Opportunities for graph learning in robotics

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***Abstract*—In the last few years, robotics highly benefited from the use of machine and deep learning to process data stream captured by robots during their tasks. Yet, encoding data in grids (images) or vectors (time-series) significantly limits the type of data that can be processed to euclidean only. To unlock the potential of deep learning also to unstructured data, such as point clouds or functional relations, a rising - yet under-explored - approach lies on the use of graph neural networks (GNNs). With this manuscript, we intend to deliver a brief introduction to GNNs for robotics applications, together with a concise revision of notable applications in the field, with the aim of fostering the use of this learning strategy in a wider context and highlighting potential future research directions.**

***Index Terms*—Graph Neural Networks, Robotics, Deep Learning, Human-Machine Interaction**

I. Introduction

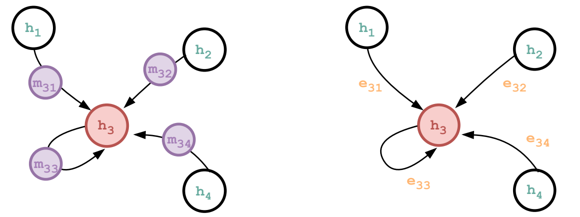
Robotics represent the perfect ultimate application for deep learning methods, where theoretical methods can meet realistic and challenging applications. Recently, in robotic learning has emerged the necessity to use a richer knowledge representation, able to represent three-dimensional data, functional and geometrical representation in contrast to a simple embedding of bi-dimensional or temporal sequence representations. A promising approach, inspired from the signal processing and computer vision communities, rely of graph representations. Graph neural networks are powerful mathematical tools for knowledge representation, able to encode structured and unstructured information through nodes which model entities, and edges that encode their spatial, temporal or functional relationship. In computer vision, learning on graphs has emerged as an effective approach to deal with data lying on irregular domains, such as point clouds [1], [2], to uncover non-local similarities in the data [3], and video understanding [4], [5]. In the last few years, these methods have gained the attention of the robotic community, opening interesting perspectives for novel tasks and applications, ranging from grasping and manipulation, where three-dimensional data are predominant, to robot-object interaction, where graphs can be used to model the environment, the objects and their relationships. Notably, GNNs showed promising results also in the context of reinforcement learning, showing interesting abilities in predicting future states based on current state and action signals. One of the main limitation of deep reinforcement learning is the limited generalisation ability, and GNNs are able to naturally overcome this issue and learn robust policies across scenarios [6]–[8].

II. Preliminaries on Graph Neural Networks

Learning on graph structures has gained significant relevance in the community, thanks to their ability to process data lying on irregular domains, spatio-temporal and functional relationships [9]–[11]. A graph is defined as a set of nodes, the entities of the space under observation, and edges, the connections between nodes. Each node and edge can be associated with a feature vector to encode information about elements and their relationship. GNNs process data represented on graph structures by performing a local share of information, also known as message-passing, in order to update the elements features. A graph convolution operation can be formulated in two different domains, spectral or spatial. The first family of methods [12]–[16] usually exploits graph Fourier transform, eventually complemented with polynomial approximations to reduce the computational burden [14], [15]. Among these, it is worth mentioning the Graph Convolutional Network (GCN) [15], which demonstrated notable results for semi-supervised problems. However, a critical limitation of this formulation is the inability to generalise the learned filters, computed over the spectrum of the graph Laplacian, to a variable graph structure. The second class of approaches defines the graph-convolution operation in the spatial domain. In this case, the graph convolution is defined as a local, i.e. computed over a neighbourhood, weighted aggregation of signals. Since the interaction between nodes is local, this formulation is suitable for any type of signal that can be defined over a graph, even with a variable graph structure. Several definitions have been presented in the literature, among which it is worth mentioning [1], [2], [18]–[24]. Typically, the formulations differ on the computation of the weights used in the aggregation. For a compact overview, the reader is referred to Fig. 1 where we show different graph convolution formulations.

III. Robot applications

We identified two main macro-problems in which GNNs represent a valid learning tools. The first, which we refer to as "Single-Agent Systems", collects cases where the graph is used to model only one intelligent system (single-robot or human), or passive body (objects modelling). One of the most important tasks in this scenario is modelling of bodies. When we interact with an object very likely it will suffer a non-linear deformation, and modelling its dynamic and deformation poses several challenges such as the high-dimensionality of the configuration space, complex dynamic of materials and self-occlusions. One promising approach [25], [26] consists in



$$m_{ij}^{MPNN} = f_e(h_i, h_j, e_{ij})$$
$$\hat{h}_i = f_v(h_i, \sum_{j \in N(i)} m_{ij})$$

$$e_{ij}^{GCN} = \frac{1}{\sqrt{|N(i)|}\sqrt{|N(j)|}}$$
$$e_{ij}^{GAT} = softmax_j(a(\mathbf{W}h_i, \mathbf{W}h_j))$$
$$\hat{h}_i = \sigma(\sum_{j \in N(i)} e_{ij} W h_j)$$

$$e_{ij}^{ECC} = MLP(h_i - h_j)$$
$$\hat{h}_i = \frac{1}{|N(i)|} \sum_{j \in N(i)} e_{ij} h_j$$
$$e_{ij}^{DGCNN} = ReLU(\theta(h_i - h_j) + \phi(h_i))$$
$$\hat{h}_i = max(e_{ij})$$

Fig. 1. Comparison of different information sharing mechanisms. MPNN [17] implements message passing conditioned by edge attributes. GCN [15] implements a simple aggregation of the k-nn nodes. GAT [18] exploits self-attention to weight the contributions of the k-nn. ECC [1] implements an edge-depended weighting function to weight the contribution of each node in the neighbourhood. DGCNN [2] aggregates by means of learned edge features.

describing the body as a collection of keypoints. This approximated representation is suitable to a graph construction, where each keypoint is a node and the edges represent the spatial and kinetic relationships between them, able to describe the dynamic behaviour of the body. Recently, graph-based learning control policies from deformable objects keypoints has gained attention [26]–[31] thanks to their effective low-dimensional representation. One challenge of modelling deformable objects rely on the object connectivity, due to the large number of degree of freedom and self-occlusion. Graphs can easily overcome this issue by directly learning the connectivity from the visual data [32], [33]. Furthermore, graphs represent one of the most suitable choice to process three-dimensional visual data, such as point cloud and meshes, and recently this type of data - especially mesh - have gained attention for particles and keypoints representation, promoting even more the use of GNNs in the context of body modelling [32]–[35]. Similarly to keypoints object representations, graphs can be used to model the robot itself, exploiting the natural discrete graph structure of human, humanoid or animal bodies, where nodes are joints and edges their physical dependencies [36], [37]. Once we have learned how to model robots and objects it is important to learn how to interact safely and effectively with them. Albeit being a research problem for decades [38], [39], in robotic grasping and manipulation several problems are still open, such as learning to interact with objects in motion or in clutter [40]–[42] with partial observability, novel objects and human-robot or multi-robot co-manipulation [43]–[46]. In the last few years, learning for graphs has provided interesting results in tackling many open problems in this field. Graphs can efficiently model the environment and the interaction between objects [47], [48], learn semantic global information to build knowledge graphs [49]–[51] or process unstructured data input [52]–[54]. Graph-based structures have been also profitably used to encode spatial relations in complex scenes, where multiple objects are present and/or the environment is only partially observable [48], [55]–[62].

The second macro-problem we identified refers to the modeling of fleets of intelligent systems (a.k.a. Multi-agent systems). This scenario comes with the additional challenge that an effective coordination and communication between robots is of paramount importance to enable a fruitful cooperation, which is clearly critical for several downstream tasks. Traditionally, this problem has been addressed by exploiting centralised approaches, where all the intelligence and computation complexity is centralised on a common controller node. Such approach has the strong benefits of reasoning on the status of whole set of agents and requiring only little computation on the device. However, it also comes with the limitations of i) a low fault tolerance, and ii) a poor scalability w.r.t. the number of agents [63].To address these issues, decentralised approaches, where each agent learns its set of actions according to environmental data and shared information from other agents, have gained attention. In this configuration, each robot has to deal with limited observability and partial communication, but GNNs offer generalized and flexible structural representations of the elements to face such limitations. Many notable works [64]–[74] focus the attention on the communication between robots and exploit graph encoding to efficiently model inter-agents relationships. Other methods, instead, propose to encode the information related to the environment topology, in the form of waypoints or point-of-interest [6], [7], [75]–[78]. Works as [6], [7], [75] focus on the spatio-temporal relationship between entities in the environment to build a graph, and use GNNs to learn environmental features for the robot. Differently, [76], [77] propose a more comprehensive topological representation where both robots and environments are directly encoded in the graph.

IV. Future Prospectives

After a literature analysis, it is evident how graph-based representations opened interesting research perspectives, such as for the modelling of functional, spatial, or temporal relationships between passive or active elements. Interestingly, we observed an exponential increase in the use of this learning method for robotics applications, which at the moment is consolidated as one of the most prominent for complex tasks. For the field to progress to a higher maturity phase, however, we strongly believe that some aspects still deserve additional work. First, the analysis we performed strongly motivates a more extensive and informed use of graphs as a convenient tool. Yet, it is often used in a naive fashion. Furthermore, graph learning could unlock many novel tasks, going from action recognition to modelling of soft-bodes. We believe that robotics should not only be an harbour for graph learning applications, but also actively contribute in the development of novel techniques that better face real-world problems.

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