

Revealing the geometry of duration space

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Abstract

Is there a geometry of time in the human mind? Here, we asked whether the experience of duration can be reduced to a simple mental timeline, or whether it is better described as a richer representational space. To address this question, we tested the same participants in two experiments: a behavioural similarity judgement task, in which participants rated the similarity of duration pairs, and an electroencephalography (EEG) experiment in which they detected oddball durations in a sequence. Behavioural and EEG data were used to construct representational dissimilarity matrices, whose geometry was compared against theoretical models of duration organisation. Behavioural similarity judgements revealed a three-dimensional duration space structured by monotonic magnitude, contextual encoding, and a periodic component. These three dimensions were jointly consistent with a latent generalised helical model, which provided excellent fit to the behavioural data. At the neural level, the geometry unfolded dynamically in two successive stages: a strong logarithmic encoding of durations peaking around 150 ms after duration offset, followed by a spring-like geometry, converging with the behavioural structure, from around 300 ms onward. Together, these findings support a multidimensional and dynamic representational geometry of duration.

Introduction

All experience unfolds in time, making time a fundamental dimension of perception, action, and cognition. Yet the representational principles governing the coding of subjective duration remain poorly understood. Several influential frameworks have proposed that duration is spatialised along a mental timeline (e.g., Bonato et al., 2012; Vallesi et al., 2008; Vicario et al., 2008). In many of these accounts, durations are conceived as magnitudes organised along a single internal dimension, with shorter and longer intervals ordered monotonically along a time axis (e.g., Bender & Beller, 2014; Buetti & Walsh, 2009; Walsh, 2003). Although this view captures important features of subjective duration, it leaves unresolved the structure of duration representations themselves. More specifically, it remains unclear whether the psychological and neural representation of duration can be reduced to a single latent axis, or whether it is better characterised as a higher-dimensional geometry.

A constructive way to address this question is to adopt a relational approach to the representation of durations. Instead of asking how a given duration is represented in isolation, this perspective asks how durations are positioned relative to one another in terms of perceived similarity. This idea builds on the insight that lawful structure may be recovered from the relations among representations (Shepard & Chipman, 1970). Pairwise similarity judgements therefore offer an empirical window onto the structure of mental representations, while multidimensional scaling (MDS) provides a formal tool for recovering the latent geometry that organises those judgements (e.g., Kruskal, 1964; Kruskal & Wish, 1978; Shepard, 1980, 1987; Shepard et al., 1975; Sievers et al., 2021; Torgerson, 1977). This relational logic has been extended to neural data through representational similarity analysis (RSA; Kriegeskorte & Kievit, 2013).

A key advantage of this framework is that the geometry of representational spaces can reveal the computational principles structuring a cognitive domain. Applied to colour or pitch perception, similarity-based approaches have revealed representational organisations that are not reducible to a single linear axis (e.g., Marjeh et al., 2023, 2024; Rosenthal et al., 2021; Shepard, 1982). Here, we applied this framework to time perception and asked how many latent dimensions organise the human psychological space of durations, and whether similar organising principles can be tracked in neural activity following duration offset. We hypothesised that duration would not be adequately captured by a single dimension, but would instead require a richer representational structure (e.g., Bailly et al., 2011).

Methods

Thirty-three healthy adults completed two sessions. Stimuli were 10 auditory pure tones (440 Hz) with durations spanning 400 to 2200 ms in 200-ms steps. In the first session, participants rated the perceived similarity of all 45 possible pairs of durations on a 7-point Likert scale, with four repetitions per pair and both presentation orders counterbalanced, yielding one behavioural RDM per participant. One week later, the same durations were presented in a continuous oddball detection task with rare short (70 ms) and long (3400 ms) oddballs. EEG was recorded from 64 channels, preprocessed with ICA-



based artefact correction (Gramfort, 2013), and analysed at stimulus offset.

Behavioural RDMs were analysed using non-metric MDS (Kruskal, 1964) and compared with candidate theoretical models using RSA and leave-one-duration-out cross-validation. Candidate models included a Linear, Logarithmic, Binary, Random, Power, Helix, and Regularness model; differing in their assumed dissimilarity structure. The Helix model embedded durations on a parametrised generalised helical trajectory in a three-dimensional latent space. EEG RDMs were computed over time using cross-validated squared Euclidean distances, as implemented in `mne-rsa` (Van Vliet et al., 2025). Commonality analysis was then used to quantify the variance shared between EEG, behavioural similarity, and theoretical models, while statistically controlling for the remaining predictors (e.g., Cichy & Oliva, 2020; Hebart et al., 2018; Seibold & McPhee, 1979).

Results

Behavioural similarity judgements revealed a coherent three-dimensional organisation of duration space. The first dimension varied monotonically with objective duration, consistent with a magnitude-like ordering. The second followed a U-shaped profile with a minimum close to the geometric mean of the duration set, suggesting contextual encoding. The third displayed a periodic modulation, pointing to a periodic component not reducible to magnitude or context alone. Cross-validated RSA showed that the Helix model provided the best overall account of individual behavioural RDMs, with the Power model also performing well.

Time-resolved RSA on EEG RDMs revealed two successive representational stages. The variance explained by the model space increased sharply from approximately 100 ms after duration offset. Around 150–200 ms, unique variance was best explained by the Logarithmic and Regularness models, suggesting an early compressed and task-relevant code. Around 300 ms, the variance shared between EEG RDMs and behavioural similarity peaked, indicating convergence between neural and psychological geometries. These results suggest a constructive sequence in the emergence of post-offset duration representations: an early stage dominated by compressed and anchor-relative coding, followed by a later stage that more closely resembles the structure expressed in explicit similarity judgements.

Finally, individual differences in the fitted helix parameters correlated positively with resting-state alpha and beta oscillatory power, suggesting that endogenous neural dynamics constrain the geometry of individual duration spaces.

Discussion

These findings challenge the view that durations are represented along a simple one-dimensional mental timeline. Instead, behavioural similarity judgements reveal a multidimensional psychological space structured by monotonic magnitude, contextual position within the stimulus set, and a recurrent component. A generalised helical model provided a parsimonious account of this structure by combining monotonic progression with recurrent variation in a single latent trajectory.

The EEG results add a temporal dimension to this picture. Neural representations of duration did not simply reflect a static readout of elapsed time. Rather, they evolved through at least two stages: a compressed and task-contingent code shortly after offset, and a later geometry more closely aligned with behavioural similarity. This temporal unfolding suggests that explicit judgements of duration similarity may reflect a relatively late representational format integrating multiple constraints rather than a direct readout of the earliest neural duration signal.

More broadly, these results support the idea that duration, like other perceptual variables, may be organised in a structured low-dimensional manifold rather than along a single scalar axis (Marjeh et al., 2023, 2024; Rosenthal et al., 2021; Shepard, 1982). This perspective provides a principled bridge between psychophysics, neural dynamics, and computational models of time representation.

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