LITERATURE REVIEW:
Parallel Beam Search for Functionality Partial Matching

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In the context of 3D shape modeling, functionality partial matching refers to the process of localizing the functionality analysis of 3D shapes from the category/object level down to the patch/part level, which can help today's cross-category shape modeling systems that generate multi-functional shapes to evaluate the functionality of the generated shapes [7]. Specifically, in functionality partial matching, a shape is considered as a connected graph with each node denoting a part of the shape and each edge representing two parts being connected. Thus, functional partial matching can be seen as a graph/tree traversal process that finds out all functionally plausible combinations of parts within a shape. Recently, a functionality partial matching method was proposed based on the beam search [6]. Beam search is a generalized breadth-first search that only expands it's search tree at the most "promising" nodes at each depth level, using a heuristic function. However, the current implementation of functionality partial matching uses a sequential beam search which is unoptimized and time-consuming. Thus, based on the idea of level synchronization [27, 2, 14], similar to a parallel breadth-first search with shared memory, we can develop a parallel beam search to improve the running time of functionality partial matching.

1 Functionality Analysis in 3D Shape Modeling

Analyzing the functionality of 3D shapes [9] is a widely studied area in 3D shape modeling. Existing works on this topic have all focused on characterizing, comparing, or categorizing 3D objects based on their functions, which are typically inferred from their geometry and interactions with other objects or agents [13, 20, 12, 10, 19, 11]. In this work, we utilize the category functionality model developed by Hu et al. [10]. Furthermore, we localize the functionality model to shape parts/part groups instead of directly applying it to an entire object, so as to enable functionality partial matching.

2 Parallel Algorithms for Graph Search

There are basically two types of graph search algorithms, i.e., depth-first search (DFS) and breadth-first search (BFS). For DFS, there has been a rich amount of work on studying its parallel variations, including parallel depth-first search for planar graphs [23, 22, 8], directed acyclic graphs (DAGs) [4, 26, 5, 3, 18], and directed graphs with cycles [1]. For BFS, researches are focused on its implementation for different architectures, e.g., for multi-cores [27, 2, 21, 14], for GPUs [15, 17, 24], and for distributed systems [16, 25]. The key idea of parallelizing a breadth-first search is based on level synchronization [27, 2, 14], where level is defined as the set of leaf nodes that have the same depth to the root node of the search tree. Specifically, level synchronization makes sure that at each iteration only nodes having the same depth level are expanded to the next level.

Our method is based on the beam search, which can be seen as a special form of BFS. So, we follow the idea of level synchronization. However, for a beam search, we also need to store the best nodes to a beam list according to a heuristic function after each expansion of search tree.

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