MAGIK - A Technical Introduction

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Description of MAGIK

MAGIK is a geometric deep-learning framework for the analysis of biological system dynamics from time-lapse microscopy [1]. MAGIK models the movement and interactions of objects through a directed graph, where nodes represent object detections at a specific time and edges connect nodes that are spatiotemporally close (Figure 1**a**-**b**). In its simplest form, each node contains the object's centroid as a feature, while edges encode the Euclidean distance between the centroids of the connected objects. However, there are no intrinsic restrictions on the type or number of descriptors (e.g., location and morphological features, image-based quantities, biological events, interaction strength, distance, direction) that can be encoded in the graph feature representation.

The framework casts the detection linking task as an edge-classification problem with a binary label (linked/unlinked). The initial graph structure includes a redundant number of edges with respect to the actual associations between objects. MAGIK aims to prune the redundant edges while retaining the true connections. This is achieved using a Message Passing Neural Network that seeks to modulate the associative form between connected nodes by minimizing the binary cross-entropy between the predicted edge probabilities and the ground-truth associations. From the predicted edge probabilities, trajectories are built through a postprocessing algorithm that eliminates spurious connections (Figure 1**c**).

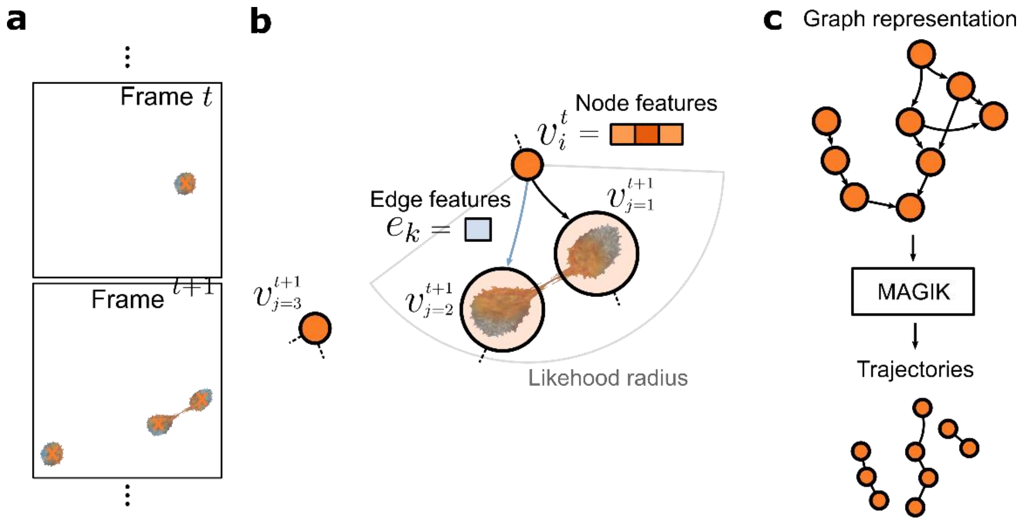

Figure 1. Estimation of spatiotemporal features using MAGIK. a Sequence of images illustrating the evolution of a group of cells over two consecutive frames. **b** The movement and interactions of the objects are modelled geometrically using a directed graph. In this graph, nodes (*v*) represent detections and edges connect spatiotemporally close objects. Each node contains the object's centroid as features. Edges (*e*), in turn, encode Euclidean distance between the centroids of the connecting objects. In this example, the node of interest (labelled with the subindex *i* and located in frame *t*) is connected to neighbouring nodes in frame *t*+1 (labelled with the subindex *j*) within a distance-based likelihood radius. **c** The graph is processed to predict connection probabilities between objects as a binary edge-classification task. The final trajectories are constructed by applying a postprocessing algorithm that eliminates spurious connections based on the predicted edge probabilities.

Execution details

Accompanying this document is a Python Notebook that provide a comprehensive, step-by-step guide on how to train and apply MAGIK for estimating object trajectories in each 2D dataset from the Cell Tracking Challenge. This notebook is designed to be user-friendly and adaptable, ensuring that researchers can modify the code to suit their specific requirements.

The notebook is divided into five sections:

1. **Reading and Viewing the Data**: This section demonstrates how to download datasets directly from the Cell Tracking Challenge webpage. The downloaded data is visualized for verification, allowing users to explore and understand its structure before proceeding.
2. **Graph Construction**: Here, the notebook explains how MAGIK constructs a directed spatiotemporal graph using segmentation maps as input. It details the underlying methodology and implementation, including parameter choices that define the maximum spatial and temporal distances for connecting nodes. Specific parameters used for each dataset are documented, ensuring reproducibility and enabling users to tailor the graph construction process for other datasets if needed.
3. **Dataset Construction**: In this section, a training dataset is created from the spatiotemporal graph. Samples are extracted as sequences of consecutive frames, representing a fraction of the total video duration. The extraction is performed stochastically to ensure diverse and representative samples. Details on the fraction of frames sampled, the duration of sequences, augmentations, and the total number of data points for each dataset are provided.
4. **MAGIK Definition and Training**: This section provides the code necessary to define and train MAGIK, which is implemented as part of the deeplay deep learning package. Users can follow the provided instructions to train the model from scratch using their own datasets. For convenience, an alternative option to load and apply a pre-trained MAGIK model is also included, allowing users to bypass the training process if desired.
5. **Model Evaluation**: The final section focuses on evaluating the performance of the trained MAGIK model. Tools are provided for assessing the quality of predicted connections, visualizing the generated paths, and overlaying these trajectories onto the original video frames. The outputs include visual representations to help users gauge the model's accuracy and effectiveness.

References

[1] Pineda, J., Midtvedt, B., Bachimanchi, H., Noé, S., Midtvedt, D., Volpe, G., & Manzo, C. Geometric deep learning reveals the spatiotemporal features of microscopic motion. *Nature Machine Intelligence,* **5**: 71-82 (2023).