we modeled the effect of different lengths of history trials by varying the number of history trials from one to five. Fig. 2A shows the weights for each of the five models containing a specific number of history trials, for a 16% contrast block in an example session. Specifically, the history terms consisted of b_s and b_f in t-1 trial when we modeled the effect of one trial back (Fig. 2A, first row), and consisted of b_s and b_f in t-1, t-2, and t-3 trials when we modeled the effect of three trials back (Fig. 2A, third row). We used each of the five models to predict the animal's choices with a cross-validation analysis. For each contrast block, we also compared the predictive accuracy between the model containing a specific number of history trials and a simple model without history terms, yielding a ΔPR. Baseline ΔPRs (gray dots in Fig. 2B) were computed using the other contrast blocks in the same session and a threshold was defined as 3 SD above the mean baseline ΔPR. As shown in Fig. 2B, the ΔPR for an example session in a 16% contrast block was higher than the threshold for one, two, and three trials back, and was maximum at two trials back, indicating that including the history terms for two trials back (i.e., b_s and b_f in t-1 and t-2 trials) produces the largest improvement in PR relative to the PR of a simple model. For the ΔPR in a

session in 58% contrast block (Fig. 2B), the ΔPR did not cross the threshold for one through five trials back, indicating that including history terms does not improve the predictive accuracy.

For each contrast block in each session, we assigned the optimal number of history trials as the one producing the maximum ΔPR above the threshold. If the ΔPR was lower than the threshold for one through five trials back, the optimal number of history trials was set to zero. For a population of 131 sessions from 9 mice, the number of history trials contributing to current choice was significantly different at different contrasts ($F_{(3.7,\ 481.4)} = 21$, $P = 5 \times 10^{-15}$, one-way repeated measures ANOVA with the Greenhouse–Geisser correction), with more history trials at lower contrast (Spearman's rank correlation coefficient r = −1, $P = 0.017$, Fig. 2C). For each contrast block in each session, we predicted the choices of each mouse using the model containing history terms for the optimal length of history trial, and computed a ΔPR relative to the PR of a simple model (Fig. 3A). Across the population, the ΔPR negatively correlated with stimulus contrast (Spearman's rank correlation coefficient r = −1, $P = 0.017$, Fig. 3B), indicating a stronger effect of trial history on current choice at lower stimulus strength. Together, these data suggest that the influence of trial history is stronger and comes from a longer past when the stimulus strength is weaker.

As the sequence of different contrast blocks varied across sessions, behavioral performance in different blocks may be regulated by other factors, such as changes in the motivational state (Berditchevskaia et al., 2016). We next examined the trial history influence separately for each type of block sequence. As shown in Fig. 4A – 4F, although the Spearman's rank correlation coefficient between the number of history trials and stimulus contrast varied with block sequence, longer length of history influence at lower stimulus contrast was observed in all cases.

For the experiments described above, the stimulus position (left or right) across trials was not completely random (see EXPERIMENTAL PROCEDURES). In another group of mice for which the sequence of stimulus position was completely random, we found that the optimal number of history trials was also significantly higher at lower stimulus contrast ($F_{(3.2,\ 162)} = 6.8$, $P = 1.8 \times 10^{-4}$, one-way repeated measures ANOVA with the Greenhouse–Geisser correction; Spearman's rank correlation coefficient r = −0.9, $P = 0.083$, n = 52 sessions from 7 mice, Fig. 4G).

It has been shown that trial duration affects the trial history influence (Kwak et al., 2014). We further manipulated trial duration of the behavior, by requiring the mouse to hold its head at the central port for different amount of time, changing the duration of the timeout period, or by adding/removing dividers in the behavioral chamber. For low stimulus contrast at 16%, the number of history trials that could influence current choice tended to decrease with trial duration (Spearman's rank correlation coefficient r = −1, $P = 0.083$, Fig. 5), suggesting that the memory of trial history decays over time.

We further determined to what degree the mouse used history-dependent strategy in making choices. For each session, we used the model including only history terms at the optimal number of previous trials to predict choices to a set of visual stimuli similar to those in the behavioral experiments, and defined a history strategy index as the fraction of correctly predicted trials (Hwang et al., 2017). We found that the history strategy index was significantly higher at low contrast than at high contrast ($P = 3.7 \times 10^{-7}$, ANOVA; Spearman's rank correlation coefficient r = −1, $P = 0.017$, Fig. 6A), suggesting that the mice

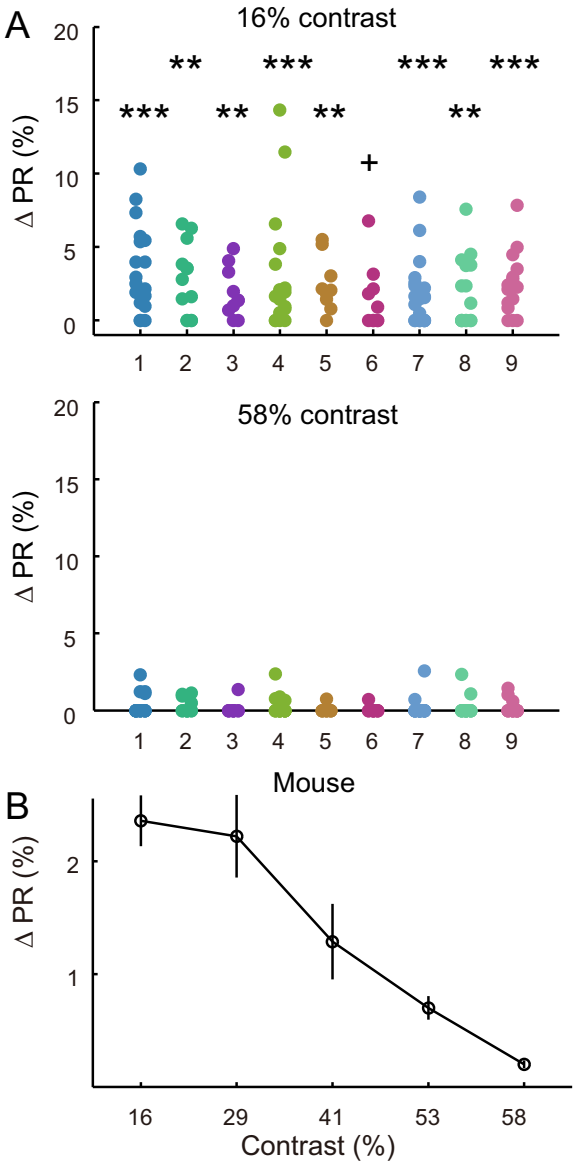
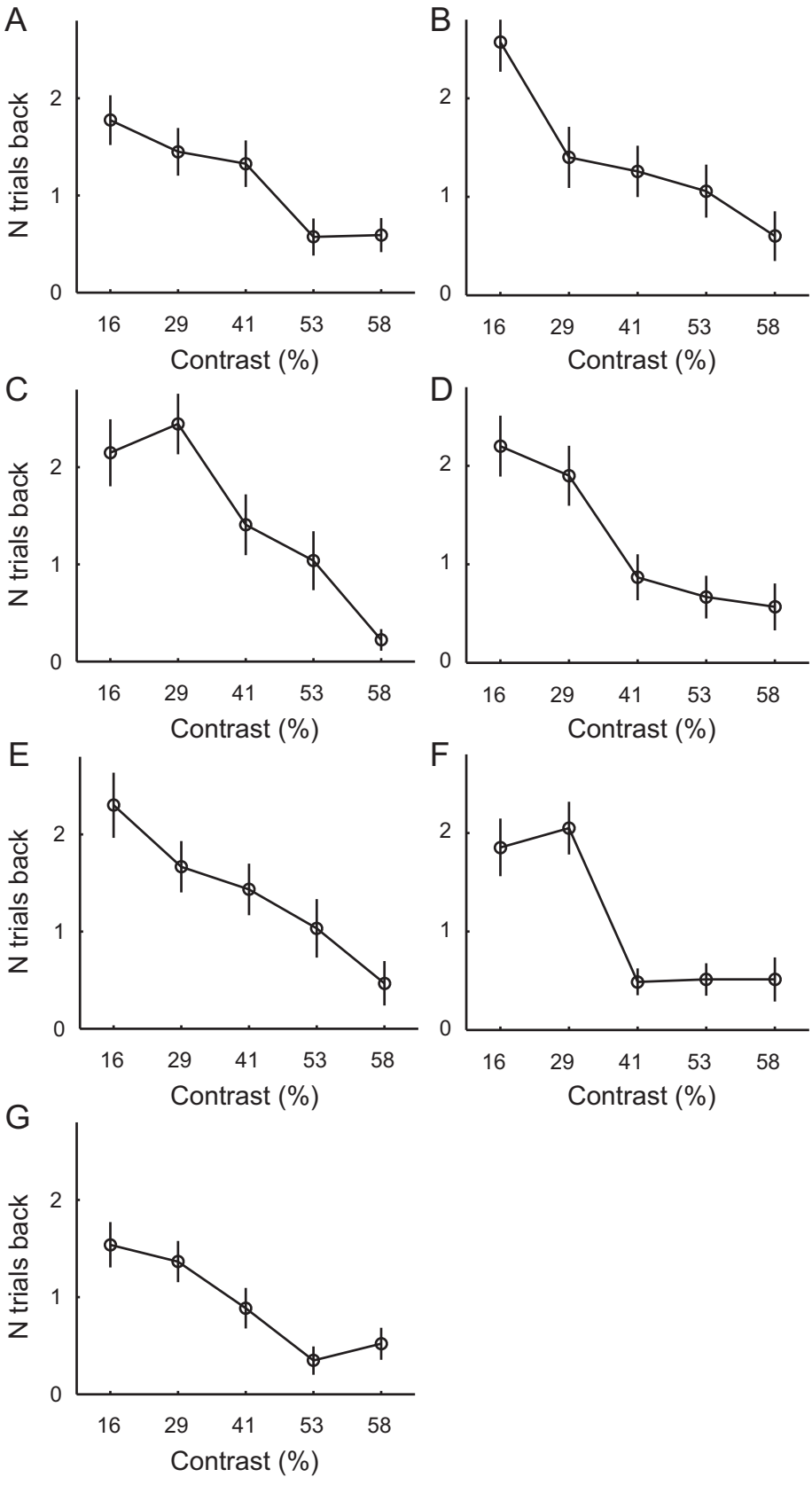


Fig. 3. The influence of trial history on perceptual choice is stronger when the stimulus contrast is lower. (A) Upper, contrast = 16%. Compared to a simple model without history terms, models including history terms improved prediction accuracy for all mice. Each data point represents one session. +, $P < 0.1$, **, $P < 0.01$, ***, $P < 0.001$, Wilcoxon signed rank test. Lower, contrast = 58%, models including history terms did not significantly improve prediction accuracy for any mouse. (B) The increase in prediction accuracy for models with history terms negatively correlated with stimulus contrast (Spearman's rank correlation coefficient r = −1, $P = 0.017$). The data were from 131 sessions from 9 mice, in which hold time = 450 ms and timeout period = 2 s. Error bar, ±SEM.

tend to rely more on recent trial history in making choices when the stimulus is weaker. For low stimulus contrast at 16%, when we divided the sessions into three groups based on the history strategy index, we found that the behavioral performance decreased with history strategy index (P = 0.02, ANOVA, Fig. 6B). Nevertheless, the variability of performance was lower for the sessions with higher history strategy index (P < 0.05, F test, Fig. 6B). Thus, the results suggest that history-dependent strategy impairs behavioral performance and reduces the variability of performance.



Trial history-related activity in M2 is modulated by stimulus contrast

To examine the neural basis of stimulus strength-dependent history influence, we recorded from M2, a

Fig. 4. Stimulus strength-dependent history influence is observed in different block sequences. (A-C) The data were from those sessions in which hold time = 450 ms and timeout period = 2 s (n = 9 mice). (A) The sequence of contrast blocks was [58%, 53%, 41%, 29%, 16%], n = 49 sessions. $F_{(3.7,\ 178.1)}$ = 5.7, $P = 3.7 \times 10^{-4}$; Spearman's rank correlation coefficient r = −0.9, P = 0.083. (B) The sequence of contrast blocks was [58%, 16%, 53%, 41%, 29%], n = 35 sessions. $F_{(3.6,\ 122.6)}$ = 6.8, $P = 1.1 \times 10^{-4}$; Spearman's rank correlation coefficient r = −1, P = 0.017. (C) The sequence of contrast blocks was [41%, 29%, 58%, 53%, 16%], n = 27 sessions. $F_{(3.2,\ 83.8)}$ = 10, $P = 6.6 \times 10^{-6}$; Spearman's rank correlation coefficient r = −0.9, P = 0.083. (D-F) The data were from those sessions in which hold time = 0 ms and timeout period = 1 s (n = 10 mice). (D) The sequence of contrast blocks was [58%, 53%, 41%, 16%, 29%], n = 30 sessions. $F_{(3.1,\ 89.1)}$ = 9.8, $P = 1 \times 10^{-5}$; Spearman's rank correlation coefficient r = −1, P = 0.017. (E) The sequence of contrast blocks was [41%, 29%, 16%, 58%, 53%], n = 30 sessions. $F_{(3.5,\ 102.7)}$ = 5.9, $P = 4.3 \times 10^{-4}$; Spearman's rank correlation coefficient r = −1, P = 0.017. (F) The sequence of contrast blocks was [16%, 53%, 41%, 58%, 29%], n = 41 sessions. $F_{(3.3,\ 130.4)}$ = 13.2, $P = 5.6 \times 10^{-8}$; Spearman's rank correlation coefficient r = −0.56, P = 0.37. (G) The data were from those experiments in which the sequence of contrast blocks was [58%, 53%, 41%, 29%, 16%], hold time = 450 ms and timeout period = 4 s, and the light bar position across trials was completely random (n = 52 sessions from 7 mice). $F_{(3.2,\ 162)}$ = 6.8, $P = 1.8 \times 10^{-4}$; Spearman's rank correlation coefficient r = −0.9, P = 0.083. For the data in each panel, we performed one-way repeated measures ANOVA with the Greenhouse–Geisser correction. Error bar, ±SEM.

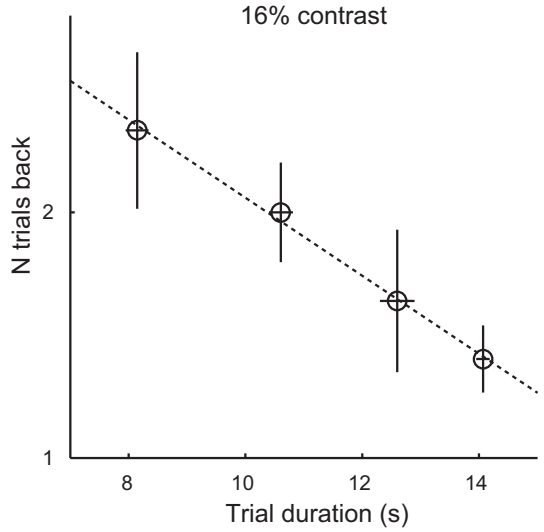


Fig. 5. The number of history trials that could influence current choice negatively correlated with trial duration. Spearman's rank correlation coefficient r = −1, P = 0.083. For this experiment, the sequence of contrast blocks was [58%, 53%, 41%, 29%, 16%]. Only those sessions in which the mean trial duration was <20 s were included in the analysis. For mean trial duration at 8.2, 10.6, 12.6, and 14.1 s, n = 36, 76, 36, and 159 sessions from 7, 10, 9, and 12 mice, respectively. Dashed line represents linear fit of the data. Error bar, ±SEM.

region that shows the earliest action selection signals among several frontal cortical and striatal areas and conveys information about past trials (Sul et al., 2011; Yuan et al., 2015; Scott et al., 2017; Siniscalchi et al., 2019). To ensure enough number of trials for low and high stimulus contrasts, we used two blocks of contrast (16% and 53%) for the electrophysiological experiments. We focused on the responses within the 1 s period before the mouse exited the central port, during which the mouse viewed the visual stimulus and could integrate sensory input with recent trial experience. Fig. 7A and B show the spikes and peristimulus time histograms (PSTHs) for an example M2 neuron in response to stimuli at 16% and 53% contrasts, respectively, aligned to the time of central port exit. We grouped the responses by the choice on the current trial or previous trial (from one trial back to three trials back) (left panel in Fig. 7A, B), or by the outcome on the current trial or previous trial (right panel in Fig. 7A, B). To quantify the selectivity of each neuron for choice or outcome, we used an algorithm based on the ROC analysis (Green and Swets, 1966), which measures the probability of an ideal observer to correctly classify a given response as left or right (correct or wrong) choice. A preference index was defined as $2(ROC_{area} - 0.5)$, with a value ranging from −1 to 1 (Felsen and Mainen, 2008; Thompson et al., 2016). For the responses of the example neuron to stimulus at 16% contrast, the choice preference was statistically significant at two trials back (P < 0.05, Monte Carlo permutation test), but not significant at current trial or other previous trials (P > 0.3, Monte Carlo permutation test, Fig. 7A). For the responses to stimulus at 53% contrast, the outcome preference was statistically significant at one trial back (P < 0.05, Monte Carlo permutation test), but not significant at current trial or other previous trials (P > 0.2, Monte Carlo permutation test, Fig. 7B).

We next compared the choice (or outcome) preference between 16% and 53% contrasts across the population (Fig. 8A, B). For choice preference, the fraction of significant neurons measured at 16% contrast was above chance level for choices on one trial back or two trials back ($\chi^2_{(3)}$ = 10.7, P = 0.01), and the fraction of significant neurons for choices on previous trials was significantly higher at 16% contrast than at 53% contrast ($\chi^2_{(2)}$ = 8, P = 0.02, Fig. 8C). For outcome preference, the fraction of significant neurons for outcomes on previous trials was not significantly different between 16% and 53% contrasts ($\chi^2_{(2)}$ = 4.4, P = 0.11, Fig. 8D). These data suggest that M2 activity in a perceptual decision task is influenced by the animal's choice or outcome in history trials, and the fractions of neurons conveying information for choices on different past trials depend on stimulus strength.

Because trial duration influenced the effect of trial history on behavioral choice at 16% contrast (Fig. 5), we also examined whether trial duration affects the trial history-related activity in M2 at 16% contrast. For the responses of each neuron grouped by choice at one trial back, we divided the trials into two subsets with duration shorter and longer than the mean duration, respectively (short vs long duration: $P = 5.9 \times 10^{-13}$, Wilcoxon signed rank test, Fig. 8E). We found that the fraction of neurons with significant choice preference for one trial back was significantly higher for trials with short than with long duration ($\chi^2_{(1)}$ = 6.94, P = 0.008, Fig. 8E), consistent with the modulation of history influence by trial duration observed at the behavioral level.

To further analyze the information related to stimulus strength-dependent history influence in M2, we used a SVM classifier to decode

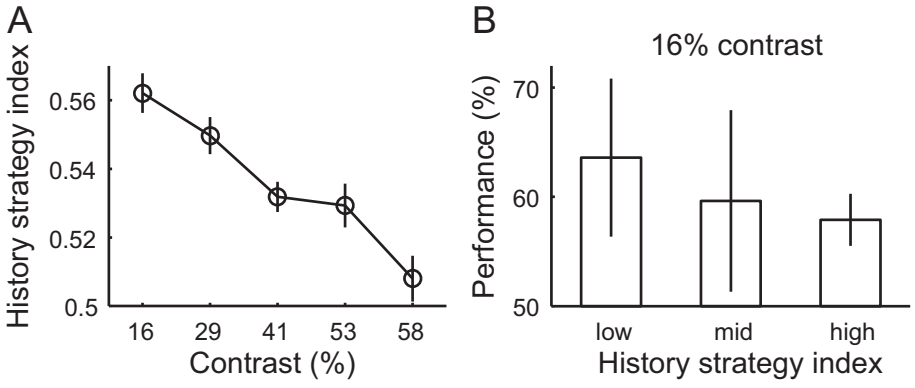


Fig. 6. History-dependent strategy is influenced by stimulus contrast. (A) History strategy index for stimuli at different contrasts ($P = 3.7 \times 10^{-7}$, ANOVA). Spearman's rank correlation coefficient r = −1, P = 0.017. Error bar, ±SEM. (B) Behavioral performance for sessions with low (<0.55), middle (>0.55 and ≤.65), and high (>0.65) history strategy index (stimulus contrast = 16%). P = 0.02, ANOVA. The data were from 131 sessions from 9 mice, in which hold time = 450 ms and timeout period = 2 s. Error bar, ±SD.

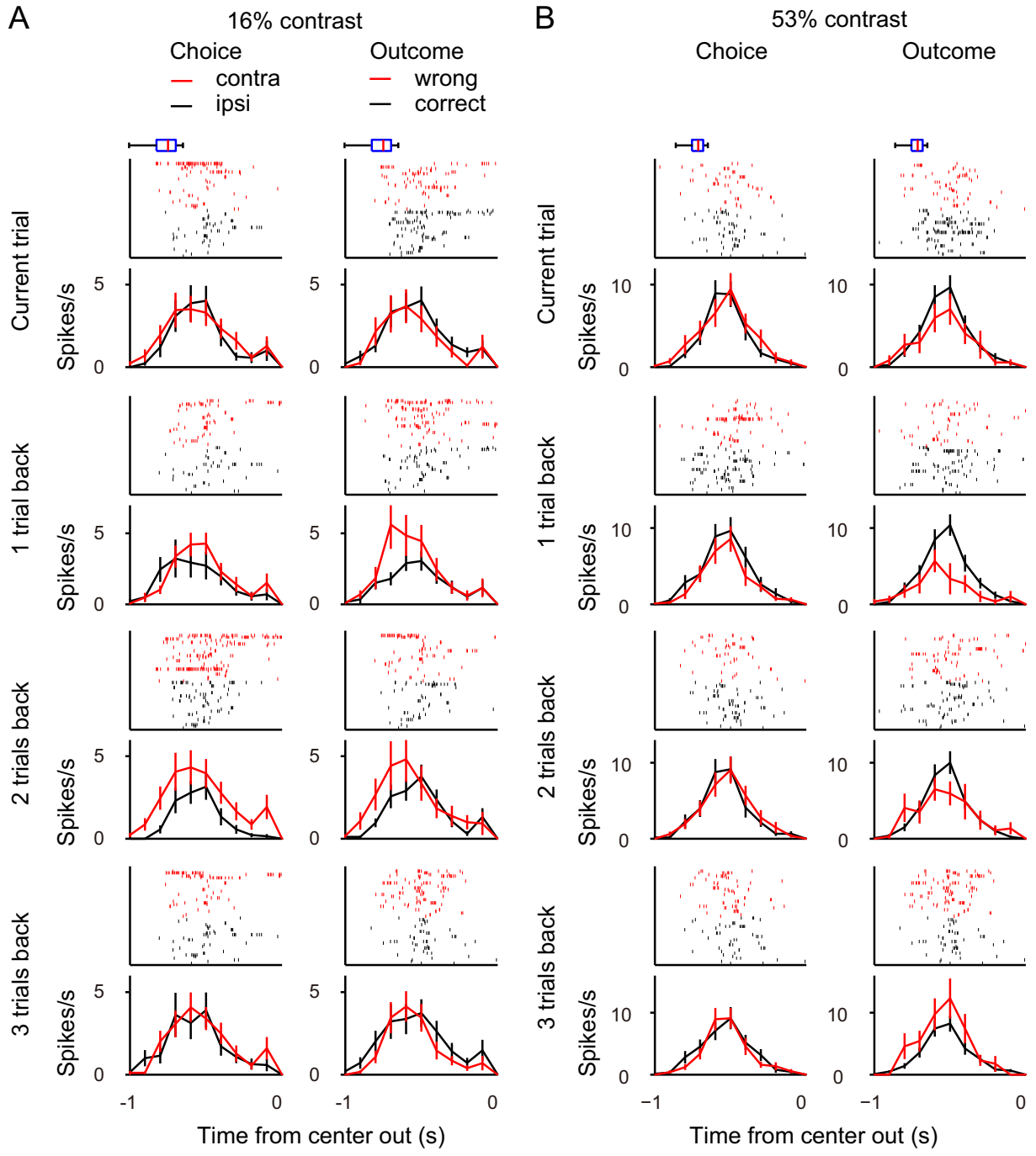


Fig. 7. The responses of an example M2 neuron during the period of hold time in the contrast detection task. (A) Stimulus contrast = 16%. Spike rasters and PSTHs for the neuron grouped by choice (left) and outcome (right) on the current trial, 1 trial back, 2 trials back, and 3 trials back. A boxplot above the spike raster indicates the distribution of central-port entry time. For this neuron the minimum number of trials across all conditions was 28, we thus pseudorandomly selected 28 trials to display spikes for each condition (ipsilateral, contralateral, correct, or wrong choice). All trials were used to compute the PSTH. (B) Similar to that described in (A) except that stimulus contrast = 53%. Red and black indicate contralateral and ipsilateral choice (or wrong and correct choice), respectively. Error bar, ±SEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

neuronal information about the animal's choice (or outcome) in current or previous trials (Chang and Lin, 2011; Astrand et al., 2014). We trained the classifier on 90% of the data (training dataset) and tested it on the remaining 10% of the data (test dataset). During training, the classifier separated the data into two classes according to choice (or outcome) on the current trial, one trial back, or two trials back. During testing, the decoder was presented with M2 responses in the test dataset and produced prediction about choice (or outcome) on the current trial, one trial back, or two trials back. For 16% contrast, we found that the performance was significantly higher for classifying choice on two trials back than that on current trial ($P < 0.05$), and significantly higher for classifying outcome on one trial back than that on current trial ($P < 0.05$, one-way

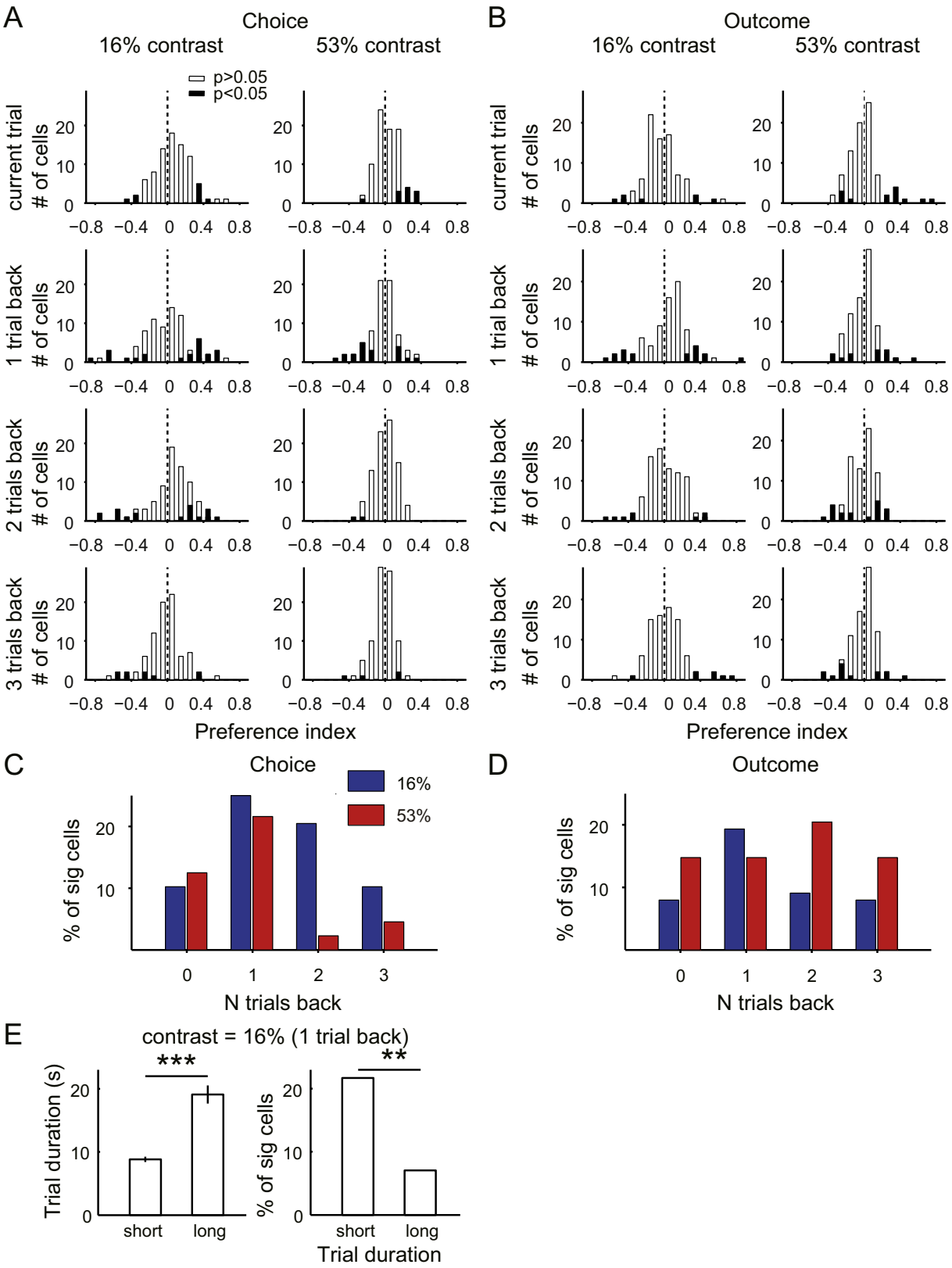


Fig. 8. Stimulus contrast modulates the fractions of M2 neurons showing significant preference for choice in current and past trials. (A) Histograms of choice preference index for responses grouped by choice on current or previous trials. Left panel, 16% contrast. Right panel, 53% contrast. Black bars indicate neurons with significant preferences. (B) Histograms of outcome preference index for responses grouped by outcome on current or previous trials. Similar to that described in (A). (C and D) Fractions of neurons showing significant choice (C) or outcome (D) preferences in current and past trials. Blue, 16% contrast; red, 53% contrast. (E) Left, for the responses of each neuron grouped by choice at one trial back (contrast = 16%), the trials were divided into two subsets with short and long duration, respectively. ***, $P < 0.001$, Wilcoxon signed rank test. Right, the fraction of neurons with significant choice preference for one trial back was significantly higher for trials with short than with long duration. $\chi^2_{(1)} = 6.94$, **, $P < 0.01$. Error bar, ±SEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

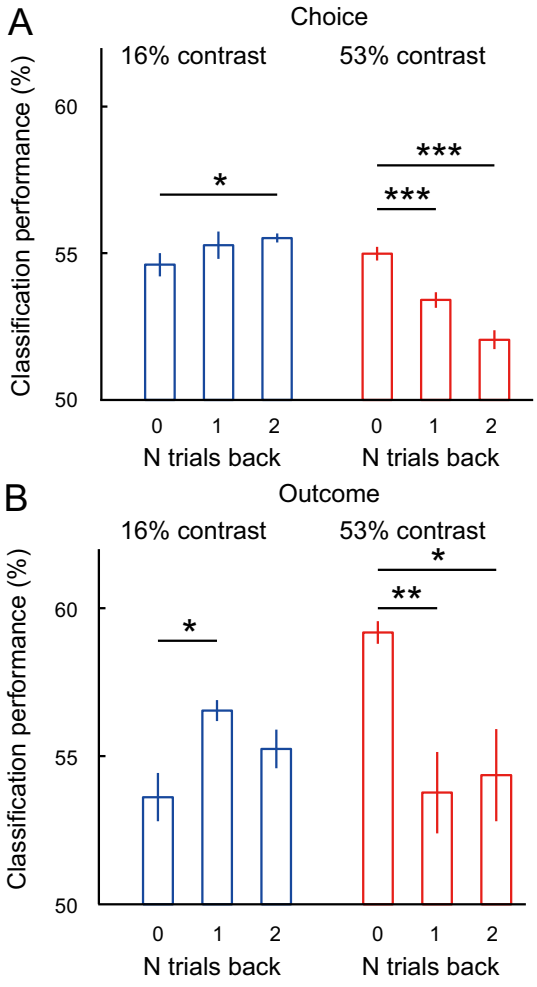


Fig. 9. Decode neuronal information about the animal's choice (or outcome) in current or previous trials using SVM classifier. (A) Classification performance for choice in current or previous trials. Blue, 16% contrast; red, 53% contrast. *, $P < 0.05$; ***, $P < 0.001$. (B) Classification performance for outcome in current or previous trials. Blue, 16% contrast; red, 53% contrast. *, $P < 0.05$; **, $P < 0.01$. For each case, the classification was repeated 10 times. Error bar, ±SEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

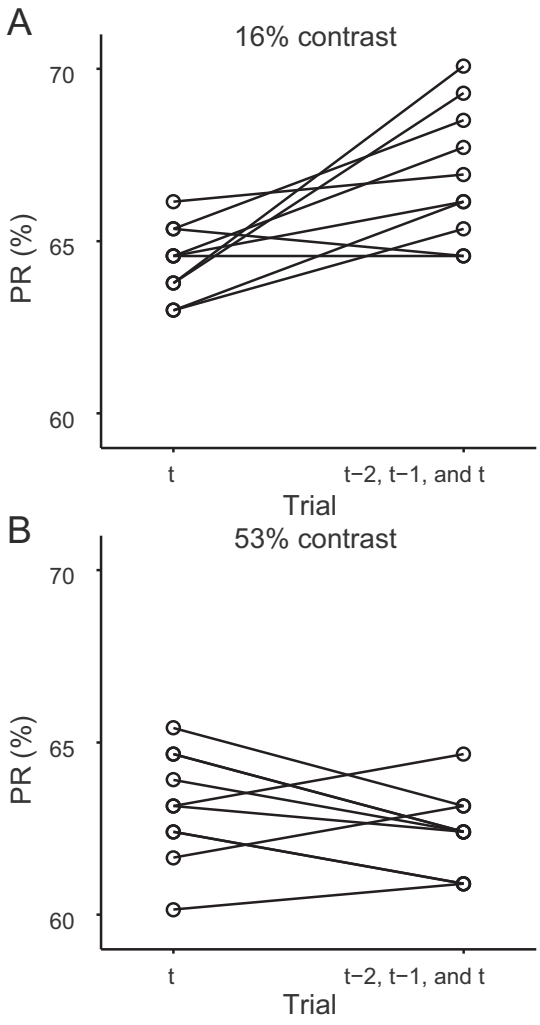


Fig. 10. Using SVM classifier to decode the animal's upcoming choice. (A) Comparison of the accuracy of decoding upcoming choice between the model using responses in current trial only and that using responses in both current and previous two trials. The decoding was repeated 10 times, and data points in each line were from one repeat. Stimulus contrast = 16%. $P = 0.012$, Wilcoxon signed rank test. (B) Same as that described in (A) except that stimulus contrast = 53%. $P = 0.12$, Wilcoxon signed rank test.

repeated measures ANOVA followed by Tukey's multiple comparisons test, Fig. 9). For 53% contrast, the performance for classifying choice or outcome was both higher for current trial than for previous 1–2 trials ($P < 0.05$, one-way repeated measures ANOVA followed by Tukey's multiple comparisons test, Fig. 9). Thus, at low stimulus contrast, choice or outcome information of past 1–2 trials encoded by M2 neurons can be extracted more reliably as compared to that in current trial; at high stimulus contrast, current choice or outcome information can be extracted more reliably as compared to that in previous trials.

History-trial activity in M2 is important for decoding behavioral choice at low contrast

To examine whether history-trial responses in M2 are used to guide behavior, we used a SVM classifier to decode the animal's upcoming choice from M2 responses. We hypothesized that, if history-trial activity in M2 contributes to upcoming choice, including history-trial responses in the algorithm would increase the accuracy of the decoder to predict current choice. To compare the decoding accuracy with and without responses in the past trials, the SVM decoding was performed separately for data using responses in current trial only and data using responses in both current and previous two trials. We found that, for 16% contrast, the accuracy of decoding upcoming choice was significantly higher for the model including responses in the past two trials than that using responses in current trial only ($P = 0.012$, Wilcoxon signed rank test, Fig. 10A). For 53% contrast, including responses in the past two trials did not significantly affect the decoding accuracy ($P = 0.12$, Wilcoxon signed rank test, Fig. 10B). These data suggest that M2

responses in the past two trials are used to integrate with current sensory input to guide the animal's choice when the stimulus was weak.

DISCUSSION

In this study, we examined how stimulus contrast modulates the integration of trial history and sensory input in perceptual decision making. We found that the influence of trial history on perceptual choice is stronger and more prolonged in time when stimulus contrast is lower. We also found that the activities of M2 neurons can be modulated by choice in one or two trials back in a stimulus strength-dependent manner. The integration of history trial signal and sensory input in M2 is important for decoding behavioral choice at low stimulus contrast. Our results demonstrate that, for perceptual choice, the short-term influence by recent trial history is dynamically regulated by stimulus strength.

Relationship to previous works on trial history influence

Trial history influence is widely observed in a variety of tasks (Fecteau and Munoz, 2003). For value-based decision making, choice behavior is influenced by the choices and outcomes in previous trials (Sugrue et al., 2004; Corrado et al., 2005; Lau and Glimcher, 2005; Sul et al., 2011), and performance is well described by RL model (Sutton and Barto, 1998; Daw and Doya, 2006; Lee and Seo, 2007; Sul et al., 2011). In the framework of RL, signals related to the animal's previous choices may be necessary for the association between choices and their delayed outcomes (Lee and Seo, 2007), and signals related to previous outcomes may be used to monitor the successfulness of the animal's current strategy (Seo et al., 2007; Seo and Lee, 2008). For typical perceptual decision making task, the stimulus sequence is random and perceptual judgment should be based on the current sensory input. However, the perceptual choices of humans and other animals are also affected by the history of choices or outcomes (Fernberger, 1920; Gold et al., 2008; Busse et al., 2011; Fründ et al., 2014; Scott et al., 2015; Abrahamyan et al., 2016; St John-Saaltink et al., 2016; Thompson et al., 2016; Hwang et al., 2017; Braun et al., 2018). Previous studies have applied logistic regression models to understand the contribution of history trials to current choice in perceptual decision making task, in which trials of different stimulus strengths were randomized (Busse et al., 2011; Abrahamyan et al., 2016; Thompson et al., 2016). These studies either used previous one trial in the model (Busse et al., 2011; Abrahamyan et al., 2016) or found negligible influence for two trials back (Thompson et al., 2016). In our study, we found that the magnitude of trial history influence was stronger at lower stimulus strength, consistent with previous reports (de Lafuente and Romo, 2005; Gold et al., 2008; Fründ et al., 2014; Abrahamyan et al., 2016; Thompson et al., 2016; Akrami et al., 2018). We extended previous studies by revealing that the current choice could be influenced by more number of history trials when the stimulus was weaker. We also showed that the number of history trials that could influence current choice decreased with trial duration. This suggests that in perceptual task the memory of recent trial history decays with time, similar to the temporal discounting of past rewards in dynamic foraging task (Sugrue et al., 2004; Corrado et al., 2005).

For humans judging the orientation of grating stimuli embedded in random noise (St John-Saaltink et al., 2016) or rats performing visual accumulation of evidence task (Scott et al., 2015), the influence of previous trials on perceptual choice could last for three trials. In our study, the influence of history trials came from an average of two trials back at 16% contrast. The difference between our study and previous works (Gold et al., 2008; Scott et al., 2015; St John-Saaltink et al., 2016; Thompson et al., 2016) in terms of the timescale of the history influence may be due to task design, stimulus difficulty, trial duration, or the difference in species.

The history influence in humans is often manifest as a bias to repeat or alternate choices (choice history bias), which is due to previous perceptual choices rather than previous motor responses (Akaishi et al., 2014; Braun et al., 2018) or previously presented stimuli (St John-Saaltink et al., 2016). The choice history bias could be adjusted following changes in environmental statistics (Abrahamyan et al., 2016; Braun et al., 2018), and the adjustment of choice bias correlated with performance when stimulus sequences exhibited autocorrelations (Braun et al., 2018). In tasks using random stimulus sequence, however, choice history bias was found to impair performance (Abrahamyan et al., 2016). Our analysis showed that strong history influence was associated with a decrease in behavioral performance and a reduction in the variability of performance, implying a trade-off between the effect of history influence on performance and that on performance consistency.

Neural mechanism underlying trial history influence

Many studies have examined neural correlates of trial history influence in different brain regions. Neural signals encoding trial history information were found in the prefrontal cortex, parietal cortex, dorsal anterior cingulate cortex, and supplementary eye field in monkey (Barraclough et al., 2004; Genovesio et al., 2006; Seo and Lee, 2007; Seo et al., 2009; Abzug and Sommer, 2018), and the striatum, medial prefrontal cortex, orbitofrontal cortex, posterior parietal cortex (PPC), and M2 in rodent (Kim et al., 2007; Sul et al., 2010; Sul et al., 2011; Kim et al., 2013; Yuan et al., 2015; Murakami et al., 2017; Scott et al., 2017). In monkey premotor cortex, the variability of neuronal responses was modulated by trial history (Marcos et al., 2013). In monkeys performing a matching pennies task, the timescale for the memory of past reward events was diverse across cortical neurons and cortical areas (Bernacchia et al., 2011). For humans performing perceptual judgements on stimulus orientation, fMRI activity in primary visual cortex was biased by the perceptual choice on the previous trial, reflecting history-dependent perceptual decision (St John-Saaltink et al., 2016). For motion discrimination task in monkey,

although choice behavior was influenced by previous trials, neural activities in the middle temporal visual or lateral intraparietal areas were not correlated with choice bias (Gold et al., 2008). Recent studies also examined the causal role of history-related neural signals in choice behavior. For instance, rodent PPC exhibited history-related signals that causally contributed to behavioral performance (Hwang et al., 2017; Akrami et al., 2018). The activity of the pedunculopontine tegmental nucleus (PPTg) reflected recent trial history and inactivation of the PPTg could decrease the history influence on action selection (Thompson et al., 2016).

In our study, we recorded from M2 to examine the neural correlate of stimulus strength-dependent influence of trial history on perceptual choice. Previous studies have shown that rodent M2 plays an important role in cue-guided actions and memory-guided behaviors (Erlich et al., 2011; Li et al., 2015; Goard et al., 2016; Siniscalchi et al., 2016; Barthas and Kwan, 2017; Kamigaki and Dan, 2017; Makino et al., 2017; Gilad et al., 2018; Itokazu et al., 2018; Svoboda and Li, 2018). Rodent M2 receives inputs from sensory areas, sends output to many cortical and subcortical regions, and is suggested to be a homolog of the premotor cortex, supplementary motor area, or frontal eye field of monkey (Zingg et al., 2014; Barthas and Kwan, 2017; Svoboda and Li, 2018). M2 neurons in rodent exhibit the earliest choice-related activity among several frontal and striatal brain regions and their activity reflects the past choice or outcome (Sul et al., 2011; Yuan et al., 2015; Scott et al., 2017; Siniscalchi et al., 2019). However, how M2 neurons dynamically integrate sensory input and memory of recent experience is not well understood. Our results showed that M2 activities related to previous choice could be modulated by stimulus strength, and the history-trial responses in M2 were important for decoding current choice when the stimulus was weak. It is of interest for future study to examine whether the history-related signals in M2 play a causal role in the trial history influence of perceptual decision.

AUTHOR CONTRIBUTIONS

WJ and HY designed experiments, WJ performed behavioral and electrophysiological experiments, WJ analyzed data, JL performed experiments of electrode implantation, DZ and TX performed some behavioral experiments, HY and WJ wrote and edited the paper.

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DECLARATIONS OF INTEREST

None.

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