Research on Information Integration Mechanisms in Dynamic Vision-Action Control Based on the Kalman Filter Model

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Abstract

Psychological research has long assumed that an individual' s behavioral responses can be directly mapped to their mental processing, and operational definitions and experimental designs have been based on this assumption. However, in recent years, researchers have begun to re-examine this relationship, exploring how "stimulus-response" patterns undergo systematic changes due to different response modalities and further revealing the underlying mechanisms. One research approach is to adopt a Bayesian framework to reconstruct the relationship between information input, mental processing, and behavioral response, thereby explaining how the "stimulus-response" relationship adjusts according to task characteristics. Based on the core issue of the "stimulus-response" relationship, this proposal intends to employ a Kalman filter model based on a Bayesian framework. By observing, analyzing, and tracking behavioral performance and related visual cortical electrophysiological activity, it aims to inversely parse the optokinetic control process, isolate the two key components of perceptual processing and information integration, and respectively examine their impact on the optokinetic process, with a particular focus on the influence of the information integration component on the "stimulus-response" mapping. The focus of the proposal is to verify the effectiveness of the Kalman filter model in explaining the relationship between "information input—mental processing—behavioral response" and to explore its potential applications in optimizing psychological experimental design.

Full Text

Research on Information Integration Mechanisms in Dynamic Visual-Motor Control Based on the Kalman Filter Model

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Psychological research has long operated under the default assumption that an individual' s behavioral responses can be directly mapped to their underlying mental processes. Based on this assumption, researchers have traditionally developed operational definitions and experimental designs. However, in recent years, scholars have begun to re-examine this relationship, exploring how mapping patterns systematically change across different response modalities and further revealing the mechanisms underlying these shifts. One prominent research approach utilizes the Bayesian framework to reconstruct the relationship between sensory input, mental processing, and behavioral response, thereby explaining how the stimulus-response relationship adjusts according to task characteristics.

Building upon the core issue of the stimulus-response relationship, this proposal intends to employ a Kalman filter model based on the Bayesian framework. By observing, analyzing, and tracking behavioral performance alongside relevant electrophysiological activity in the visual cortex, we aim to reverse-engineer the visual-motor control process. This approach will allow us to isolate two key components—perceptual processing and information integration—and independently examine their influence on the visual-motor process. We are particularly interested in how the information integration component affects the stimulus-response mapping. The focus of this conceptual framework is to validate the effectiveness of the Kalman filter model in explaining the relationship between input, processing, and behavior, while exploring its potential applications for optimizing experimental design in psychology.

Abstract

This paper explores the mechanisms of motor control and motion-related perception through the lens of Bayesian modeling and sensorimotor integration. We investigate how the central nervous system processes multi-sensory information to achieve precise physical interactions, specifically focusing on the application of the Kalman filter in modeling these internal processes. By synthesizing current research in machine learning and neuroscience, we provide a comprehensive framework for understanding how humans compensate for sensory noise and temporal delays during goal-directed movements.

Introduction

The human ability to perform complex motor tasks—ranging from simple reaching movements to professional athletic maneuvers—relies on the seamless integration of sensory feedback and internal motor commands. This process, known as sensorimotor integration, requires the brain to resolve ambiguities inherent in sensory signals. Recent advancements in computational neuroscience suggest that the brain functions as an optimal estimator, utilizing Bayesian inference to combine prior knowledge with real-time sensory data.

Bayesian Modeling in Motor Control

At the core of modern motor control theory is the Bayesian framework. When an individual performs an action, the brain must estimate the state of both the body and the environment. This estimation is not based solely on immediate sensory input, which is often noisy and delayed, but also on a "prior" distribution derived from past experiences.

The Role of Prior Knowledge

In Bayesian modeling, the posterior distribution—representing the most likely state of the system—is proportional to the product of the likelihood (current sensory evidence) and the prior (expected outcome). In the context of motion-related perception, this explains why humans tend to perceive movement trajectories as smoother or more consistent than the raw visual data might suggest.

Sensorimotor Integration and Visual-Motor Feedback

Visual-motor integration is a critical component of action control. The brain must map visual information (the position of a target) onto motor coordinates (the activation of specific muscle groups). This transformation is computationally demanding due to the inherent noise in the visual system and the mechanical properties of the musculoskeletal system.

[Figure 1: see original paper]

As shown in [Figure 1: see original paper], the feedback loop between the visual system and the motor cortex involves continuous error correction. When a discrepancy arises between the intended movement and the perceived trajectory, the system updates its internal model to minimize future errors.

The Kalman Filter as a Computational Model

The Kalman filter provides a robust mathematical framework for understanding how the brain performs state estimation in real-time. By treating motor control as a dynamic system, the Kalman filter allows for the integration of "forward models."

1 Problem Statement

Contemporary psychological research extensively employs experimental paradigms to reveal the mechanisms of human information processing, yielding rich findings across various domains. However, the exact nature of the correspondence between stimuli and responses remains an unresolved fundamental theoretical issue. Existing research indicates that under different task conditions, even when facing identical visual input, the information processing mechanisms reflected in individual behavioral responses can differ significantly. This suggests that the task context may influence the relationship between stimuli by altering the underlying processing mechanisms [?, ?, ?, ?, ?, ?]. For example, in motion tracking tasks, individual responses are more stable and exhibit stronger resistance to the effects of illusions [?, ?, ?, ?, ?, ?]. These phenomena suggest that traditional models are currently insufficient to fully explain the mapping variations between stimulus input and behavioral output.

To address these theoretical difficulties, some researchers have proposed understanding the psychological processing mechanisms of perceptual-motor control from the perspective of Bayesian information integration. This viewpoint posits that task structure regulates the generation of behavior by influencing the relative weights of perceptual input, feedback signals, and prior knowledge [?, ?, ?, ?]. Consequently, Bayesian optimal integration models have been introduced to this field. For instance, in hand-movement offset tasks, this model successfully explains systematic behavioral shifts under feedback manipulation [?, ?]; in continuous tracking tasks, the Kalman filter model can derive perceptual processing characteristics from behavioral data [?, ?, ?, ?]; and in oculomotor control, this model has been used to integrate sensory-driven and memory-driven control mechanisms [?, ?, ?, ?].

Despite these preliminary achievements, current research still exhibits significant deficiencies in both theoretical construction and empirical testing. On one hand, relevant empirical studies remain relatively fragmented, and a unified model has yet to be formed to integrate behavioral mechanisms across different task types. On the other hand, model construction has focused largely on the descriptive prediction of behavior, lacking an explanation of its neural mechanisms. Although some scholars have emphasized the need to consider the regulatory role of task context on processing mechanisms [?, ?], there is a lack of theoretical models that systematically explain the changes in integration weights and their measurable indicators under different task conditions.

The present study intends to introduce the Kalman filtering model within a Bayesian theoretical framework to analyze how perceptual input, feedback information, and prior predictions are dynamically combined in visual-motor control through a unified information integration model. We will systematically manipulate stimulus attributes, response modes, and feedback structures to model behavioral data in dynamic tasks. The extracted parameters will then be compared with behavioral thresholds and electrophysiological indicators (such as steady-state visual evoked potentials) obtained from traditional tasks. By manipulating variables such as feedback reliability and the regularity of motion trajectories, we will test the hypothesis of dynamic adjustment in integration strategies and evaluate the applicability and explanatory power of the model at both behavioral and neural levels. This approach aims to provide a unified theoretical framework and mathematical tool for explaining the information integration mechanisms of visual-motor control.

2.1 Task-Dependent Information Processing Mechanisms

In traditional vision research, an individual's response to external stimuli is often assumed to be a direct expression of the results of perceptual processing; that is, a stable and reproducible mapping relationship is presumed to exist. Constrained by traditional experimental paradigms, such studies frequently employ a static trial-based design. This approach utilizes discrete stimulus presentations and response recordings as basic units to manipulate and analyze perceptual processing. However, an increasing number of studies in recent years have demonstrated that within dynamic task environments—which possess greater ecological validity—perceptual outcomes can vary significantly even when the stimulus input remains consistent.

The behavioral response patterns exhibited by individuals undergo systematic changes over time, suggesting that the relationship between information input and behavioral output may not remain constant. This trend is evident across multiple research domains. In the study of hand movement control, for instance, a substantial body of research within dynamic tracking or online correction contexts has revealed a continuous interaction between perceptual feedback and motor planning [?, ?, ?, ?, ?, ?, ?, ?, ?]. Similarly, in motor adaptation research, many studies have moved away from traditional trial-based manipulations in favor of designs utilizing continuous perturbations and uninterrupted feedback. This approach more accurately captures strategic adjustments and the utilization of error signals during the adaptation process [?, ?, ?, ?, ?].

A similar trend has emerged in the field of eye-tracking. By introducing tasks involving the tracking of continuously moving targets, researchers have discovered that oculomotor control is driven not only by perceptual information but also by dynamic processing mechanisms such as strategic prediction and temporal integration [?, ?, ?, ?, ?]. These methods have been further applied to investigate changes in processing capabilities among populations with cognitive impairments [?, ?, ?]. In cognitive neuroscience, researchers have also attempted to manipulate the dynamic perturbation characteristics of visual input to observe their regulatory effects on neural responses during processes such as attention and working memory [?, ?, ?, ?].

In these types of tasks, behavioral responses no longer appear as independent outputs within a single trial. Instead, they manifest as trajectory signals corresponding to temporal changes, such as hand position, eye movement velocity, or gaze location. Consequently, the method of recording responses has shifted toward high-temporal-resolution sampling of continuous behavioral states, which maintains a direct correspondence with the time dimension at the data level. In this context, the behavioral output at any given moment can be viewed as an instantaneous expression of the current information integration result; it encompasses both the drive from external stimuli and the cumulative influence of prior states and feedback information.

Collectively, these studies indicate that within the context of continuous interaction, real-time feedback, and stable task goals, the individual' s information processing exhibits structural characteristics significantly different from those found in static tasks. For example, in continuous visuomotor tracking tasks, individuals typically demonstrate higher movement precision and smoother response trajectories [**?**, **?**]. Furthermore, the degree to which they are affected by visual illusions is significantly lower than in static judgment tasks [**?**, **?**]. The behavioral stability and interference resistance demonstrated in these scenarios have become critical evidence challenging traditional assumptions of processing models, providing an empirical foundation for further exploring the task-dependent nature and integrative structure of processing mechanisms.

Consequently, some researchers have further proposed that the processing mechanisms for the same information should be examined across the dimension of task structure—specifically comparing static trial-based tasks with dynamic continuous tasks—to determine if fundamental differences exist. The most representative perspective in this regard is the classic dual-stream theory, which posits that the ventral stream primarily supports perceptual judgment, while the dorsal stream is responsible for vision-guided action [**?**, **?**, **?**, **?**].

This model has received empirical support under certain experimental conditions. For instance, [**?**, **?**] found enhanced activation of the dorsal stream during interactive tasks. Similarly, [**?**, **?**] pointed out that eye movements and related motor processes involve dual-mechanism structures characterized by fast reaction and long-term integration. However, such processing pathway models struggle to explain the synergistic regulation between perception and response in dynamic tasks. In particular, these models tend to overlook the systematic influence of factors such as feedback latency, trajectory continuity, and prior prediction on the underlying processing mechanisms.

This is particularly prominent in dynamic visual-motor tasks characterized by continuous responses. A critical question that remains to be clarified is whether the visual processing involved in such tasks shares the same underlying mechanisms as those involved in traditional single-trial experiments. If the mechanisms are indeed identical, an individual' s perceptual ability should possess a stable parametric structure across different tasks, which could be captured by a unified model. Clarifying this issue is not only critical for testing current mainstream theories but also determines whether it is necessary to construct a new integrative model to explain the mechanistic pathways through which task modulation influences information processing.

2.2 Bayesian Integration Models for Visual-Motor Control

In recent years, researchers have increasingly argued that traditional modular processing models struggle to explain how humans utilize information across different tasks. These classical frameworks typically assume a rigid separation between perception, cognition, and action. However, empirical evidence suggests that the boundaries between these stages are far more fluid than previously thought.

Traditional models often posit a linear pipeline where sensory input is processed, a cognitive decision is made, and a motor command is executed. Yet, this serial approach fails to account for the dynamic integration of information observed in complex human behavior. For instance, in many real-world scenarios, the way we perceive an object is inextricably linked to our intended action toward it, a phenomenon that modular models cannot easily accommodate.

Research indicates that human information utilization is highly context-dependent and flexible. Rather than relying on fixed modules, the cognitive system appears to employ a more integrated strategy where feedback loops and parallel processing play a central role. This shift in understanding suggests that action control is not merely the final output of a cognitive chain, but an active participant in the shaping of perception and decision-making processes. Consequently, newer theoretical frameworks are moving toward more holistic, ecological approaches to explain how humans navigate and interact with their environment.

Due to the systematic changes in strategies, it is necessary to re-examine the dynamic generation process from stimulus to response through the lens of information integration. Within this framework, the transition from sensory input to behavioral output is not a simple linear mapping but rather a complex integration of prior knowledge, contextual cues, and real-time feedback.

The Bayesian optimization integration framework is widely regarded as a powerful tool for characterizing the flexibility of human processing strategies. This framework posits that, during task execution, individuals dynamically assign weights to different information sources—such as sensory input, prior experience, and external feedback—based on their respective levels of uncertainty, thereby generating adaptive responses [**?**, **?**, **?**]. Existing empirical research has provided preliminary validation for the plausibility of this integrative perspective.

Körding and Wolpert (2004) demonstrated that when the visual feedback received by an individual during a pointing task is manipulated, their movement trajectories exhibit systematic offsets. These observed offsets, along with their associated error structures, can be effectively modeled and explained through the framework of Bayesian integration. Bonnen et al. (2015, 2017) further demonstrated in continuous visual tracking tasks that an individual' s reactive behavior can be used to infer latent perceptual processing characteristics, such as spatial discrimination thresholds. This suggests that response trajectories contain quantifiable structures of perceptual information. In a recent study, Ambrosi et al. (2022) utilized a Bayesian Ideal Observer model to effectively distinguish the contributions of perceptual factors from motor execution factors within continuous tracking tasks, providing model-based support for the separability of these processing mechanisms.

This framework has also been extended to the field of oculomotor control research. Specifically, de Xivry et al. (2013) demonstrated that in smooth pursuit tasks, sensory-driven immediate control and memory- or strategy-based control modes can be modeled through a unified Bayesian integration principle. Furthermore, the relative weights of these two mechanisms on behavior change dynamically as sensory information accumulates. Crevecoeur and Körding (2017) further proposed that even in the phenomenon of saccadic suppression —traditionally regarded as a boundary marker for stage-based processing—the underlying information processing can be explained through a Bayesian integration mechanism. This suggests that there is no need to assume a fundamental difference in processing pathways between saccadic and non-saccadic states.

In summary, these studies provide evidence across diverse task types and response modalities, supporting the view that sensory input, feedback regulation, and prior knowledge serve as integrable information sources. These elements are synthesized into a unified processing strategy within a Bayesian framework.

2.3 Application of the Kalman Filter Model

To parametrically model the aforementioned integration mechanism in empirical research, it is necessary to introduce operational mathematical tools. As a dynamic implementation of Bayesian principles, the Kalman filter model has been widely applied to characterize the collaborative process of perception and prediction in continuous response tasks. As a data analysis technique based on Bayesian statistical principles, the Kalman filter reduces estimation error by linearly combining known measurement errors with existing observational data (Kalman, 1960; Sorenson, 1966).

While this method is extensively utilized in engineering fields such as telemetry, the present study attempts to apply the model in reverse to analyze continuous visual-motor processes. [Figure 1: see original paper] uses a simple visual tracking task as an example to briefly illustrate how the Kalman filter model describes and explains the process of continuous visual-motor control. When an observer tracks a continuously moving visual signal, the effective information source is not limited to the visual signal input; another critical source of information is the individual' s prior tracking response signal. From a dynamic feedback perspective, although the response signal contains no effective information about the stimulus when the observer first begins the tracking task, the accumulation of prior visual signals as the task progresses ensures that the response signal itself begins to carry effective information about the stimulus.

Specifically, the subject' s response update at time t can be expressed as:

$$\hat{S}_t = \hat{S}_{t-1} + K_t(I_{t-\Delta} - \hat{S}_{t-1})$$

The participant' s tracking response at time t is formed by a weighted combination of the current physical stimulus at $t - \Delta$ and the tracking response from the previous moment. The stimulus weight, represented by the Kalman gain K, can be expressed as:

$$K_t = \frac{P_{t-1} + Q}{P_{t-1} + Q + R_p}$$

This parameter is jointly determined by three sources of uncertainty: the prediction uncertainty from the previous time step (P_{t-1}), the degree of change in the stimulus itself (Q), and the sensory noise variance (R_p). The sensory noise variance represents the magnitude of internal error introduced when the subject perceives the current stimulus [**?**, **?**]. Furthermore, the prediction uncertainty reflects the system' s confidence when predicting the current state based on the response from the previous time step. Together, these parameters determine whether the system should rely more heavily on past information or current sensory input when updating its response.

[Figure 1: see original paper] *Schematic analysis of the action tracking process*

From the perspective of the Kalman filter model, we can re-examine the relationship between dynamic visual action control and visual processing. In common visual experimental tasks, the entire process is trial-based rather than driven by dynamic feedback, and responses are typically brief and discrete. Consequently, the effective visual information contained within the response signal is highly limited. Therefore, in trial-based experimental designs, the observer' s response is primarily dominated by the immediate visual signal. However, in the context of dynamic feedback, as prior visual information rapidly accumulates within the continuous response signal, the influence of the response signal on subsequent actions increases. This reciprocal process may ultimately lead to the significant differences observed in individual visual processing mechanisms across various types of visual tasks.

3 Research Framework

This study aims to address the unified modeling of information processing mechanisms in visual-motor control by systematically exploring the dynamic integration between sensory input, feedback regulation, and prior prediction under varying task conditions. We operationally define the control relationship as a mapping between effects and responses that undergoes recursive updating across a joint stimulus time series. Specifically, at any given moment, the behavioral output is a function of the current stimulus state combined with the output from the previous moment.

The overall research framework is organized into three modules. Module 1 focuses on isolating core parameters of the perceptual process from continuous response behavior. Module 2 further investigates how task characteristics—such as feedback structure and stimulus predictability—influence the integration weights of different information sources. Module 3 introduces neurophysiological methods to examine whether the aforementioned integration mechanisms have observable neural correlates.

3.1 Module 1: Decomposition and Measurement of the Visual-Motor Process

The first module attempts to decompose the optomotor control process using a Kalman filter model, enabling the separation of visual processing from the information integration process. A primary focus is to compare the visual processing components derived from this model with characteristics obtained through traditional single-trial experimental methods.

Study 1 employs a visual tracking task to analyze hand movement tracking (Experiment 1) and eye movement tracking (Experiment 2). We investigate whether the manual tracking process reflects the visual perceptual processing noise associated with different stimulus dimensions (contrast and hue). Participants perform three tasks: (1) continuous manual tracking, (2) continuous eye-tracking, and (3) a trial-based discrimination task. Target stimuli are defined using three categories based on the DKL color space [**?**, **?**]: luminance contrast, red-green hue, and blue-yellow hue.

Based on preliminary data ($N = 28$), visual processing noise extracted from manual tracking is significantly correlated with ground truth processing noise ($r(145) = .66, p < .001$). In Study 2, we utilize continuous oculomotor tracking combined with a Kalman filter to rapidly assess individual color discrimination (Experiment 2a) and stereoacuity (Experiment 2b). Preliminary results show that analyzing only the first 5 seconds of tracking data is sufficient to achieve a classification accuracy of 1.00 (AUC = 1.00), whereas traditional detection tasks require approximately 20 minutes. These findings have been documented in [**?**, **?**].

3.2 Module 2: Information Integration in the Visual-Motor Process

Module 2 explores the influence of environmental factors on visuo-motor integration. Research 3 aims to enhance visual processing precision through perceptual learning. Experiment 5 tests whether improving luminance contrast sensitivity leads to a decrease in visual processing noise σ_v and an increase in the weight of visual information K. Experiment 6 utilizes the tracking task itself as the training task to investigate if learning effects are consistent with traditional discrimination tasks.

Research 4 focuses on feedback signal adjustment. Experiment 7 manipulates feedback redundancy by changing the visual feedback from a single point to a contour-matching circle. Experiment 8 manipulates feedback uncertainty by causing the signal to disappear randomly.

Research 5 manipulates trajectory predictability. Experiment 9 compares tracking performance across random Gaussian noise trajectories and trajectories generated by superimposed sine waves. Preliminary data ($N = 32$) shows that regular trajectories (sine-weighted) lead to shorter response latencies but larger tracking errors compared to pure Gaussian trajectories. Kalman filter analysis revealed that more regular trajectories induce participants to rely more heavily on internal feedback rather than external perceptual information, leading to a decline in perceptual processing precision.

3.3 Module 3: Neural Mechanisms of Visual-Motor Integration

This module compares neural oscillatory responses during optomotor control with those during general visual perception. We utilize the steady-state visual evoked potential (SSVEP) as a neural marker. SSVEP is selected because it stably reflects perceptual sensitivity and is less susceptible to high-frequency EMG interference.

Study 6 (Experiment 11) compares SSVEP signals during tracking versus passive observation. Study 7 (Experiment 12) explores whether changes in information feedback and prior knowledge influence SSVEP generation in the visual cortex and corresponding α oscillations, reflecting shifts in cognitive states during information integration.

4 Theoretical Construction

This proposal suggests constructing a dynamic processing mechanism model from the perspective of Bayesian integration, utilizing the Kalman filter as the primary mathematical tool. Bayesian integration theory posits that the system dynamically integrates sensory input, prior experience, and feedback information, adjusting weights based on uncertainty [**?**, **?**, **?**].

The proposed framework intends to use the Kalman filter to perform parameter estimation of the relative contributions of sensory input, feedback, and prior knowledge. By manipulating the information and response structures of sequential tasks, we aim to reveal common mechanisms underlying dynamic continuous tracking and static trial-based tasks. Furthermore, we will explore the model' s adaptability in socialized visual tasks, such as sequential face recognition, to fit effects like serial dependence.

Ultimately, this research seeks to construct a unified processing framework with cross-task explanatory power supported by neural evidence. Methodologically, it extends the application of the Kalman filter in psychology. In practice, it promotes the standardization and ecological validity of perceptual measurement technologies.

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Note: Figure translations are in progress. See original paper for figures.