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System identification in Priming of Pop-Out

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ABSTRACT

Inter-trial repetitions of a target's features in a visual search task reduce the time needed to find the target. Here I examine these sequential dependencies in the Priming of Pop-Out task (PoP) by means of system identification techniques. The results are as follows. Response time facilitation due to repetition of the target's features increases linearly with difficulty in segmenting the target from the distracters. However, z-scoring the reaction times normalizes responses by equating facilitation across levels of difficulty. Memory kernels, representing the influence of the current trial on any future trial, can then be calculated from data normalized and averaged across conditions and observers. The average target-defining feature kernel and the target position kernel are well fit by a sum of two exponentials model, comprised of a high-gain, fast-decay component and a low-gain, slow-decay component. In contrast, the average response-defining feature kernel is well fit by a single exponential model with very low-gain and decay similar to the slow component of the target-defining feature kernel. Analysis of single participant's data reveals that a fast-decay component is often also present for the response-defining feature, but can be either facilitatory or inhibitory and thus tends to cancel out in pooled data. Overall, the results are similar to integration functions of reward history recently observed in primates during frequency-matching experiments. I speculate that sequential dependencies in PoP result from learning mechanisms that bias the attentional weighting of certain aspects of the stimulus in an effort to minimize a prediction error signal.

1. Introduction

Inter-trial repetitions of a target's features in a visual search task reduce the time needed to find the target relative to the series' average, whereas alternations tend to increase it (Maljkovic & Nakayama, 1994). By adopting a form of reverse correlation analysis of reaction times and stimulus sequences, Maljkovic and Nakayama computed kernel functions for such sequential effects in the Priming of Pop-Out task (PoP), documenting the influence that a current trial exerts on future trials. Subsequent studies (Kristjansson, 2008; Maljkovic & Martini, 2005; Maljkovic & Nakayama, 1996, 2000) have mapped a variety of conditions that alter the characteristics of such kernels in varying degrees. However, a quantitative modeling of such dependencies has yet to be attempted and there appears to be no general consensus on the interpretation of the nature and the functional significance of the sequential dependencies observed in PoP. Proceeding from these observations, the goal of the present study is twofold: firstly, to provide a quantitative characterization of PoP kernels and secondly to propose a new theoretical account of their nature and functional significance. To such effect, I chose to study the effect of stimulus contrast on PoP. Varying stimulus contrast is a means to manipulate difficulty in segmenting the target from the distracters and here I show that the magnitude of sequential dependencies depends on difficulty. As such, manipulations of contrast provide a way of exploring the dynamic range of the sequential effects.

The plan of the paper is as follows. I start by demonstrating a way to normalize responses across conditions and across observers, showing that z-scoring the reaction times removes the effect of task difficulty on the magnitude of response facilitation. I then identify the system in two steps: firstly, I compute kernels non-parametrically from normalized data by cross-correlation; secondly, I fit a parametric model to the recovered kernels averaged across observers. I then conduct similar analyses on data from single observers and discuss individual differences. Finally, I discuss functional implications of the modeling.

2. Methods

2.1. Participants

Forty-seven undergraduate students participated in the experiment for course credit. Three additional experienced observers were also tested: observers PM (the Author) and VM have several years of practice in the task and were aware of the purpose of the experiment, whereas LB is an experienced psychophysical

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observer, but was unaware of the scope of the experiment she was running.

2.2. Stimuli

Three diamonds (1.0° × 1.0°), each with a cutoff (.14°) on the left or right side, were presented on an imaginary ellipse (10° × 8°) and spaced equidistantly, such that they fell on three of 12 possible clock positions (see Fig. 1). All spatial configurations were covered uniformly across trials by random choice. The color of each diamond was either a grayscale increment or a decrement over a 47 cd/m^2 mid-gray background. Increments or decrements of 5%, 10% and 40% were used for naïve participants and two additional steps of 20% and 80% for the experienced observers. The target diamond was a different color than the two remaining distracters. Each display always had a left and a right side cut distracter, while the target cut was chosen randomly on each trial. The displays were presented on a CRT monitor at a refresh rate of 120 Hz, with a fixation point always present at the center.

2.3. Procedure

On each trial, participants selected the odd-colored diamond and pressed as quickly as possible a key on the computer's keyboard (USB interface) with the hand corresponding to the side of the target's cut. Stimuli stayed on-screen until a response was entered. An inter-trial interval followed, with duration chosen randomly from a uniform distribution between 600 and 1100 ms. Response times were collected during uninterrupted series of 500 trials. Each naïve participant completed three series of responses separated by brief interruptions, one for each contrast level in randomized order. The three experienced observers completed several sessions of testing across different days. Target color (bright or dark), side of cut (left or right) and position (one of 12 clock locations) alternated randomly, independently and with equal probabilities across trials. As such, each sequence is a sample of uncorrelated noise.

2.4. Data analysis

The aim of this study is to recover the best linear predictor of the response times to a sequence of stimulus features in the search task. When the input time series is uncorrelated noise this can be achieved conveniently by cross-correlation (Marmarelis & Marmarelis, 1978). The recovered predictor is a first-order kernel that when convolved with the input sequence reproduces the response time series up to an error. The residual error may still contain dynamics of higher order that are ignored in the present analysis. First-order kernels for the target-selecting feature (color), for the target's position and for the response-selecting feature (cut-off side) were computed from the reaction time series. For each participant, each individual reaction time series was first de-trended up to second order. Separate sub-series were then formed, two comprising only reaction times to bright or dark targets, two for left or right responses and twelve for the target's positions. Each reaction time was then z-scored (mean subtracted and divided by the standard deviation) and empty cells were assigned the value zero. Corresponding [0, 1] binary stimulus sub-series were also formed, assigning the value 1 to trials containing the feature, response or position of interest. Kernels were then recovered by cross-correlating the reaction time sub-series with the corresponding stimulus sub-series and by scaling the result by the inverse of the stimulus series' power. Justification and a model for such computation was given in Maljkovic and Martini (2005). Further computational details may be found in (Marmarelis & Berger, 2005). For each individual observer, the pairs of kernels for color (bright and dark) and response (left and right) and the 12 position kernels were averaged, and finally the resulting average kernels were averaged again across observers. Following this initial nonparametric analysis, a parametric model was fitted by non-linear regression to each recovered kernel, obtaining estimates of model parameters of interest.

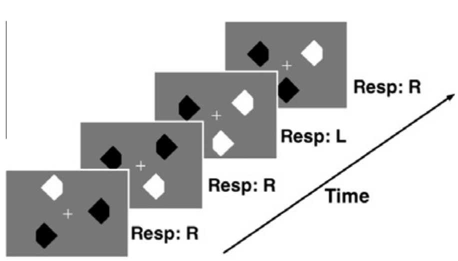

Fig. 1. Example of stimuli used in the experiment. Participants responded by pressing a key with the hand corresponding to the side of the cut in the odd-colored diamond.

3. Results

3.1. Contrast dependence and kernel normalization

Finding the pop-out target is more difficult at low than at high contrast, as evidenced by the fact that responses are slower on average and more variable the lower the contrast (mean and SD, Fig. 2).

Kernels for the target-defining feature are also affected by contrast. The facilitatory effect of repeating the target-defining feature depends on difficulty, lag-1 facilitation being larger at low than at high contrast (lag-1, Fig. 2). Shown in Fig. 3 are target-defining feature kernels averaged across participants, for the three levels of contrast tested in the experiment. The diagrams represent the amount of facilitation (speeding up) of a response to a bright or dark target encountered in a future trial, elicited by a bright or dark target encountered in the current trial. A similar pattern is observed across contrast levels: facilitation is maximal in the immediately following trial (lag-1) and decays to average response time in about 10–15 trials. However, facilitation tends to decrease with increasing contrast, following a similar trend as the mean response time and the standard deviation.

The effect of contrast on all three statistics (mean, SD and sequential dependencies) is systematic, with regression slopes on the log–log-transformed data of Fig. 2 of −0.086, but only marginally significant ($p < 0.1$).

The relationships between sequential effects, mean and standard deviation of response times are further examined in the scatterplots of Fig. 4. Individual dots in each graph represent a summary statistic calculated on a block of responses at a single contrast level from a single participant. Replicating a well-known

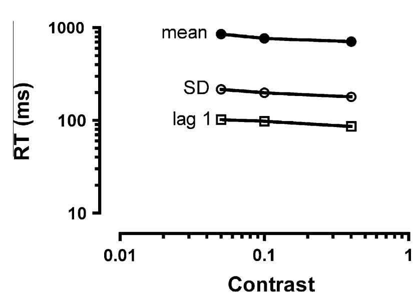

Fig. 2. Summary statistics for reaction times at different contrasts. Mean and standard deviation of reaction times and lag-1 facilitation for repetition of the selection-defining feature decrease with increasing contrast. Data are averages across all observers.