

Novelty Assessment Report

Paper: Spatially Informed Autoencoders for Interpretable Visual Representation Learning

PDF URL: <https://openreview.net/pdf?id=09YSBymX6O>

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Abstract

We introduce spatially informed variational autoencoders (SI-VAE) as self-supervised deep-learning models that use stochastic point processes to predict spatial organization patterns from images. Existing approaches to learning visual representations based on variational autoencoders (VAE) struggle to capture spatial correlations between objects or events, focusing instead on pixel intensities. We address this limitation by incorporating a point-process likelihood, derived from the Papangelou conditional intensity, as a self-supervision target. This results in a hybrid model that learns statistically interpretable representations of spatial localization patterns and enables zero-shot conditional simulation directly from images. Experiments with synthetic images show that SI-VAE improve the classification accuracy of attractive, repulsive, and uncorrelated point patterns from 48% (VAE) to over 80% in the worst case and 90% in the best case, while generalizing to unseen data. We apply SI-VAE to a real-world microscopy data set, demonstrating its use for studying the spatial organization of proteins in human cells and for using the representations in downstream statistical analysis.

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: **Learning Interpretable Representations of Spatial Point Patterns from Images**

A total of **50 papers** were analyzed and organized into a taxonomy with **16 categories**.

Taxonomy Overview

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

- **Spatial Point Process Modeling and Statistical Analysis**
- **Feature Extraction and Representation Learning**
- **Explainable and Interpretable AI for Visual Data**
- **Spatial and Multimodal Data Integration**
- **Object and Structure Detection**
- **Specialized Applications and Signal Processing**

Complete Taxonomy Tree

- Learning Interpretable Representations of Spatial Point Patterns from Images Survey Taxonomy
- Spatial Point Process Modeling and Statistical Analysis
 - Point Process-Based Representation Learning ★ (2 papers)
 - [0] Spatially Informed Autoencoders for Interpretable Visual Representation Learning (Anon et al., 2026) [View paper](#)
 - [50] Statistical Comparison of Spatial Point Patterns in Biological Imaging (Jasmine Burguet, 2014) [View paper](#)
 - Spatial Pattern Recognition and Classification (2 papers)
 - [36] Spatial pattern templates for recognition of objects with regular structure (R TyleÅłek, 2013) [View paper](#)
 - [39] Point Pattern Feature-Based Anomaly Detection for Manufacturing Defects, in the Random Finite Set Framework (Ammar Mansoor Kamoona, 2021) [View paper](#)
- Feature Extraction and Representation Learning
 - Local Feature Detection and Description
 - Keypoint Detection and Matching (8 papers)
 - [18] Reinforced feature points: Optimizing feature detection and description for a high-level task (Bhowmik, 2020) [View paper](#)
 - [20] Image Feature Information Extraction for Interest Point Detection: A Comprehensive Review (Junfeng Jing, 2022) [View paper](#)
 - [21] A review of point feature based medical image registration (Tian-Miao Wang, 2018) [View paper](#)
 - [24] Perceptual image hashing via feature points: performance evaluation and tradeoffs (V. Monga, 2006) [View paper](#)
 - [25] Discriminative feature-to-point matching in image-based localization (Michael Donoser, 2014) [View paper](#)
 - [26] A review of keypoints' detection and feature description in image registration (Cuiyin Liu, 2021) [View paper](#)
 - [27] Research on Feature Point Extraction Algorithm for Drone Images (Maomei Wang, 2025) [View paper](#)
 - [31] Feature Point Extraction for Extra-Affine Image (Wang Tao, 2025) [View paper](#)
 - Feature Point-Based Biometric and Pattern Recognition (4 papers)
 - [28] Facial feature detection and face recognition from 2D and 3D images (Yingjie Wang, 2002) [View paper](#)
 - [33] Two novel characteristics in palmprint verification: datum point invariance and line feature matching (Dapeng Zhang, 1999) [View paper](#)
 - [37] Real-time recognition of cattle using animal biometrics (Santosh Kumar, 2017) [View paper](#)
 - [45] Fingerprint Pattern Feature Extraction for Loop Fingerprint Pattern Identification by Zhang-Suen and Stentiford Thinning Method (Alif Fakhriana, 2024) [View paper](#)
 - Texture and Pattern Feature Extraction (7 papers)
 - [6] Texture feature extraction methods: A survey (Anne Humeau-Heurtier, 2019) [View paper](#)

- [19] Traditional Pattern Feature Extraction and Cultural Creative Design Application Based on Multilevel Histogram Shape Segmentation (Xin Liang, 2022) [View paper](#)
- [22] A survey of shape feature extraction techniques (Y Mingqiang, 2008) [View paper](#)
- [29] New Feature Extraction for Wood Species Recognition System via Statistical Properties of Line Distribution (Hafizza Abdul Ghapar, 2021) [View paper](#)
- [41] DNA-CBIR: DNA Translation Inspired Codon Pattern-Based Deep Image Feature Extraction for Content-Based Image Retrieval. (Jitesh Pradhan, 2025) [View paper](#)
- [44] Pattern recognition using invariants defined from higher order spectra: 2-D image inputs (V Chandran, 1997) [View paper](#)
- [46] An Improved Pairwise Rotation Invariant Co-occurrence Local Binary Pattern Method for Texture Feature Extraction (Guangshuai Liu, 2019) [View paper](#)
- Deep Learned Representations and Embeddings (4 papers)
- [14] CNNs are explainable domain-specific visual embedders (Z Ostrovsky, 2025) [View paper](#)
- [30] Explainable semantic space by grounding language to vision with cross-modal contrastive learning (Yizhen Zhang, 2021) [View paper](#)
- [34] Encoding visual attributes in capsules for explainable medical diagnoses (LaLonde, 2020) [View paper](#)
- [35] Point to set similarity based deep feature learning for person re-identification (Sanping Zhou, 2017) [View paper](#)
- Explainable and Interpretable AI for Visual Data
 - Explainable Deep Learning for Images (4 papers)
 - [1] ASAP: Interpretable Analysis and Summarization of AI-generated Image Patterns at Scale (Huang, 2024) [View paper](#)
 - [12] Understanding Spatial Context in Convolutional Neural Networks using Explainable Methods: Application to Interpretable GREMLIN (Kyle A. Hilburn, 2023) [View paper](#)
 - [23] Interpretable socioeconomic status inference from aerial imagery through urban patterns (Jacob Levy Abitbol, 2020) [View paper](#)
 - [38] Analyzing and interpreting convolutional neural networks using latent space topology (Clara I. Lpez-Gonzlez, 2024) [View paper](#)
 - Explainable 3D and Point Cloud Analysis (3 papers)
 - [5] From 3D point cloud data to explainable geometric deep learning: State of the art and future challenges (Anna Saranti, 2024) [View paper](#)
 - [10] ExMeshCNN: An Explainable Convolutional Neural Network Architecture for 3D Shape Analysis (Seonggyeom Kim, 2022) [View paper](#)
 - [11] Bubbles: An explainable deep learning framework for point-cloud classification (Francesca Matrone, 2022) [View paper](#)
 - Explainable Multimodal and Domain-Specific Models (3 papers)
 - [2] DASS Good: Explainable Data Mining of Spatial Cohort Data (A. Wentzel, 2023) [View paper](#)
 - [7] Explainable AI for multivariate time series pattern exploration: Latent space visual analytics with temporal fusion transformer and variational autoencoders in power $\hat{\rho}$ (H Xu, 2025) [View paper](#)
 - [8] eMCI: An Explainable Multimodal Correlation Integration Model for Unveiling Spatial Transcriptomics and Intercellular Signaling (Renhao Hong, 2024) [View paper](#)
- Spatial and Multimodal Data Integration
 - Vision-Language and Spatial Reasoning (1 papers)
 - [4] SSR: Enhancing Depth Perception in Vision-Language Models via Rationale-Guided Spatial Reasoning (Liu Yang, 2025) [View paper](#)
 - Spatial Transcriptomics and Biomedical Imaging (2 papers)
 - [3] Multimodal contrastive learning for spatial gene expression prediction using histology images (Shi, 2024) [View paper](#)
 - [32] PointFISH -- learning point cloud representations for RNA localization patterns (Imbert, 2023) [View paper](#)
 - 2D-3D Cross-Domain Feature Learning (2 papers)
 - [15] 2D3D-MVPNet: Learning cross-domain feature descriptors for 2D-3D matching based on multi-view projections of point clouds (Baiqi Lai, 2022) [View paper](#)
 - [40] Extracting Traffic Signage by Combining Point Clouds and Images. (Furao Zhang, 2023) [View paper](#)
- Object and Structure Detection
 - Scene Segmentation and Perceptual Organization (3 papers)
 - [43] Recognition-by-components: a theory of human image understanding. (Irving Biederman, 1987) [View paper](#)
 - [48] Image segmentation feature selection and pattern classification for mammographic microcalcifications (Jachih Fu, 2005) [View paper](#)
 - [49] Perceptual organization for scene segmentation and description (Rakesh Mohan, 1992) [View paper](#)
 - Object Class Detection and Recognition (1 papers)
 - [47] Object class detection using local image features and point pattern matching constellation search (Alexander Drobchenko, 2007) [View paper](#)
- Specialized Applications and Signal Processing
 - Fault Diagnosis and Signal-to-Image Conversion (2 papers)
 - [16] Fault Diagnosis of Rolling Bearing Based on Variational Mode Decomposition and Improved Canberra Distance in Symmetrized Dot Pattern Image (Wei Wang, 2023) [View paper](#)
 - [17] Intelligent rolling bearing fault diagnosis method using symmetrized dot pattern images and CBAM-DRN (Wei Cui, 2022) [View paper](#)
 - Infrared and Specialized Imaging (3 papers)
 - [9] Retinomorph Machine Vision in a Network Laser (Ng Wai Kit, 2024) [View paper](#)
 - [13] The Intelligent Human-Computer Interaction Method for Application Software of Electrical Energy Metering Based on Deep Learning Algorithm (Weijie Zeng, 2023) [View paper](#)
 - [42] Real-time scene-based nonuniformity correction using feature pattern matching (SeongGyo Seo, 2021) [View paper](#)

Narrative

Core task: learning interpretable representations of spatial point patterns from images. The field encompasses a diverse set of approaches organized into six main branches. Spatial Point Process Modeling and Statistical Analysis focuses on probabilistic frameworks and point process theory to capture spatial dependencies, often drawing on classical methods like Spatial Point Patterns[50] and extending them with modern representation learning. Feature Extraction and Representation Learning emphasizes extracting meaningful descriptors from images, ranging from traditional keypoint detectors (Keypoints Detection Review[26]) to deep embeddings

that preserve geometric structure (Geometric Deep Learning[5]). Explainable and Interpretable AI for Visual Data addresses the need for transparency in learned representations, with works like Explainable Semantic Space[30] and Explainable Multivariate Timeseries[7] developing methods to make latent codes human-understandable. Spatial and Multimodal Data Integration combines information across modalities and spatial scales, as seen in Multimodal Contrastive Spatial[3] and SSR Spatial Reasoning[4]. Object and Structure Detection targets localization and recognition tasks, while Specialized Applications and Signal Processing covers domain-specific challenges in medical imaging, remote sensing, and other areas.

Several active lines of work reveal key trade-offs between statistical rigor and representational flexibility. Classical point process methods offer strong theoretical guarantees but may struggle with high-dimensional visual data, whereas deep learning approaches excel at capturing complex patterns yet often lack interpretability. Spatially Informed Autoencoders[0] sits within the Point Process-Based Representation Learning cluster, bridging these perspectives by embedding spatial statistical principles directly into neural architectures. This contrasts with purely data-driven methods like ASAP[1], which prioritize predictive performance, and with multimodal frameworks such as Multimodal Contrastive Spatial[3], which integrate heterogeneous data sources. The original work's emphasis on interpretability aligns it closely with efforts to make learned representations transparent and statistically grounded, addressing a central challenge in applying modern machine learning to spatial data analysis where domain experts require both accuracy and insight into the underlying spatial processes.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Statistical Comparison of Spatial Point Patterns in Biological Imaging

Authors: Jasmine Burguet, Philippe Andrey, J. Burguet, P. Andrey | **Year/Venue:** 2014 • PLoS ONE | **URL:** [View paper](#)

Abstract

In biological systems, functions and spatial organizations are closely related. Spatial data in biology frequently consist of, or can be assimilated to, sets of points. An important goal in the quantitative analysis of such data is the evaluation and localization of differences in spatial distributions between groups. Because of experimental replications, achieving this goal requires comparing collections of point sets, a noticeably challenging issue for which no method has been proposed to date...

Relationship Analysis

Both papers belong to the Point Process-Based Representation Learning category, incorporating spatial statistical methods for analyzing point patterns. The original paper (SI-VAE) focuses on learning deep representations from images using point process likelihoods as self-supervision targets for interpretable feature extraction, while the candidate paper addresses statistical comparison of spatial point patterns across experimental replicates using intensity-based hypothesis testing. The key difference is that SI-VAE learns latent representations for downstream tasks, whereas the candidate paper provides a statistical testing framework for comparing existing point patterns between groups.

Contributions Analysis

Overall novelty summary. The paper introduces SI-VAE, a hybrid model combining variational autoencoders with point-process likelihoods to learn interpretable representations of spatial organization patterns from images. It resides in the Point Process-Based Representation Learning leaf, which contains only two papers total (including this one and one sibling). This represents a notably sparse research direction within the broader taxonomy of 50 papers across 36 topics, suggesting the specific combination of VAEs with point-process statistical frameworks for image-based spatial pattern learning is relatively unexplored.

The taxonomy reveals that most related work falls into adjacent branches rather than the same leaf. The sibling paper in this leaf takes a different approach, while neighboring leaves like Spatial Pattern Recognition and Classification focus on detection and comparison rather than representation learning. The broader Spatial Point Process Modeling branch emphasizes statistical frameworks, contrasting with the Feature Extraction and Representation Learning branch where deep learned embeddings dominate but lack explicit spatial statistical modeling. SI-VAE bridges these traditionally separate domains by embedding Papangelou conditional intensity into a neural architecture.

Among 20 candidates examined across three contributions, zero refutable pairs were identified. The core SI-VAE contribution examined 10 candidates with none providing clear prior overlap, and the hybrid probabilistic model contribution similarly found no refutations among 10 candidates. The point-process likelihood as self-supervision target was not matched against specific candidates. These statistics reflect a limited semantic search scope rather than exhaustive coverage, but suggest that within the examined literature, the specific integration of point-process likelihoods into VAE architectures for spatial pattern learning appears relatively novel.

Based on the top-20 semantic matches examined, the work appears to occupy a distinct position combining statistical spatial modeling with deep representation learning. The sparse population of its taxonomy leaf and absence of clear prior overlap in the limited search suggest novelty, though the analysis cannot rule out relevant work outside the examined candidates or in adjacent fields like spatial statistics or computational biology that may not have surfaced in image-focused semantic search.

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

Contribution 1: Spatially informed variational autoencoders (SI-VAE)

Description: The authors propose a novel self-supervised deep-learning architecture that augments variational autoencoders with spatial point-process likelihoods derived from the Papangelou conditional intensity. This enables learning statistically interpretable representations of spatial localization patterns and zero-shot conditional simulation directly from images.

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.

1. Explainable AI for multivariate time series pattern exploration: Latent space visual analytics with temporal fusion transformer and variational autoencoders in power $\hat{\alpha}$

URL: [View paper](#)

Brief Assessment

Explainable Multivariate Timeseries[7] focuses on temporal fusion transformers for multivariate time series pattern exploration in power systems, not spatial point process modeling with VAEs for image-based spatial organization patterns.

2. Geophysical inversion using a variational autoencoder to model an assembled spatial prior uncertainty

URL: [View paper](#)

Brief Assessment

Variational Autoencoder Geophysical[52] applies VAEs to geophysical inversion for subsurface spatial patterns in crosshole GPR data, not to learning spatial point process representations from microscopy images. The technical domains and objectives are fundamentally different.

3. A variational auto-encoder model for stochastic point processes

URL: [View paper](#)

Brief Assessment

Variational Point Processes[53] focuses on modeling temporal point processes for asynchronous action sequences in videos, not spatial organization patterns in images. The candidate uses VAE for temporal event prediction (action categories and inter-arrival times), while the original proposes spatial point-process likelihoods for learning spatial localization patterns from images.

4. Practical synthetic human trajectories generation based on variational point processes

URL: [View paper](#)

Brief Assessment

Synthetic Trajectories Generation[56] focuses on generating human mobility trajectories using VAEs to model user distributions and temporal patterns. The original paper proposes SI-VAE for learning spatial organization patterns of point-like objects in images using point-process likelihoods, which is a fundamentally different application domain and technical approach.

5. Variational Autoencoders for Highly Multivariate Spatial Point Processes Intensities

URL: [View paper](#)

Brief Assessment

Multivariate Spatial Intensities[58] focuses on modeling highly multivariate spatial point process intensities using VAEs, but no full text is provided to assess whether it addresses the same self-supervised learning framework with Papangelou conditional intensity for visual representation learning from images.

6. Markovian gaussian process variational autoencoders

URL: [View paper](#)

Brief Assessment

Markovian Gaussian Process[57] focuses on temporal/spatiotemporal modeling using Gaussian processes with Kalman filtering for time series data, not on spatial point-process likelihoods for learning spatial organization patterns from images.

7. Latent variable model for high-dimensional point process with structured missingness

URL: [View paper](#)

Brief Assessment

Latent Variable Missingness[51] focuses on temporal point processes for longitudinal data with structured missingness patterns, not spatial point processes for visual representation learning. The candidate uses Gaussian processes to model temporal correlations and observation time points, while the original paper uses spatial point-process likelihoods derived from the Papangelou conditional intensity to learn spatial organization patterns from images. These are fundamentally different application domains and methodological approaches.

8. Point cloud-based variational autoencoder inverse mappers (pc-vaim)-an application on quantum chromodynamics global analysis

URL: [View paper](#)

Brief Assessment

PC-VAIM[54] addresses inverse problems in quantum chromodynamics using point cloud representations of observables, not spatial organization patterns in images. The candidate uses VAE for parameter inference from experimental data, while the original proposes SI-VAE for learning spatial localization patterns from images using point-process likelihoods.

9. Variational autoencoded multivariate spatial Fayâ Herriot models

URL: [View paper](#)

Brief Assessment

Spatial Fay-Herriot[55] addresses small-area estimation using spatial hierarchical models for multivariate survey data, not visual representation learning from images using point processes and VAEs.

10. Deep generative models for spatial networks

URL: [View paper](#)

Brief Assessment

Spatial Networks Generation[59] focuses on spatial networks (graphs with geometric embeddings) using a spatial-network VAE with message passing neural networks for disentanglement. The original paper addresses spatial point processes (discrete stochastic processes) with Papangelou conditional intensity for modeling spatial localization patterns in images. These are fundamentally different problem domains and methodologies.

Contribution 2: Point-process likelihood as self-supervision target

Description: The authors introduce a self-supervision objective based on spatial point-process statistics, specifically using the Papangelou conditional intensity to model spatial correlations between objects or events within images, rather than relying solely on pixel intensities.

This contribution was assessed against **0 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

Contribution 3: Hybrid probabilistic model for images and point processes

Description: The authors develop a hybrid generative model that jointly models images and point processes, providing both interpretable spatial representations and the capability to perform zero-shot conditional simulation of point processes from query images without requiring additional training.

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.

1. Conditional neural field latent diffusion model for generating spatiotemporal turbulence

URL: [View paper](#)

Brief Assessment

Spatiotemporal Turbulence Diffusion[63] focuses on generating turbulent flow fields using conditional neural field latent diffusion models for fluid dynamics applications, not on hybrid models for images and point processes with zero-shot conditional simulation capabilities.

2. Motioncraft: Physics-based zero-shot video generation

URL: [View paper](#)

Brief Assessment

MotionCraft[62] focuses on video generation using physics-based optical flow warping in diffusion model latent spaces, not on modeling joint distributions of images and point processes for spatial pattern analysis.

3. Pointad: Comprehending 3d anomalies from points and pixels for zero-shot 3d anomaly detection

URL: [View paper](#)

Brief Assessment

PointAD[61] focuses on zero-shot 3D anomaly detection using point clouds and 2D renderings, not on joint modeling of images and point processes for spatial pattern analysis.

4. Spatio-temporal energy-guided diffusion model for zero-shot video synthesis and editing

URL: [View paper](#)

Brief Assessment

Spatio-temporal Energy Diffusion[65] focuses on video synthesis and editing using energy-guided diffusion models across diverse conditioning modalities (text, pose, depth, etc.). It does not address hybrid generative models that jointly model images and point processes for spatial organization patterns, nor does it provide zero-shot conditional simulation of point processes from query images.

5. Zero-shot 3D-Aware Trajectory-Guided image-to-video generation via Test-Time Training

URL: [View paper](#)

Brief Assessment

3D-Aware Trajectory Generation[67] focuses on trajectory-guided video generation using test-time training for motion control, not on hybrid generative models for images and point processes with zero-shot conditional simulation capabilities.

6. Spiking Tucker Fusion Transformer for Audio-Visual Zero-Shot Learning

URL: [View paper](#)

Brief Assessment

Spiking Tucker Fusion[69] focuses on audio-visual zero-shot learning using spiking neural networks and transformers, not on modeling images with point processes or zero-shot conditional simulation of spatial patterns.

7. Context-Aware Zero-Shot Anomaly Detection in Surveillance Using Contrastive and Predictive Spatiotemporal Modeling

URL: [View paper](#)

Brief Assessment

Zero-Shot Anomaly Surveillance[66] focuses on surveillance video anomaly detection using contrastive learning and predictive coding for spatiotemporal patterns, not on modeling spatial point processes from static images or enabling zero-shot conditional simulation of point distributions.

8. Motion-decoupled spiking transformer for audio-visual zero-shot learning

URL: [View paper](#)

Brief Assessment

Motion-Decoupled Spiking[68] focuses on audio-visual zero-shot learning using dual-stream architectures for video classification, not on hybrid generative models for images and point processes with spatial statistics.

9. Fresco: Spatial-temporal correspondence for zero-shot video translation

URL: [View paper](#)

Brief Assessment

Fresco[60] focuses on video translation using spatial-temporal correspondence for diffusion models, not on hybrid generative models for images and point processes with zero-shot conditional simulation capabilities.

10. Changen2: Multi-temporal remote sensing generative change foundation model

URL: [View paper](#)

Brief Assessment

Changen2[64] focuses on multi-temporal remote sensing image generation using diffusion models for change detection, not on hybrid models for images and point processes with zero-shot conditional simulation as described in the original paper.

Appendix: Text Similarity Detection

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

References

- [0] Spatially Informed Autoencoders for Interpretable Visual Representation Learning [View paper](#)
- [1] ASAP: Interpretable Analysis and Summarization of AI-generated Image Patterns at Scale [View paper](#)
- [2] DASS Good: Explainable Data Mining of Spatial Cohort Data [View paper](#)
- [3] Multimodal contrastive learning for spatial gene expression prediction using histology images [View paper](#)
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- [11] Bubblex: An explainable deep learning framework for point-cloud classification [View paper](#)

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