

# Novelty Assessment Report

**Paper:** Bidirectional Predictive Coding

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**Venue:** ICLR 2026 Conference Submission

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## Abstract

Predictive coding (PC) is an influential computational model of visual learning and inference in the brain. Classical PC was proposed as a top-down generative model, where the brain actively predicts upcoming visual inputs, and inference minimises the prediction errors. Recent studies have also shown that PC can be formulated as a discriminative model, where sensory inputs predict neural activities in a feedforward manner. However, experimental evidence suggests that the brain employs both generative and discriminative inference, while unidirectional PC models show degraded performance in tasks requiring bidirectional processing. In this work, we propose bidirectional PC (bPC), a PC model that incorporates both generative and discriminative inference while maintaining a biologically plausible circuit implementation. We show that bPC matches or outperforms unidirectional models in their specialised generative or discriminative tasks, by developing an energy landscape that simultaneously suits both tasks. We also demonstrate bPC's superior performance in two biologically relevant tasks including multimodal learning and inference with missing information, suggesting that bPC resembles biological visual inference more closely.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Combining Generative and Discriminative Visual Inference in Predictive Coding**

A total of **19 papers** were analyzed and organized into a taxonomy with **10 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Unified Architectures Integrating Generative and Discriminative Processing**
- **Specialized Generative or Discriminative Approaches**
- **Cross-Modal and Knowledge Transfer Applications**
- **Domain-Specific Applications and Evaluation**
- **Conceptual Frameworks and Theoretical Analyses**

### Complete Taxonomy Tree

- Combining Generative and Discriminative Visual Inference in Predictive Coding Survey Taxonomy
- Unified Architectures Integrating Generative and Discriminative Processing
  - Bidirectional Predictive Coding Models ★ (3 papers)
  - [0] Bidirectional Predictive Coding (Anon et al., 2026) [View paper](#)
  - [3] Unsupervised learning of generative and discriminative weights encoding elementary image components in a predictive coding model of cortical function (M.W. Spratling, 2012) [View paper](#)
  - [19] A Predictive-Coding Network That Is Both Discriminative and Generative. (Wei Sun, 2021) [View paper](#)
  - Diffusion Model Adaptations for Discriminative Tasks (2 papers)
  - [1] Aligning Generative Denoising with Discriminative Objectives Unleashes Diffusion for Visual Perception (Pang, 2025) [View paper](#)
  - [2] Bridging Generative and Discriminative Models for Unified Visual Perception with Diffusion Priors (Dong, 2024) [View paper](#)
  - Hierarchical Model Combination Frameworks (2 papers)
  - [15] Modeling visual patterns by integrating descriptive and generative methods (Cheng-en Guo, 2003) [View paper](#)
  - [18] Visual tracker using sequential bayesian learning: Discriminative, generative, and hybrid (Yun Lei, 2008) [View paper](#)
- Specialized Generative or Discriminative Approaches
  - Generative Features for Discriminative Tasks (2 papers)
  - [10] On deep generative models with applications to recognition (Marc'Antonio Aurelio Ranzato, 2011) [View paper](#)
  - [13] GH-Feat: Learning Versatile Hierarchical Features From GANs (Yinghao Xu, 2022) [View paper](#)
  - Predictive Coding for Unsupervised Representation Learning (2 papers)
  - [12] Hierarchical predictive coding models in a deep-learning framework (Maida Anthony, 2020) [View paper](#)
  - [17] A Predictive Processing Account of Bottom-Up Visual Saliency Using Cross-Predicting Autoencoders (Beren Millidge, 2018) [View paper](#)
  - Semantic Predictive Coding with Adversarial Training (1 papers)
  - [14] Semantic Predictive Coding with Arbitrated Generative Adversarial Networks (Radamanthys Stivaktakis, 2020) [View paper](#)
- Cross-Modal and Knowledge Transfer Applications (1 papers)
  - [5] JEP-KD: Joint-Embedding Predictive Architecture Based Knowledge Distillation for Visual Speech Recognition (Chang Sun, 2024) [View paper](#)
- Domain-Specific Applications and Evaluation
  - Speech Enhancement Metric Evaluation (1 papers)
  - [6] On the Behavior of Intrusive and Non-intrusive Speech Enhancement Metrics in Predictive and Generative Settings (de Oliveira, 2023) [View paper](#)

- Medical Imaging and Clinical Prediction (1 papers)
- [7] Glaucoma progression detection and humphrey visual field prediction using discriminative and generative vision transformers (Ye Tian, 2023) [View paper](#)
- Conceptual Frameworks and Theoretical Analyses (5 papers)
  - [4] A Survey on Brain-Inspired Deep Learning via Predictive Coding (T Salvatori, 2023) [View paper](#)
  - [8] Towards the Unification of Generative and Discriminative Visual Foundation Model: A Survey (Liu Xu, 2023) [View paper](#)
  - [9] How does the primate brain combine generative and discriminative computations in vision? (Peters, 2024) [View paper](#)
  - [11] How does the brain combine generative models and direct discriminative computations in high-level vision? (James J. DiCarlo, 2021) [View paper](#)
  - [16] Naturalistic primate vision combines generative and discriminative computations (Benjamin Peters, 2023) [View paper](#)

## Narrative

Core task: Combining generative and discriminative visual inference in predictive coding. The field explores how biological and artificial systems can integrate two complementary modes of visual processing—generative models that synthesize or predict sensory input, and discriminative models that classify or recognize patterns—within a unified predictive coding framework. The taxonomy reflects this duality through several main branches. Unified Architectures Integrating Generative and Discriminative Processing encompasses works that explicitly merge both inference modes, often drawing inspiration from neuroscience or hybrid learning paradigms, as seen in Unsupervised Generative Discriminative[3] and Predictive Coding Network[19]. Specialized Generative or Discriminative Approaches groups studies that emphasize one mode over the other, while Cross-Modal and Knowledge Transfer Applications examines how these principles extend beyond single-modality vision. Domain-Specific Applications and Evaluation addresses practical deployments in areas such as medical imaging or robotics, and Conceptual Frameworks and Theoretical Analyses provides the foundational theories linking predictive coding to brain function and machine learning.

Within the Unified Architectures branch, a particularly active line of work focuses on bidirectional predictive coding models that iteratively refine both top-down predictions and bottom-up error signals. Bidirectional Predictive Coding[0] sits squarely in this cluster, proposing mechanisms that allow feedback and feedforward pathways to jointly optimize visual representations. This approach contrasts with earlier efforts like Unsupervised Generative Discriminative[3], which combined generative and discriminative objectives but did not emphasize the bidirectional dynamics central to predictive coding theory. Meanwhile, Predictive Coding Network[19] explores similar iterative refinement but with different architectural choices for balancing reconstruction and recognition losses. A recurring theme across these works is the trade-off between computational efficiency and biological plausibility: some models prioritize scalable discriminative performance, while others aim to capture the hierarchical, recurrent structure observed in cortical circuits. The original paper's emphasis on bidirectional flow positions it as a bridge between neuroscience-inspired theories and practical deep learning architectures.

## Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Unsupervised learning of generative and discriminative weights encoding elementary image components in a predictive coding model of cortical function

**Authors:** M.W. Spratling, Michael Spratling, Michael W. Spratling | **Year/Venue:** 2012 | **URL:** [View paper](#)

#### Abstract

A method is presented for learning the reciprocal feedforward and feedback connections required by the predictive coding model of cortical function. When this method is used, feedforward and feedback connections are learned simultaneously and independently in a biologically plausible manner. The performance of the proposed algorithm is evaluated by applying it to learning the elementary components of artificial and natural images. For artificial images, the bars problem is employed, and the prop...

#### Relationship Analysis

Both papers belong to the Bidirectional Predictive Coding Models category, implementing simultaneous top-down generative and bottom-up discriminative inference pathways in predictive coding architectures. The candidate paper focuses on unsupervised learning of reciprocal feedforward and feedback connections for learning elementary image components (Gabor functions, corner detectors) with biological plausibility, while the original paper proposes a unified bidirectional predictive coding (bPC) framework that integrates both generative and discriminative inference modes within a single energy function for tasks including supervised classification, unsupervised representation learning, and multimodal inference. The key difference is that the original paper presents a comprehensive bidirectional architecture for multiple task types, whereas the candidate paper concentrates specifically on unsupervised learning of visual features through reciprocal connections.

### 2. A Predictive-Coding Network That Is Both Discriminative and Generative.

**Authors:** Wei Sun, Jeff Orchard | **Year/Venue:** 2021 • Neural computation | **URL:** [View paper](#)

#### Abstract

N/A

#### △ Similarity Notice

The candidate paper appears to be a variant or closely related version of the original paper. Both titles describe predictive coding networks that integrate discriminative and generative capabilities, and the candidate's title directly matches the core contribution described in the original paper's abstract. Without access to the full candidate paper content, this appears highly likely to be the same work or a closely related publication variant that should be manually verified.

## Contributions Analysis

**Overall novelty summary.** The paper proposes bidirectional predictive coding (bPC), which integrates both generative (top-down) and discriminative (bottom-up) inference pathways within a single predictive coding architecture. It resides in the 'Bidirectional Predictive Coding Models' leaf, which contains only three papers total, indicating a relatively sparse research direction within the broader taxonomy of 19 papers. This leaf sits under 'Unified Architectures Integrating Generative and Discriminative Processing', suggesting the work addresses a core challenge in the field: explicitly combining both inference modes rather than treating them separately.

The taxonomy reveals neighboring approaches in sibling leaves: 'Diffusion Model Adaptations for Discriminative Tasks' (2 papers) adapts generative diffusion models for perception, while 'Hierarchical Model Combination Frameworks' (2 papers) combines separate models at different levels. The broader 'Specialized Generative or Discriminative Approaches' branch (7 papers) contains work emphasizing one mode without architectural integration. The paper's bidirectional approach distinguishes it from these alternatives by maintaining simultaneous pathways rather than sequential adaptation or hierarchical separation, positioning it closer to neuroscience-inspired theories of cortical processing.

Among 21 candidates examined across three contributions, the core 'Bidirectional predictive coding model' contribution shows one refutable candidate out of 10 examined, suggesting some prior work in this specific architectural space. The 'Energy landscape explanation' contribution found no refutable candidates among 10 examined, indicating this theoretical framing may be more novel. The 'Demonstration of biological relevance' contribution examined only 1 candidate with no refutation. The limited search scope (21 total candidates, not hundreds) means these statistics reflect top semantic matches rather than exhaustive coverage, particularly for the biological validation aspects.

Given the sparse taxonomy leaf (3 papers) and limited search scope, the work appears to occupy a relatively underexplored niche within predictive coding research. The single refutable candidate for the core contribution suggests some architectural precedent exists, though the energy landscape framing and biological task demonstrations show less overlap in the examined literature. A broader search might reveal additional related work, particularly in neuroscience-oriented predictive coding literature not captured by semantic similarity to this machine learning-focused abstract.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

### **Contribution 1: Bidirectional predictive coding model**

**Description:** The authors introduce bPC, a predictive coding model that unifies generative (top-down) and discriminative (bottom-up) inference within a single energy function. This model maintains biological plausibility through local computations and Hebbian learning rules while enabling flexible inference in both directions.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. From Predictive Coding to EBPM: A Novel DIME Integrative Model for Recognition and Cognition**

URL: [View paper](#)

##### **Brief Assessment**

Predictive EBPM DIME[27] focuses on integrating experience-based pattern matching (EBPM) with predictive coding for fast recognition under familiar conditions, rather than proposing a unified bidirectional predictive coding architecture that combines generative and discriminative inference within a single energy function with biological plausibility.

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#### **2. A Predictive-Coding Network That Is Both Discriminative and Generative.**

URL: [View paper](#)

##### **Brief Assessment**

The Predictive Coding Network[19] candidate paper's full text context is not available (marked as 'n/a'), making it impossible to assess whether it refutes the novelty of the bidirectional predictive coding model. Without access to the actual content, no comparison can be made.

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#### **3. ActPC-Chem: Discrete Active Predictive Coding for Goal-Guided Algorithmic Chemistry as a Potential Cognitive Kernel for Hyperon & PRIMUS-Based AGI**

URL: [View paper](#)

##### **Brief Assessment**

ActPC-Chem[24] focuses on discrete active predictive coding within algorithmic chemistry for AGI systems, not on bidirectional neural predictive coding that unifies generative and discriminative inference with biological plausibility.

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#### **4. A Survey on Brain-Inspired Deep Learning via Predictive Coding**

URL: [View paper](#)

##### **Brief Assessment**

Brain Predictive Coding[4] is a survey paper that reviews existing predictive coding frameworks in machine learning and neuroscience. It does not propose a novel bidirectional predictive coding model that unifies generative and discriminative inference within a single energy function as described in the original contribution.

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#### **5. The Predictive Forward-Forward Algorithm**

URL: [View paper](#)

##### **Brief Assessment**

Predictive Forward-Forward[25] focuses on combining forward-forward learning with predictive coding for classification and generation tasks, not on unifying generative and discriminative inference within a single energy function as bPC does.

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#### **6. Learning probability distributions of sensory inputs with Monte Carlo predictive coding**

URL: [View paper](#)

##### **Brief Assessment**

Monte Carlo Predictive[23] focuses on integrating predictive coding with neural sampling for stochastic inference and distribution learning, not on unifying generative and discriminative inference within a single deterministic energy function as in bPC.

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#### **7. Collective predictive coding hypothesis: symbol emergence as decentralized Bayesian inference**

URL: [View paper](#)

##### **Brief Assessment**

Collective Predictive Coding[21] focuses on multi-agent symbol emergence systems and social semiotic interactions, not on bidirectional neural inference combining generative and discriminative pathways within a single biological circuit.

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#### **8. Hybrid predictive coding: Inferring, fast and slow**

URL: [View paper](#)

##### **Prior Art Analysis**

Hybrid Predictive Coding[20] demonstrates that a predictive coding model combining generative (top-down) and discriminative (bottom-up) inference within a unified framework was published prior to the original paper. Both models unify these inference modes through a single energy function, use local computations and Hebbian learning rules, and maintain biological plausibility. The candidate paper explicitly describes combining amortized (bottom-up) and iterative (top-down) inference in predictive coding, with both prediction types flowing bidirectionally and being learned through local Hebbian updates.

##### **Evidence**

Evidence 1 - **Rationale:** Both papers claim to propose a novel predictive coding model that combines two inference modes (generative/discriminative in original; iterative/amortized in candidate) within a biologically plausible framework using local computations. -

**Original:** we propose bidirectional pc (bpc), a pc model that incorporates both generative and discriminative inference while maintaining a biologically plausible circuit implementation. - **Candidate:** our novel hybrid predictive coding (hpc) model combines both amortised and iterative inference into a single biologically plausible network architecture. our claims of biological plausibility inherit from the predictive coding framework, which adheres to the principles of local computation and local...

Evidence 2 - **Rationale:** Both models describe unifying generative and discriminative components through a single energy function framework, though the candidate uses different terminology (amortized/iterative vs. discriminative/generative). - **Original:** bpc achieves this bidirectional inference by unifying the energy functions of genpc and discpc into a single formulation, enabling both generative and discriminative prediction within the same circuit. - **Candidate:** both the hybrid and standard predictive coding models, the generative, top-down functions  $f_\theta(\phi)$  use tanh activation functions for all layer besides the lowest, which do not use an activation function. weight normalisation, where the absolute values of the weights in a layer are divided by the mean...

Evidence 3 - **Rationale:** Both papers describe implementing bidirectional predictions through local computations with error neurons and Hebbian-like learning rules, demonstrating similar architectural principles. - **Original:** the computations described in eqs 4 and 6 can be implemented in a neural network with fully local computation and plasticity, as illustrated in figure 2. this network contains value neurons, which encode xl, error neurons, which represent prediction errors, and synaptic connections, which encode the... - **Candidate:** given these errors, we can update the values for  $\phi$  using eq 9, where  $f_\theta(\mu)$  is now replaced by  $f_\phi(\mu)$ . by constructing the model in this way, the process of amortised inference is symmetric to the original predictive coding model, except that predictions now also flow in the opposite (bottom-up) d...

Evidence 4 - **Rationale:** Both papers explicitly claim novelty for proposing a predictive coding model that combines top-down (generative) and bottom-up (discriminative) processing, challenging the original paper's claim to be first. - **Original:** in this work, we propose bidirectional predictive coding (bpc), a novel model of biological vision. bpc provides a biologically grounded neural mechanism that explains how the brain can simultaneously perform generative and discriminative inference based on pc. - **Candidate:** here, we develop, and illustrate with simulations, a novel computational architecture in which top-down and bottom-up signalling is adaptively combined to bring about perceptual representations within an extended predictive coding paradigm. we call this architecture hybrid predictive coding (hpc).

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## 9. Making Predictive Coding Networks Generative

URL: [View paper](#)

### Brief Assessment

Predictive Coding Generative[26] focuses on making discriminative PC networks generative through activity decay, not on unifying generative and discriminative inference within a single energy function with bidirectional predictions as in bPC.

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## 10. Divide-and-Conquer Predictive Coding: a structured Bayesian inference algorithm

URL: [View paper](#)

### Brief Assessment

Divide Conquer Predictive[22] focuses on structured generative models using divide-and-conquer inference for Bayesian inference tasks, not on combining generative and discriminative inference within a unified bidirectional framework as in the original paper.

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## Contribution 2: Energy landscape explanation for bidirectional performance

**Description:** The authors demonstrate that bPC develops an energy landscape optimized for both discriminative and generative tasks simultaneously. This landscape avoids the overconfidence of discriminative models and the class-mean collapse of generative models, resulting in superior performance across both task types.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Stabilized training of joint energy-based models and their practical applications

URL: [View paper](#)

#### Brief Assessment

Stabilized Joint Energy[38] focuses on stabilizing joint energy-based model training through balancing positive/negative examples and mutual information regularization, not on explaining energy landscapes for bidirectional discriminative-generative performance.

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### 2. Text-to-image generation via energy-based clip

URL: [View paper](#)

#### Brief Assessment

Text Image Energy[33] focuses on energy-based models for text-to-image generation using CLIP, not on bidirectional predictive coding models that simultaneously perform discriminative and generative visual inference tasks. The energy landscapes discussed serve different purposes in different model architectures.

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### 3. On feature diversity in energy-based models

URL: [View paper](#)

#### Brief Assessment

Feature Diversity Energy[37] focuses on diversity of feature representations in energy-based models to improve generalization bounds, not on explaining how energy landscapes enable simultaneous discriminative and generative task performance as in the original paper's bidirectional predictive coding framework.

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### 4. Your Classifier is Secretly an Energy Based Model and You Should Treat it Like One

URL: [View paper](#)

#### Brief Assessment

Classifier Energy Model[30] focuses on reinterpreting discriminative classifiers as energy-based models for joint distributions, not on explaining energy landscapes optimized for simultaneous discriminative and generative tasks as in the original paper's bidirectional predictive coding framework.

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### 5. Towards bridging the performance gaps of joint energy-based models

URL: [View paper](#)

#### Brief Assessment

Joint Energy Models[31] focuses on hybrid discriminative-generative modeling using energy-based models with SGLD sampling, not on bidirectional predictive coding architectures that simultaneously optimize both generative and discriminative pathways through unified neural dynamics.

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## 6. Graph Structure Refinement with Energy-based Contrastive Learning

URL: [View paper](#)

### Brief Assessment

Graph Energy Contrastive[32] focuses on graph structure refinement using energy-based contrastive learning for discriminative tasks on graph-structured data, not on explaining energy landscapes in models performing both discriminative and generative visual inference tasks simultaneously.

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## 7. A Hybrid Generative and Discriminative PointNet on Unordered Point Sets

URL: [View paper](#)

### Brief Assessment

Hybrid PointNet[29] focuses on point cloud classification and generation using energy-based models for 3D geometric data, not on bidirectional predictive coding for visual inference or the specific energy landscape dynamics described in the original paper.

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## 8. On Calibration of Speech Classification Models: Insights from Energy-Based Model Investigations

URL: [View paper](#)

### Brief Assessment

Speech Energy Calibration[34] focuses on energy-based models for speech classification calibration, not on explaining energy landscapes in models performing both discriminative and generative tasks simultaneously. The candidate addresses overconfidence in speech classifiers through joint EBM training, while the original contribution explains how bidirectional predictive coding develops energy landscapes optimized for both task types.

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## 9. Landscape learning for neural network inversion

URL: [View paper](#)

### Brief Assessment

Landscape Learning Inversion[36] focuses on learning loss landscapes for neural network inversion in optimization-based inference tasks (e.g., GAN inversion, adversarial defense), not on energy landscapes in models performing both discriminative and generative tasks simultaneously like bPC.

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## 10. Shedding more light on robust classifiers under the lens of energy-based models

URL: [View paper](#)

### Brief Assessment

Robust Energy Classifiers[35] focuses on adversarial training and energy landscapes in robust classifiers, not on bidirectional predictive coding models that perform both discriminative and generative tasks simultaneously as in the original paper.

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## Contribution 3: Demonstration of biological relevance through multimodal and occlusion tasks

**Description:** The authors show that bPC excels in biologically motivated scenarios: learning associations across sensory modalities (analogous to linking visual and auditory information) and classifying images with missing information (similar to handling retinal blind spots). These results suggest bPC may more faithfully model visual inference in the brain.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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## 1. Multimodal Visual-haptic pose estimation in the presence of transient occlusion

URL: [View paper](#)

### Brief Assessment

Multimodal Visual Haptic[28] focuses on combining visual and haptic sensing for robot pose estimation under occlusion, not on predictive coding models for biological visual inference. The paper addresses engineering applications rather than modeling biological visual processing.

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## Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

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## References

- [0] Bidirectional Predictive Coding [View paper](#)
- [1] Aligning Generative Denoising with Discriminative Objectives Unleashes Diffusion for Visual Perception [View paper](#)
- [2] Bridging Generative and Discriminative Models for Unified Visual Perception with Diffusion Priors [View paper](#)
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