Exploring the Significance of Graphs in Image Processing and Computer Vision Applications

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Graph-based techniques are widely used in image processing and computer vision for tasks such as image recognition, tracking, or traffic flow predictions. These models show interesting performance, but generally omit to detail the usefulness of employing undirected graphs. This study is driven by a pivotal inquiry : What makes graphs compelling for applications in image processing and computer vision ? An important aspect for object recognition pertains to understanding the relationships among various objects within images or videos. As a result, edges on weighted graphs can be characterized as functions of pixel distance and intensity variations. The graph edges represent the probabilistic dependencies between the random variables (nodes) that make up the data in these models. By employing graphs, these models represent complex probability distributions sparsely in high-dimensional spaces. Graphs are utilized in these configurations not just to index the data but also to show relationships, similarities, and dependencies inherent in the data. In image processing and computer vision, graphs represent objects, parts, and spatial relationships between adjacent or far-off pixels, image regions, and features. Therefore, we will first discuss the advantages of transforming image and video data into graphs. To achieve this, we will delineate the information that can be extracted from a pixel region using graphs, contrasting it with the inherent properties of the pixel region. To assess the significance of extracting higher-dimensional data, we will compare Convolutional Neural Network (CNN) based approaches, such as ConvNet-GT and ConvNet-IUTIS [1], to our GraphIMOS [3] approach, based on Graph Convolutional Networks (GCNs) [2], to demonstrate that graphs facilitate improved discrimination between pixel regions for moving object segmentation. Finally, we will present some applications, as well as qualitative and quantitative results.

[1] M. Braham, M. Van Droogenbroeck. *Deep background subtraction with scene-specific convolutional neural networks.* In *2016 international conference on systems, signals and image processing (IWSSIP)*, pp. 1–4. IEEE, 2016.

[2] T. N. Kipf, M. Welling. *Semi-supervised classification with graph convolutional networks.* arXiv preprint arXiv :1609.02907, 2016.

[3] W. Prummel, J. H. Giraldo, A. Zakharova, T. Bouwmans. *Inductive graph neural networks for moving object segmentation.* In *2023 IEEE International Conference on Image Processing (ICIP)*, pp. 2730–2734. IEEE, 2023.

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