Serial dependence in emotion perception mirrors the autocorrelations in natural emotion statistics

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A critical function of the human visual system is to track emotion accurately and continuously. However, visual information about emotion fluctuates over time. Ideally, the visual system should track these temporal fluctuations—these "natural emotion statistics" of the world—over time. This would balance the need to detect changes in emotion with the need to maintain the stability of visual scene representations. The visual system could promote this goal through serial dependence, which biases our perception of facial expressions toward those seen in the recent past and thus smooths our perception of the world. Here, we quantified the natural emotion statistics in videos by measuring the autocorrelations in emotional content present in films and movies. The results showed that observers' perception of emotion was smoothed over ∼12 seconds or more, and this time-course closely followed the temporal fluctuations in visual information about emotion found in natural scenes. Moreover, the temporal and feature tuning of the perceptual smoothing was consistent with known properties of serial dependence. Our findings suggest that serial dependence is introduced in the perception of emotion to match the natural autocorrelations that are observed in the real world, an operation that could improve the efficiency, sensitivity, and stability of emotion perception.

Introduction

Emotions are dynamic and can change over the course of seconds. As a result, emotion perception must be fluid and adaptable to track and identify changes in the emotional states of others during social interactions. These temporal fluctuations in emotion consist of natural statistics that we often experience when perceiving emotion in the real world. The dynamics of these natural statistics reflect the smoothness with which emotions tend to change over time (Cunningham, Dunfield, & Stillman, 2013; Hipson & Mohammad, 2021; Kuppens, Allen, & Sheeber, 2010; Kuppens, Oravecz, & Tuerlinckx, 2010; Kuppens & Verduyn, 2017). Does the human visual system take into account these temporal dynamics—the smoothness of emotion changes—when recognizing displays of affect and emotion?

In other domains, the visual system capitalizes on the stability of visual scenes by introducing serial dependencies in its representations of the world, which bias perception towards previously seen information (Cicchini, Mikellidou, & Burr, 2018; Fischer & Whitney, 2014). These serial dependencies cause currently viewed stimuli to be perceived as being more similar to previously seen stimuli than they actually are. They effectively smooth perceptual experience and decisions over time. Serial dependence has been reported in the perception of face identity (Liberman, Fischer, & Whitney, 2014), attractiveness (Kok, Taubert, Van der Burg, Rhodes, & Alais, 2017; Taubert, Van der Burg, Alais, & Burr, 2016; Xia, Leib, & Whitney, 2016), age (Manassi & Whitney, 2022), gender (Taubert, Alais, & Burr, 2016), and facial expressions (Liberman, Manassi, & Whitney, 2018; Mei, Chen, & Dong, 2019; Taubert, Alais, et al., 2016). While the prevalence of serial dependence in perception has been well researched

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(Kiyonaga, Scimeca, Bliss, & Whitney, 2017), little is known about whether serial dependence functions in similar ways when observing dynamic natural scenes in the real world.

A recent study by Manassi and Whitney (2022) found evidence for an active mechanism of serial dependence, supporting the idea that our visual representation of the world is continuously averaged over several seconds. The authors found that observers perceived a movie of a continuously changing face as unchanging, and that age judgments of the face were attracted to previous frames of the movie up to 15 seconds in the past. The duration of this effect echoes the relatively long time-course of serial dependence reported in a range of other studies (Fischer & Whitney, 2014; Liberman et al., 2014; Manassi, Liberman, Chaney, & Whitney, 2017; Manassi, Liberman, Kosovicheva, Zhang, & Whitney, 2018; Manassi, Kristjánsson, & Whitney, 2019). One may wonder why the visual system would allow visual information from 10 seconds or more in the past to bias perception of incoming visual information.

One idea is that, all else equal, serial dependence incorporates visual information at a rate that matches the natural autocorrelations observed in the world. The autocorrelations that are present in our external environment are an example of dynamic natural scene statistics that we encounter in our visual experience (Reinagel & Zador, 1999; Stansbury, Naselaris, & Gallant, 2013). For example, when driving to work you observe the road, other cars in front of you, traffic signs, and much more. The information that you are perceiving is autocorrelated because the visual input currently arriving at your retina is similar to the visual input that will arrive a second later. We experience these same autocorrelations in emotion, a form of natural emotion statistics, where we can perceive a person smiling and infer that they are happy and predict the future time-course of their emotion. Although emotions can be downregulated to prevent overexpression of a current emotion (Kuppens & Verduyn, 2017), this change does not occur spontaneously but changes smoothly over time, which results in an autocorrelation in the natural statistics of emotion.

In this study, we aimed to investigate whether there is any correspondence between the autocorrelation in the natural emotion statistics found in the world and the serial dependence in perceived emotion found in the visual system. We measured the serial dependence of perceived emotion using random frames of film clips, documentaries, and home videos. Because observers saw the movie frames in a random sequence, the frames were unrelated to each other. Any sequential dependence of ratings therefore reflects a smoothing in perceptual decisions imposed by the visual system. On the other hand, the autocorrelation present in the natural emotion statistics in the movies was calculated by reorganizing the ratings of all frames back into their original movie-determined order. If active serial dependence does integrate or smooth information in a way that mimics the natural autocorrelations in the world, then we should observe a similar temporal decay in both the autocorrelations in the natural emotion statistics and perceptual serial dependence functions. To foreshadow our results, we found that perceptual serial dependence mirrored the autocorrelation of the natural emotion statistics in the world.

Methods

Subjects

A total of 175 (112 females, 62 males) observers participated in this study ranging in age from 18 to 32 ($M = 20.54$, $SD = 1.68$ years). All participants provided signed consent in accordance with the guidelines and regulations of the UC Berkeley Institutional Review Board and all experimental procedures were approved. All participants were affiliates of UC Berkeley. We excluded participants who completed less than 200 trials leaving a total of 155 participants for further analysis.

Stimuli and procedure

The experiment was administered online on a custom-made website designed for this experiment. Thirty-four video clips (including Hollywood movies, documentaries, and home videos) were gathered from an online video-sharing website (YouTube; materials available at https://osf.io/f9rxn/). The videos used in the experiment were comprised of 21 Hollywood movies, 12 home videos, and two documentaries. Static frames were then sampled from all videos at 2 Hz, which resulted in a total of 4057 static frames. Frames from different videos were shuffled and presented to each observer in random order, such that visual stimuli in consecutive trials were independent (Figure 1). In each trial, observers used a two-dimensional (2D) valence-arousal rating grid to report the valence and arousal of the character in the static image. Valence and arousal ratings ranged in values between -1 and 1, normalized to the size of the 2D bounding box grid. Participants had to confirm their response by clicking a “submit” button, which was located on the left of the screen. This forced participants to reset their mouse position after each trial. Participants were allowed to progress through the trials at their own pace and the stimulus frame was presented throughout the duration of the trial. Once participants had confirmed their rating, the next trial began, and a new frame was presented immediately after. For trials where the

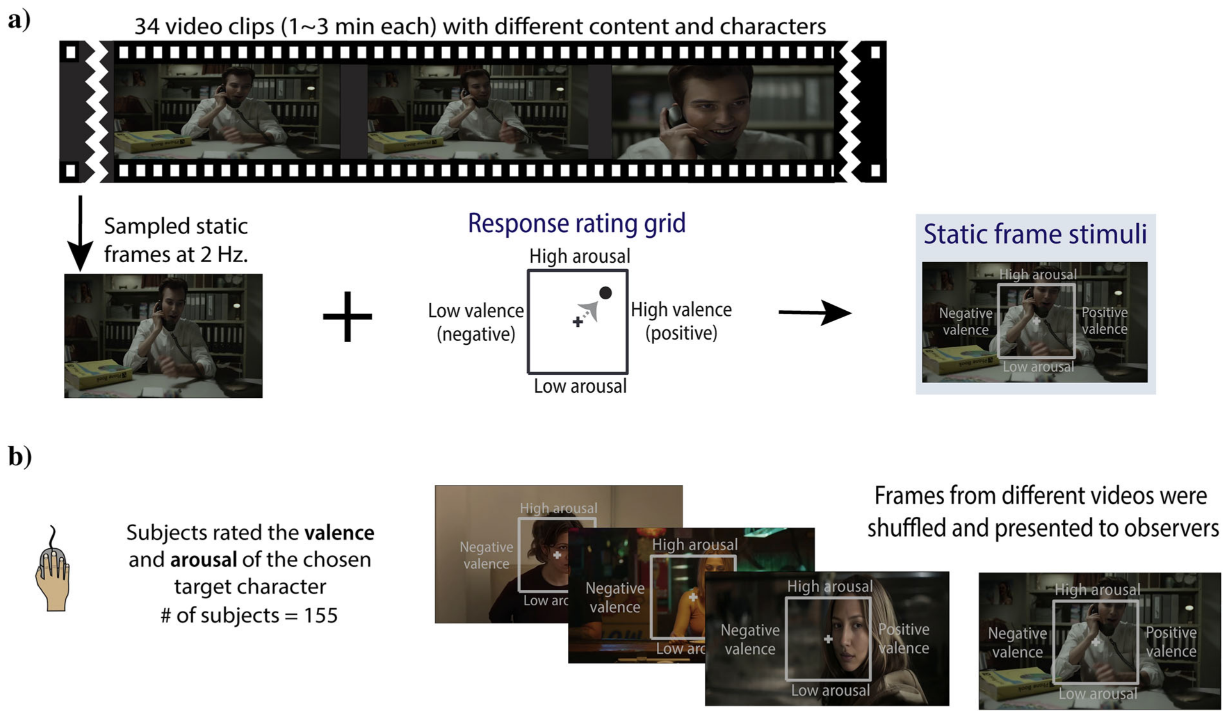

Figure 1. Experiment design. (**a**) We sampled frames from 34 video clips at 2 Hz (500 ms) and overlaid a 2D valence-arousal grid on each frame (4057 total static frames). (**b**) Static frames from videos were presented in a random order for each observer. Participants were instructed to rate the valence and arousal of the target character, using a mouse click, and then confirmed their rating with a button located to the left of the video frame. Participants completed as many trials as they could (self-paced) within 1.5 hours, for a total of up to 1000 trials per observer.

target character was not in the scene, participants were instructed to guess the emotion of the character based on other information in the scene. Participants had 1.5 hours to complete as many trials as they could, up to a total of 1000 trials ($M = 816.83$, $SD = 268.02$).

Data analysis

Autocorrelation analysis

Our goal was to compare the autocorrelations in the natural emotion statistics found in movies clips with the serial dependence of perceived emotion. To do that, we first measured two types of autocorrelations. In one, we measured autocorrelations in participants' trial-by-trial ratings, which we will refer to this as the "perceptual autocorrelation," because it reveals something about the smoothness of perceptual judgments. In a second type, we measured the autocorrelations of the natural emotion statistics in the videos themselves. This was possible because, although the video frames were presented in a random order to observers, the video frames could be reorganized into their original, proper, movie sequence. Because the movie sequence was not seen by observers, any autocorrelation in this sequence reveals a smoothing in the movie per se, independent of the observers. We will refer to this autocorrelation as the "movie-based autocorrelation." Autocorrelations were computed on both valence and arousal dimensions.

To measure the perceptual autocorrelation, we first removed trials in which the participants took longer than 30 seconds to make a response; ~10% of the data was removed, in total. For removed trials, the following trial took the place of the removed trial. We then split each participant's data into chunks of 30 trials, normalized the chunk by Z-scoring, and computed the autocorrelation within each chunk. The autocorrelation, in this case, is on the sequence of ratings that the observer made. The average response time across all participants was used to determine the distance in time between the current trial and the previous trial (mean RT = 3.96 s, $SD = 2.9$ s). To compute average autocorrelations across chunks for each participant, we first Fisher-Z transformed all correlations, averaged the transformed values, and then transformed them back to r values. We collapsed the ratings across valence and arousal during averaging because we were interested in the overall emotion rating and not the dimensions themselves. This was done by averaging the autocorrelations across observers for valence and arousal. We normalized the empirical

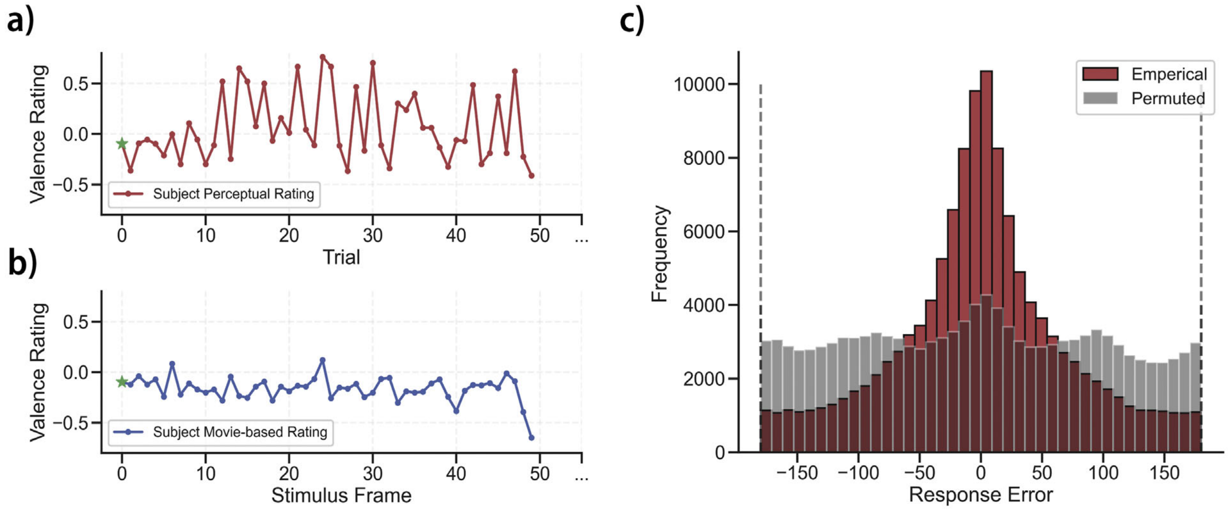

Figure 2. Single-subject example perceptual and movie-based rating and trial-by-trial subject error distribution. (**a**) Example of a single subject's perceptual rating as recorded trial-by-trial during the experiment and (**b**) the same subject's movie-based ratings for a single video with the frames re-organized in movie order (the order the frames would have appeared in the film). The star marker indicates the same rating for the same single stimulus and was used as the starting point to compare these example sets of ratings. The ellipsis indicates that trials continued past 50, but only 50 trials are shown here. Essentially, the full set of ratings in (**a**) and (**b**) (hundreds of trials per observer) are identical but they are in a different order. (**c**) Observer angular response error (red distribution) across all trials for all participants using each participant's corresponding leave-one-out consensus and permuted angular response error (gray distribution; 5000 iterations; K-S test, $p < 0.01$). Gray dashed lines indicate the possible range of error (circular distribution).

autocorrelations with the null distribution values by subtracting the permuted null autocorrelations from the empirical autocorrelations. For comparison, we also calculated permuted autocorrelations by shuffling the ratings in each chunk and calculated the difference between each participant's empirical autocorrelations and the permuted (null distribution) autocorrelations. We then bootstrapped the empirical and permuted autocorrelations 10,000 times and computed the 95% confidence intervals of the bootstrapped values.

To calculate the movie-based autocorrelation—the autocorrelation in the natural emotion statistics found in the videos themselves—we reorganized the sequence of video frame ratings into the sequence as it was intended in the movies. That is, instead of computing autocorrelations based on the presentation order (e.g., Figure 2a), we computed the autocorrelation of the ratings for each sampled video by reorganizing the ratings into the frame order appropriate for each video (e.g., Figure 2b). We then computed the autocorrelation for each video, in the same manner as described earlier. To ensure we had the same amount of data across all videos, we used the length of the shortest video as the autocorrelation length, which was 52 trials.

We quantified the similarity between the perceptual and movie-based autocorrelation by fitting decaying exponential curves to the group averaged autocorrelations. We then calculated the sum of squared errors (SSE) between the exponential curve for the group averaged perceptual and movie-based autocorrelation. Specifically, we calculated the SSE between the group averaged perceptual and movie-based exponentials for the five points that corresponded to the time lag of 0, 4, 8, 12, and 16 seconds. The SSE quantifies the similarity between the decaying exponential autocorrelation functions. We compared the SSE between the group averaged perceptual and movie-based exponential curves with the SSE between the group averaged permutation and movie-based exponentials. The group averaged permutation exponential was calculated by fitting a decaying exponential curve to the group averaged permuted perceptual autocorrelations, which, as described above, defined a null distribution. We then bootstrapped the SSE, with 5000 iterations, between exponential curves by randomly selecting n number of subjects, with replacement, where n is equal to the number of subjects in our data ($n = 155$). We then recalculated the group averaged perceptual and movie-based autocorrelations, refitted decaying exponential curves to both autocorrelations and then calculated the SSE between both exponentials (see Figures 3c, 3d).

In a separate analysis, we investigated the similarity between each observer's own perceptual autocorrelation and a version of their own movie-based autocorrelation. Since observers could only complete a maximum of 1000 trials, a single observer was not able to see and rate all 4057 static frames. Consequently, we calculated observers' individual movie-based autocorrelations by imputing the consensus rating

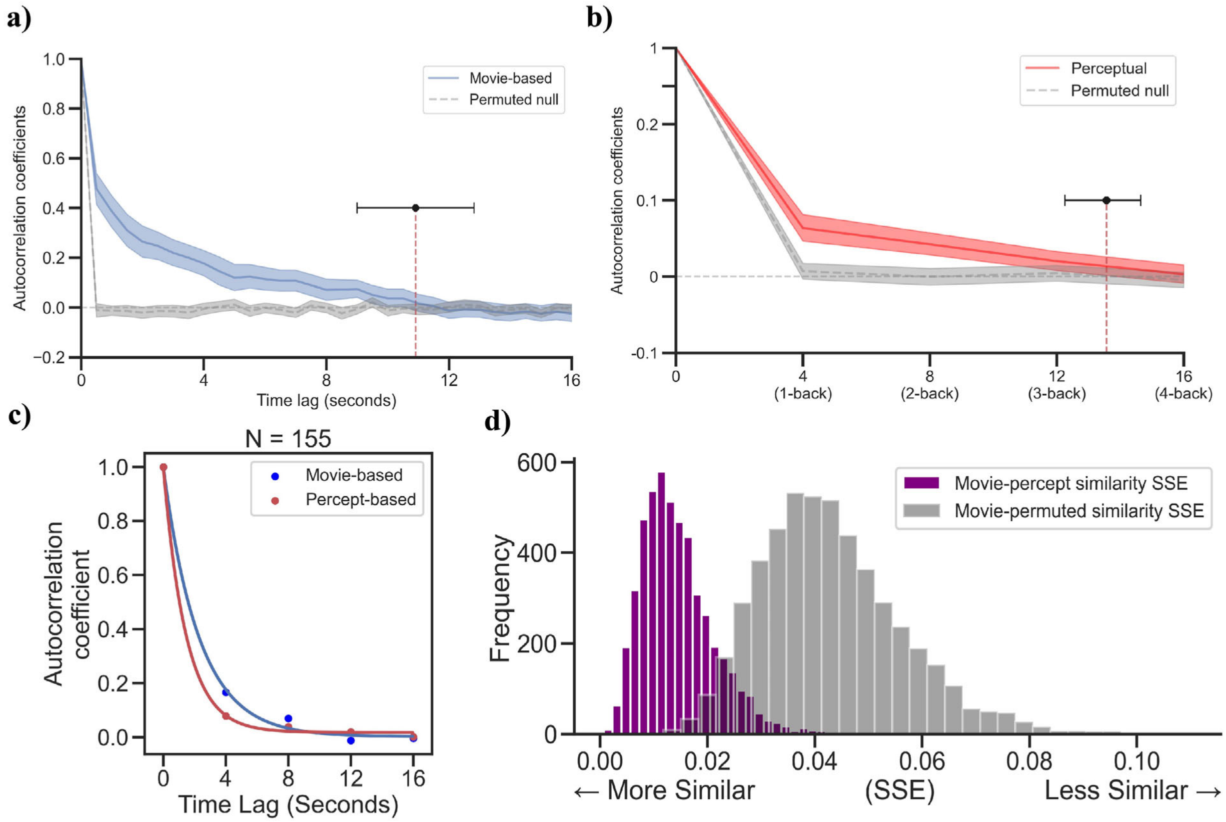

Figure 3. Group autocorrelations for the perceptual and movie-based autocorrelation. (**a**) The movie-based natural autocorrelation in the emotion expressed in movies. The blue line shows the empirical autocorrelation and the grey dashed line shows the permuted autocorrelation. Shaded regions depict 95% confidence intervals. (**b**) The perceptual autocorrelation of participants' emotion ratings. The red line shows the empirical autocorrelation and the grey dashed line shows the permuted autocorrelation. Shaded regions depict 95% confidence intervals. (**c**) Example exponential curve fit on the movie-based (blue line) and perceptual (red line) autocorrelation coefficients. (**d**) To further compare the movie-based and perceptual autocorrelations, SSE was calculated on the bootstrapped autocorrelation coefficients between the movie-based and perceptual autocorrelation (purple distribution) and the movie-based and permuted autocorrelations (gray distribution). The difference was significant ($p = 0.017$, permuted null).

for frames that observers did not rate. This only introduces noise, and it allows us to investigate the similarity between each observer's own movie-based autocorrelation and their own specific perceptual autocorrelation.

Serial dependence feature-tuning and temporal-tuning analysis

To investigate any possible feature and temporal tuning of the perceptual autocorrelations (from ratings of frames presented in random order), we measured the serial dependence in the observer's emotion ratings. We first converted the participant's ratings into polar angles, and then computed response error on each trial, which was the distance in degrees between the participant's chosen response and the consensus response. Since there is no absolute correct answer for emotion ratings (Legree, 1995; MacCann, Roberts, Matthews, & Zeidner, 2004; Mayer, Caruso, & Salovey, 2000), the leave-one-out consensus response was used as a proxy for the "correct" response for each trial (Chen & Whitney, 2019). This was calculated as the leave-one-out average response for a given trial, where the current participant is left out. We plotted the response bias for the current trial as a function of the difference between the consensus rating for the previous trial and the current trial (1-back effect). Finally, we collapsed all of the participants' data and created a super subject for the analysis. We also computed the difference between the consensus ratings on the current trial and those made two and three trials in the past (2-back and 3-back effects, respectively).

We fitted a derivative of von Mises curve on the data using the following equation:

$$y = \frac{ak\, sin\,(x - \mu)\, e^{k\, cos(x-\mu)}}{2\pi\, I_0\,(k)} \quad (1)$$

where the y parameter is the response error for each trial (subject response - consensus response), x is the difference between the consensus rating for the previous trial and the current trial, a is the amplitude modulation parameter for the curve, k indicates the concentration of the curve, and I_0 is the modified Bessel function of order 0. We then created a permuted null distribution (5000 iterations) of the DoG curve by calculating the response error between a subject's response on any given trial and the leave-one-out consensus response for a random frame. We plotted this permuted response error as a function of the difference between the consensus rating in degrees for the previous trial and the consensus rating in degrees for the current trial.

Because we had a total of 4057 frames, one participant would not be able to provide ratings for all the frames. Therefore we first used a "super-subject" approach to investigate serial dependence, which collapses the data of all participants. Previous serial dependence studies using "super-subjects" have used ∼11 participants in their study (Manassi et al., 2019; Manassi et al., 2021). Because our experiment consisted of 4057 static frames, we needed many more participants than previous studies to have multiple ratings for all frames collected from the movie clips. In addition, because of the noise in emotion ratings (Chen & Whitney, 2020) and the relatively modest effect size in studies of serial dependence (Kondo, Murai, & Whitney, 2022), we aimed to recruit a total of 175 participants in the study.

Results

Our goal was to investigate whether the smoothness with which emotion is perceived in stimuli matches the smoothness of natural emotion statistics found in the world. To address this, we measured the similarity between the autocorrelation in the perception of emotion in frames presented in random order and the autocorrelation in the natural emotion statistics found in the frames of natural movies when reorganized into proper movie order. Observers viewed shuffled static frames from films and rated each frame using a 2D valence-arousal grid. The ratings of the frames could be organized in two principled ways. In one, the frames were organized as experienced by the participant in the experiment (e.g., abscissa of Figure 2a). In a second, the frames were re-organized into the sequence of images as intended in the original film from which the frames were drawn (e.g., abscissa of Figure 2b). Figure 2a is an example of a single participant's ratings; it reflects the sequence in which the observer experienced and reported perceived emotion as they completed each trial. We call this the "percept-based" sequence because it reflects a sequence of perceptual reports. Figure 2b, on the other hand, shows the same participant's ratings reorganized for a single film with the frames sequenced into the order the frames would have appeared in the film. We call this the "movie-based" sequence because it reflects the sequence of the natural emotion statistics depicted in the film. The star marker at the first data point on the abscissa of Figures 2a and 2b is identical and indicates the same rating for the same image, such that "Trial 1" in the perceptual rating is the same as "Frame 1" in the film-based rating example. The difference in apparent variability between Figures 2a and 2b is because only a very small subset of the data is shown in the figures, and only the very first data point is actually shared between the graphs in this example.

To confirm that participants successfully completed the task, we plotted the distribution of subject errors, in polar angle, across all subjects by subtracting each participant's rating in each trial from their corresponding leave-1-out consensus (Figure 2c). The resulting error distribution appears relatively normally distributed. A two-sample Kolmogorov-Smirnov test for goodness of fit was run on the two distributions and revealed that the two distributions were significantly different ($p < 0.01$).

The percept-based sequence (Figure 2a) and the movie-based sequence (Figure 2b) are two different time series of the same data, and an autocorrelation can be calculated separately for each of them. The movie-based sequence results in a movie-based autocorrelation function (Figure 3a), which reflects the statistics of the information present in the film and is a proxy metric for the natural emotion statistics of the world. The perceptual-sequence from Figure 2a results in a percept-based autocorrelation (Figure 3b), which reflects the autocorrelations in perceived emotion of frames presented in random order. A permuted null distribution of autocorrelation functions was also computed for each condition by shuffling the trials (gray lines and ribbons). We then calculated the time constant of when the empirical autocorrelation decayed to the permuted null. For the movie-based autocorrelation, the autocorrelation remained significant with lags up to 11 seconds ($M = 10.845$, 95% confidence interval [CI] = 9, 13) (Figure 3a). For the percept-based autocorrelation in participant ratings, the autocorrelation remained significant for up to 13 seconds ($M = 12.9$, 95% CI = 12.3, 13.6) (Figure 3b). These results suggest that the percept-based and movie-based autocorrelations decayed toward the null distributions with fairly similar time-courses.

We further investigated the similarity between the movie-based and percept-based autocorrelations by fitting decaying exponential curves to the autocorrelations. To compare the movie-based and percept-based autocorrelations, we used the autocorrelation coefficient at timepoints 4, 8, 12, and 16 seconds. We bootstrapped the autocorrelation for each rating and calculated the SSE between the exponential curve for the movie-based and the percept-based autocorrelations (Figure 3c) with 5000 iterations. The SSE quantifies the similarity between the two curves; that is, the consistency between movie and percept-based autocorrelation functions. We also computed the SSE between the bootstrapped movie-based and permuted null curves, as a baseline. Figure 3d shows the distribution of SSE scores between the movie-based and percept-based fitted exponential curves (purple) compared to the distribution of SSE scores between the movie-based and permuted null fitted exponential curves (gray histogram; Figure 3d). The distribution of SSE was significantly different ($p = 0.017$, permutation test) indicating that the movie-based and percept-based autocorrelations were more similar to each other than a permuted null distribution would predict.

The similarity in the autocorrelation functions seems clear, but how do we know that this is not coincidental? If the autocorrelation in our perception of emotion attempts to match the autocorrelation observed in the natural emotion statistics found in the world, then we should find that observers own perceptual autocorrelations also match their own movie-based autocorrelation. The perceptual autocorrelation for each observer was based on the specific frames they rated. To calculate the movie-based autocorrelation for each observer, we imputed any missing frames in the observers' data using the consensus ratings, and then reorganized the frames into the proper movie sequence. We calculated the consensus rating for any given frame by averaging the valence or arousal rating across all observers who rated the frame. We then compared each individual observer's movie-based autocorrelation to their own perceptual autocorrelation to investigate if these two autocorrelations were similar at the individual observer level. For each observer, we fitted decaying exponential curves to their movie-based and percept-based autocorrelations (Figure 4a). We then bootstrapped (5000 iterations) their movie-based and percept-based autocorrelations and calculated the SSE between the exponential curves fitted on the movie-based and perceptual autocorrelation for the five points that corresponded to the time lag of 0, 4, 8, 12, and 16 seconds (Figure 4b). Finally, we calculated the average SSE for each observer's movie-percept SSE and their movie-permuted SSE and computed the difference between these two values (Figure 4c). This quantifies whether the movie-percept autocorrelation functions were more similar than expected from a permuted null distribution. The majority of individual observers had movie-percept autocorrelation functions that were more similar than expected by chance, ($\chi^2[1, N = 155] = 11.93$, $p < 0.001$; Figure 4c). These results suggest that the movie-based and percept-based autocorrelations were more similar to each other, across observers,

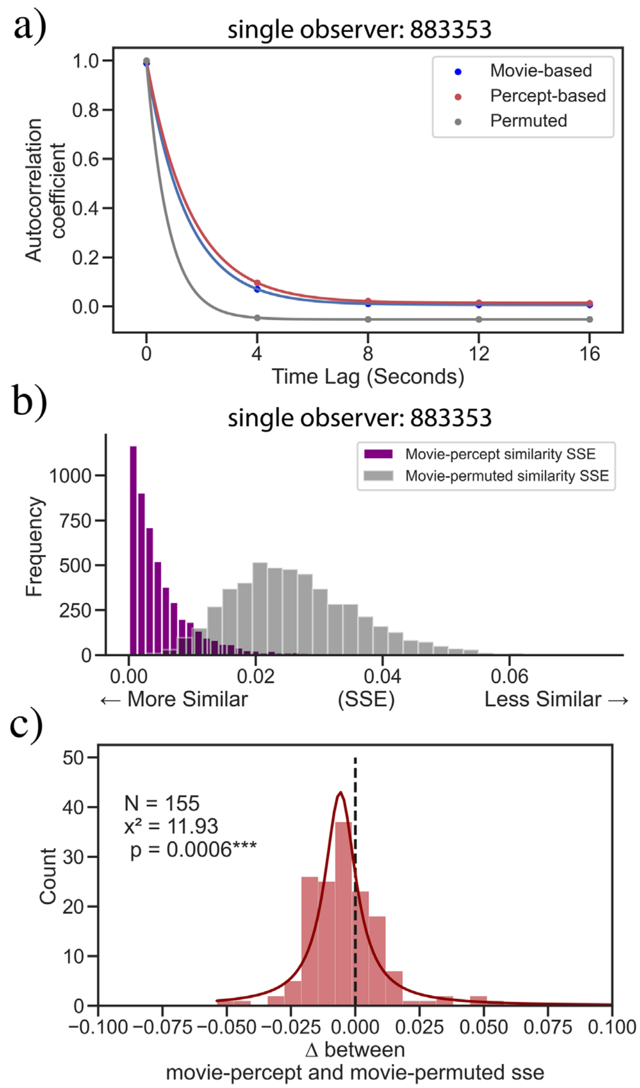

Figure 4. Individual autocorrelations for the perceptual and movie-based autocorrelation. (**a**) Example exponential curve fit on the movie-based (blue line), percept-based (red line), and permuted (gray line) autocorrelation coefficients for a single observer (883353 represents this observer's identification number). (**b**) Bootstrapped SSE calculation for a single observer's autocorrelation coefficients between the movie-based and percept-based autocorrelation (purple distribution) and the movie-based and permuted autocorrelations (gray distribution). (**c**) Distribution showing the difference between the mean SSE for the bootstrapped movie-percept and movie-permuted SSE in Figure 4b for each individual observer. Difference scores were significantly skewed toward negative values, indicating that the movie-based and percept-based autocorrelations were significantly similar to each other compared to the permuted autocorrelation ($\chi^2 = 11.93$, $p = 0.0006$). Dark red line shows a fitted Cauchy distribution.

than a permuted null distribution would predict, and it provides evidence that our group-averaged finding (Figure 3d) is not coincidental and can be generalized to individuals (Figure 4c).

The autocorrelation results for the natural movies (Figure 3a) reflect information about natural emotion statistics in the movies themselves. The rated images were presented in a random, unrelated order. Any cognitive or response biases that observers may have brought to the task (including any kind of central tendency effects, response biases, anchoring, and any other kinds of perceptual, decisional, attentional, or cognitive biases) would be reflected in the null permuted distributions (Figure 3a, gray-shaded region).

There are, however, valid concerns about the autocorrelation in the judgments themselves. For

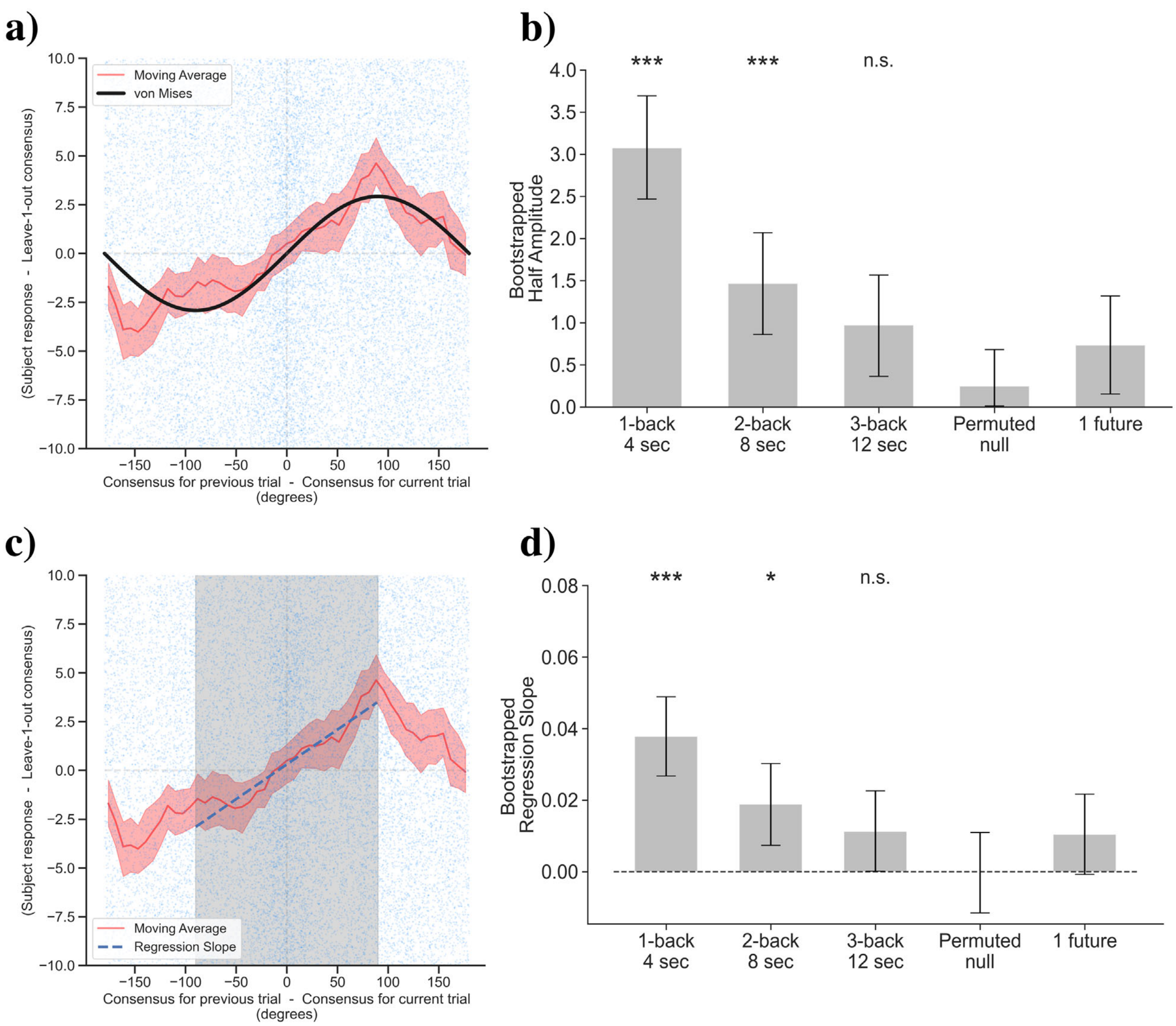

Figure 5. Serial dependence in the perception of emotion and effect sizes. (**a**) The x-axis is the distance in degrees between sequential stimuli, calculated as the difference between the consensus rating for the previous trial and the consensus rating for the current trial. The y-axis is the judgment error, which is the difference between the subject response on the current trial and the leave-one-out consensus. Individual blue dots are single trials. The red line depicts the running average across all observers. Shaded ribbons depict 95% confidence intervals. The solid black line shows the fitted derivative of von Mises. (**b**) shows the bootstrapped half amplitudes of the derivative of von Mises fit for 1, 2, and 3 trials back. The half amplitudes for the permuted null and the 1-future trial are shown as controls, for comparison. The error bars indicate bootstrapped 95% confidence intervals. (**c**) The same data from (**a**) are shown with a fitted linear regression line (blue dashed line) from peak-to-trough (shaded region). The red line depicts the running average across all observers. Shaded ribbons indicate 95% confidence intervals. (**d**) The bootstrapped regression line slopes for 1, 2, and 3 trials back are shown. The bootstrapped regression line slopes for the permuted null and the 1-future are shown for comparison. The error bars indicate bootstrapped 95% confidence intervals.

example, how do we know that the percept-based autocorrelation (Figure 3b) is actually due to cognitive or perceptual processes and not just response perseveration, hysteresis, lapsing, sluggish motor control, or some other confound? In fact, there are a range of artifacts that could cause seeming autocorrelations in response data, and typically these are seen as nuisances and controlled in various ways (Hollingworth, 1910; Valdez, Ziefle, & Sedlmair, 2018). Our hypothesis, however, is that the autocorrelations in the judgments reflect, at least in part, the visual process of serial dependence.

How can we be sure that there is serial dependence in the perceptual judgments of observers? A key characteristic of serial dependence is that is feature-tuned: only sequential things that are similar generate serial dependence (Cicchini, Mikellidou, & Burr, 2017; Cicchini et al., 2018; Fischer & Whitney, 2014; Liberman et al., 2014; Magnussen & Greenlee, 1999; Manassi et al., 2019). In contrast, a response hysteresis, sluggish motor response, perseveration on a single response, or other confound would not display any tuning to the sequential similarity between the random and unpredictable stimuli. To evaluate whether there is serial dependence, we measured the error of observers' responses in polar angle and calculated serial dependence using the standard approach of fitting a derivative of von Mises to the errors as a function of the difference in sequential stimuli (Fischer & Whitney, 2014). Response error γ was computed as the distance in degrees between an observer's response and the leave-one-out consensus response (mean angle across all other subjects). The response error was compared to the difference between the consensus for the previous stimulus and the consensus for the current trial, in degrees. We pooled all subject's data into one super-subject and then fitted a derivative of von Mises curve to the data. We quantified serial dependence as the half amplitude of the von Mises curve (Figure 5a). We bootstrapped the data 5000 times and defined the mean bootstrapped half-amplitude as the response pull towards the previous stimuli (Figures 5a, 5b). We computed a permutation test with the bootstrapped distributions for each n-back trial. A strong positive half-amplitude was observed in the 1-back trial, indicating that participants' current report was influenced by their judgment in the previous trial ($p < 0.001$, permuted null) and the 2-back trial ($p < 0.001$, permuted null). The half-amplitude for the 3-back trial was not significant ($p = 0.0528$, permuted null). The average response time across participants was 3.96 ± 2.9 seconds, suggesting that affect ratings were attracted toward similar stimuli seen up to 12 seconds ago. Additionally, the emotion tuning (Figure 5a) and temporal tuning (Figure 5b) were similar to the time constant of 12 seconds found for the movie-based autocorrelations (Figure 3a).

We further investigated the strength of the 1-back serial dependence by conducting a linear regression analysis on the response error as a function of the difference between the consensus response in the current trial and the previous trial. We fit a linear regression model on the data from peak-to-trough (from −90 to +90 on the x-axis; Figure 5c) and performed a permutation test with the bootstrapped distributions for each n-back trial. The slope for the 1-back trial was 0.039 ± 0.006, and 0.018 ± 0.006 for the 2-back trial which indicates that subjects had a ∼4% pull toward the previous stimuli and ∼2% pull toward stimuli 2 trials back (1-back, $p < 0.001$, 2-back, $p = 0.0216$, permuted null) (Figure 5d). The slope for the 3-back trial was not significant ($p = 0.216$, permuted null).

Discussion

The goal of the present study was to investigate the serial dependence of emotion perception using images from natural movies and to measure whether the autocorrelations present in the natural emotion statistics present in dynamic videos have comparable autocorrelation functions to our perceptual autocorrelations. The results revealed serial dependencies in the perception of emotion in scenes taken from natural movies (including Hollywood films, documentaries, and home videos). These positive serial dependencies suggest that perceived affective content is biased, pulled toward stimuli presented up to 12 seconds or more in the past (Figure 5a), consistent with prior research (Alais, Xu, Wardle, & Taubert, 2021; Collins, 2021; Fischer & Whitney, 2014; Liberman et al., 2018; Manassi et al., 2017; Manassi et al., 2018; Manassi & Whitney, 2022; Mei et al., 2019; Palumbo, D'Ascenzo, Quercia, & Tommasi, 2017; Van der Burg, Toet, A., Brouwer, A.-M., & Van Erp, 2021). Echoing previous work, we also found that serial dependence in emotion perception is tuned to the similarity in sequential stimuli—only similar sequential emotions are perceived to be serially dependent. A novel aspect of our study is that we measured the autocorrelations in natural movies, which reflects the natural emotion statistics present in the movies. Interestingly, the perceptual autocorrelation of emotion judgments followed a similar time course and decayed at a similar rate as the natural autocorrelation observed in the movies themselves. Additionally, we found that the perceptual autocorrelation and the serial dependence introduced by our visual system in the emotion judgments were similar to the autocorrelation in the natural emotion statistics present in the movies. This effect was found at both the group level (Figure 3d) and also at the individual observer level (Figure 4c). Together, these results suggest that the decay in the influence of previous stimuli on perceived emotion matches the decay of the autocorrelation that is naturally present in the real world.

Previous work on serial dependence in emotion is limited due to the highly controlled and unnatural faces used as stimuli in experiments (Liberman et al., 2018; Liberman & Whitney, 2015; Mei et al., 2019; Taubert, Alais, et al., 2016). These stimuli are physically similar to each other, which leads to difficulties investigating how serial dependence in emotion perception functions when perceiving emotion in the real world, where faces are less controlled and more varied. Additionally, using artificial stimuli may conflate physical pixelwise similarity with affective similarity in sequential stimuli, thus further confounding the investigation of serial dependence in emotion perception. We addressed this limitation by investigating serial dependence with independent stimuli, using frames from movie clips which includes much of the information that is normally encountered in the real world (including contextual information, multiple people, body language, etc.). In the present study, we found serial dependence in the emotion ratings of target characters using shuffled scenes from various movie clips which lacked physical similarities, suggesting that serial dependence can happen in emotion judgments even when physical or image-based similarity is not consistent.

Much of the literature on serial dependence has only employed static stimuli, leaving the question of how serial dependence works in the real world unanswered. However, a recent study using dynamic stimuli found evidence for an active mechanism of serial dependence when watching videos (Manassi & Whitney, 2022). Here, we further investigated how serial dependence might work in the real world by looking at the decay of the autocorrelation between participants' emotion ratings of characters in a scene and the decay in the natural autocorrelation observed in the emotion ratings of the frames in a video. We found a similar time-course between the autocorrelation in observers' perceptual ratings of emotion and in the autocorrelation of the natural emotion statistics present in the movies themselves. This suggests that the influence of previous stimuli on the perception of emotion may mimic the autocorrelations observed in natural emotions statistics present in the real world.

There are several possible models that could account for the results. One possible class of explanation for our findings could be a relatively simple heuristic (Gardner, 2019; Kahneman, Slovic, Slovic, & Tversky, 1982). If the autocorrelation in emotional stimuli in the world is constant, then the brain might have developed, learned, or evolved a similar autocorrelation in its representation of emotion to save neural resources and speed responses to emotional stimuli. Alternatively, variations of Bayesian and efficient observer models could be adapted to approximate the serial dependence in emotion perception in a flexible way (Cicchini, Anobile, & Burr, 2014; Cicchini et al., 2018; Cicchini & Burr, 2018; Fritsche, Spaak, & de Lange, 2020; Kalm & Norris, 2018). Even if the autocorrelations in the world were not constant, there might be individual differences (Kondo et al., 2022), because the environmental statistics can change for specific observers and because internal sources of uncertainty and noise can vary among individuals and over time as well. Our perception of emotion may even be influenced by our predictions of the future, especially at short time scales (Hogendoorn, 2022; Xia & Whitney, 2017).

Regardless of the best model, the influence of serial dependence on the perception of the currently perceived stimulus depends heavily on the distance in time between the previous and current stimuli (Fischer & Whitney, 2014; John-Saaltink, Kok, Lau, H. C., & De Lange, 2016; Liberman et al., 2014). We found a similar effect here (Figures 3, 5). Because emotional expressions typically last between 0.5 and four seconds (Ekman, 2004), the brain might continually average emotional information when inferring the emotions of an individual. This could explain why the serial dependence in the 1-back trial, which was presented four seconds in the past (on average) had twice as much influence on the current trial than the 2-back trial (Figure 5b). Additionally, averaging emotional information in relatively short windows would prove useful when inferring emotion in real-time as the emotional state of others can change (Figure 3a). Thus, observers must make quick perceptual inferences of others and react appropriately. Indeed, serial dependence has previously been shown to speed up response times (Cicchini et al., 2018), which supports the need for serial dependence in emotion perception.

One might argue that the autocorrelation in the movie-based and percept-based ratings might not signify serial dependence, but some other cognitive or perceptual process. Thus, we further investigated whether there is temporal and feature tuning of the perceptual effect, because this is a hallmark of serial dependence (Fischer & Whitney, 2014; Kiyonaga et al., 2017; Manassi et al., 2018; Manassi et al., 2019; Manassi et al., 2021; Manassi & Whitney, 2022). We found observers' emotion ratings were pulled toward the emotion in previous trials up to 12 seconds in the past (Figure 5). We also observed feature tuning, which shows that participants' ratings for the current trial were influenced by the emotion of the previous trial only if the sequential emotions were similar. This finding supports previous research that has found only similar sequential emotions to be serially dependent (Palumbo et al., 2017; Van der Burg et al., 2021). The result is also consistent with other studies that found serial dependence in the affect rating of emotional stimuli (Palumbo et al., 2017; Van der Burg et al., 2021). Although many serial dependence studies use low-level stimuli in their investigation (Kiyonaga et al., 2017), serial dependence has been found across many levels beyond just perception, including decision making (Abrahamyan, Silva, Dakin, Carandini, & Gardner, 2016; Braun, Urai, & Donner, 2018; Fritsche, Mostert, & de Lange, 2017; Lueckmann, Macke, & Nienborg, 2018; Pascucci et al., 2019) and memory (Barbosa et al., 2020; Kiyonaga et al., 2017). Thus it is not surprising that we observe serial dependence for a high-level cognitive process like emotion perception.

The direction of bias in the serial dependence of emotion has been unclear, with some studies finding positive serial dependencies for emotional expressions (Collins, 2021; Liberman et al., 2018; Mei et al., 2019) whereas another study found a negative aftereffect for judgments of emotional expression but positive serial dependence for face gender (Taubert, Alais, et al., 2016). Interestingly, Taubert et al. (2016) concluded that the direction (or time course) of serial dependence might change depending on the permanence of the relevant attribute; gender is relatively stable and emotion varies over time. It might also change depending on individual differences (Kondo et al., 2022). At first blush, our results might seem at odds with those of Taubert, et al. (2016) and consistent with those of Liberman et al. (2018), Mei et al. (2019), Van der Burg et al. (2021), and Collins (2021). However, our results are, in fact, also consistent with Taubert's suggestion that serial dependence in perception might match the statistics of the world. Serial dependence in any domain can be flipped to a negative aftereffect with sufficient adaptation duration or contrast, or sufficiently reduced noise (Alais et al., 2017; Cicchini et al., 2017; Fischer & Whitney, 2014; Manassi et al., 2018; Taubert, Alais, et al., 2016), and this could happen in the case of emotional expression, as well (Burton, Jeffery, Bonner, & Rhodes, 2016; Saad & Silvanto, 2013; Sou & Xu, 2019; Taubert, Alais, et al., 2016). The important point of Taubert et al. (2016) is supported by our findings: the serial dependence of emotion perception seems to match the actual autocorrelation statistics of expressed emotion in the real world.

The neural mechanisms that generate serial dependence in emotion perception remain a mystery, but there are intriguing hints in the existing literature. Serial dependence in emotion perception may be caused by residual activation of the emotional brain network, specifically the lateral prefrontal cortex (lPFC) (Dalgleish, 2004; Lapate et al., 2017). Previous work by Lapate et al. (2017) found that inhibition of the lPFC with transcranial magnetic stimulation led to greater bias in the evaluation of neutral faces from previously seen emotional expressions (Lapate et al., 2017). Their findings suggest that an emotional response does not just disappear, but slowly decays over time, implying that if serial dependence in emotion perception is caused by "spill-over" of previously processed stimuli, then we should expect to see a positive serial dependence.

Although serial dependence has been found in affect ratings of visual and auditory stimuli (Palumbo et al., 2017; Van der Burg et al., 2021), the temporal tuning of serial dependence in emotion perception has yet to be thoroughly investigated. Additionally, although many previous studies have investigated serial dependence in emotional expressions (Liberman et al., 2018; Liberman & Whitney, 2015; Mei et al., 2019; Taubert, Alais, et al., 2016), no previous study has looked at the serial dependence in emotion ratings of physically unrelated faces embedded in natural context. All previous studies on serial dependence, and most studies on emotion perception, use stimuli without contextual information. However, recent studies have shown that contextual information is vital in emotion perception due to the ambiguous nature of facial expressions (Aviezer, Ensenberg, & Hassin, 2017; Barrett, Mesquita, B., & Gendron, 2011; Greenaway, Kalokerinos, & Williams, 2018) and contextual information is perceived rapidly (Barrett & Kensinger, 2010; Chen & Whitney, 2021) and automatically in emotion perception (Aviezer, Bentin, Dudarev, & Hassin, 2011). Additionally, the amount of emotional information available in the context has been found to be similar to the amount of information in the face itself (Chen & Whitney, 2020, 2021). Thus investigations of serial dependence of emotion should include contextual information to improve the ecological validity of the findings.

Our results cannot be explained by central tendency (Hollingworth, 1910) because no serial dependence was found in our permuted null distributions or n + 1 control condition (Figure 5). All n-back trials were compared to the permuted null distribution to control for such artifacts. Additionally, our results cannot be explained because of physical biases or poor sensitivity to change because the frames presented in each trial were physically independent of each other.

One limitation of the current study was that we used static frames from a video instead of using a dynamic video to investigate the autocorrelation in the emotion ratings. Using static frames was necessary in order to collect independent ratings for each independent frame of a video, which decorrelates the physical autocorrelations in the stimulus from those introduced by the observers. This means that for any given frame in a single video, the emotion rating given to the frame is independent of the frame that came before it and thus is not influenced by the emotion rating in the previous frame. This allows us to measure the autocorrelation present in the natural emotion statistics of the video and removes the perceptual autocorrelation that observers introduce in their perception of sequential frames when watching a video. Dynamic stimuli have recently been used to investigate serial dependence (Manassi & Whitney, 2022) and future research should continue using dynamic stimuli to investigate how serial dependence may function in the real world. Another limitation here is that we cannot identify the specific stage(s) at which the measured serial dependencies occur, though previous studies suggest that it happens on object-level visual representations (Liberman et al., 2014; Collins, 2021). In fact, serial dependence in affective judgments could emerge at many stages, including in perceptual representations and also in decision and memory. Another limitation of the current study is that we are unable to investigate whether there were familiarity effects in participants' responses. If an observer has seen one of the movie clips before and is familiar with the context of a frame, this could influence their perceptual judgments, but it would not alter the measured natural emotion statistic. Additionally, because the stimuli were completely random across each observer, any familiarity effect would introduce noise in the data; it would not introduce spurious movie- or percept-based autocorrelations (Figure 3), nor would it introduce an artifactual serial dependence (Figure 5).

Conclusion

Our findings demonstrate that the perceptual stability of emotion may follow the stability of emotion that is naturally present in the real world. The human brain may have adapted serial dependence in represented emotion to mimic the normal autocorrelations that are present in typical experience, because this would improve the efficiency, accuracy, and consistency of emotion perception (Cicchini et al., 2017; Cicchini et al., 2018; Fischer & Whitney, 2014; Liberman et al., 2014; Manassi & Whitney, 2022).

Keywords: emotion, perception, serial dependence

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