An Explainable Robotic Perception Framework for Indoor Scene Understanding

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1 Introduction

1.1 Background and Problem Description

The field has witnessed rapid improvements in scene understanding thanks to the introduction of state-of-the-art deep learning methods and ever-improving computational resources. AI with a good scene understanding can be useful in many places. For example, it may help people with visual difficulties by creating an accurate 3D representation of the surrounding environment and providing safe guidance. Also, the recent rise of *"metaverse"* further increases the demand of scene understanding for real-time communication and interaction between its users and the real-world environment [1].

However, 3D scene understanding still remains a very challenging task till this date. This is mainly due to interactions between objects and changes in information across different scenes [2]. Also, there are fundamental differences in the ways humans and machines perceive the environment. Humans are naturally capable of understanding complex relationships between objects and their semantics from an image or a video. However, these are simply a list of numeric values for machines. Therefore, a machine learning agent must be able to extract both geometric and semantic information in order to provide useful knowledge to humans.

The house interior industry may also hugely benefit from the rise of scene understanding. Providing a 3D replica of a real house with editable objects can be hugely attractive to its customers, as they will be able to easily change and customise their houses as wished with low costs in a virtual environment. However, to the best of my knowledge, there has been very little study conducted in this area. Therefore, it will be an interesting and contributable work to develop an entire framework for full indoor perception with robots as a doctorate study.

1.2 Aim, Objectives and Contributions

This research aims to develop a real-time robotics perception framework that constructs a 3D representation of a real-world scene with editable geometric models. The objectives are to:

1. develop a real-time robotic perception and navigation method that captures information from real-world indoor scenes with explainable deep learning methods

2. develop an automated 3D scan to CAD method that uses captured information to reconstruct a scene and convert into editable geometric models with semantic contexts with minimum human interventions

Theoretical and methodological contributions in indoor scene understanding with robotic perception will be made to the relevant field by achieving these objectives.

2 Literature Review

2.1 Perception

2.1.1 Image Classification

A perception framework should perform scene image classification to give the object detection and semantic segmentation models more general and useful information about a scene. Image classification is a basic, yet very important and challenging task for scene understanding. For example, perceived data must be represented with the best method (e.g., point cloud, 3D mesh) to maximise the useful information while minimising the computational complexity. Further, the proposed framework must be able to work well with limited amount of data, 3D deformations and background clutter that occur in the real-world conditions. Socher et al. [3] introduced
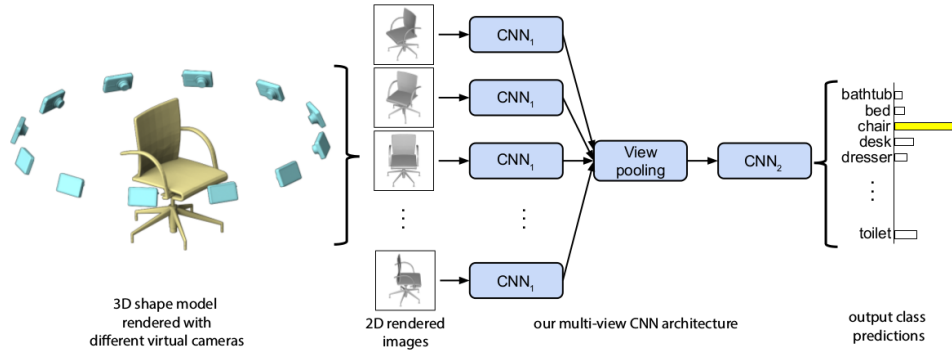
Figure 1: Multi-View CNN proposed by Su et al. [5]

the use of Recurrent Neural Network (RNN) with convolutional layers to extract low and high-level features from the perceived RGB-D data and improve the classification performance. Further, Wu et al. [4] proposed the use of convolutional Deep Belief Network (DBN) that detects patterns from unlabelled data and showed that DBN can be used to learn joint distributions from 3D voxels. The use of convolutional layers reduces the computational costs compared to fully-connected (FC) layers thanks to lower number of parameters from weight sharing.

Su et al. [5] proposed Multi-View CNN (MVCNN) that uses multiple 2D render views of 3D objects for classification, shown in Figure 1. It would be possible to capture multiple images of a 3D object in different views as it is planned to use video-recording robots for perception. Qi et al. [6] argued that MVCNNs perform better than volumetric CNNs due to input resolutions. The 3D representation of an object must be reduced to train a deep learning model in a reasonable timeframe.

Apart from MVCNN, PointNet++ [7] or volumetric CNN with 3D Generative Adversarial Network (GAN) [8] can be considered for image classification. The former uses perceived point cloud directly to obtain high-level features from several small local geometric features, whereas the latter performs unsupervised learning where the features created by GAN are used for classification.

2.1.2 Object Detection

The object detection algorithm in this project must be able to perform "amodal object detection", i.e. to find the location, shape and orientation of an object in a scene. Similar to other detection techniques in the field, the initial object detection approaches were based on handcrafted features [9]. However, the most recent approaches utilise deep neural network based algorithms (e.g.,region proposal generation [10]).

2.1.3 Semantic Segmentation

2.1.4 Object Pose Estimation

2.2 Navigation

2.2.1 Reinforcement Learning

A reinforcement learning (RL) agent can be trained to move safely in an unperceived environment while maximising the amount of perceived data.

2.3 3D Reconstruction

3D scan to CAD

2.4 Datasets

A sufficient amount of labelled images is essential to train a machine learning agent to obtain useful information from perception data. Silberman and Fergus [11] and Li et al. [12], McCormac et al. [13] has improved indoor scene understanding by providing large-scale real and synthetic indoor image datasets, respectively.

2.5 Explainable Learning Methods

3 Research Design and Methodology

3.1 Empirical Materials

3.1.1 Robot Platform

TurtleBot with a RGB-D sensor would be sufficient for perception and navigation tasks planned in this project.

3.1.2 Simulation Environment

Gazebo can be used
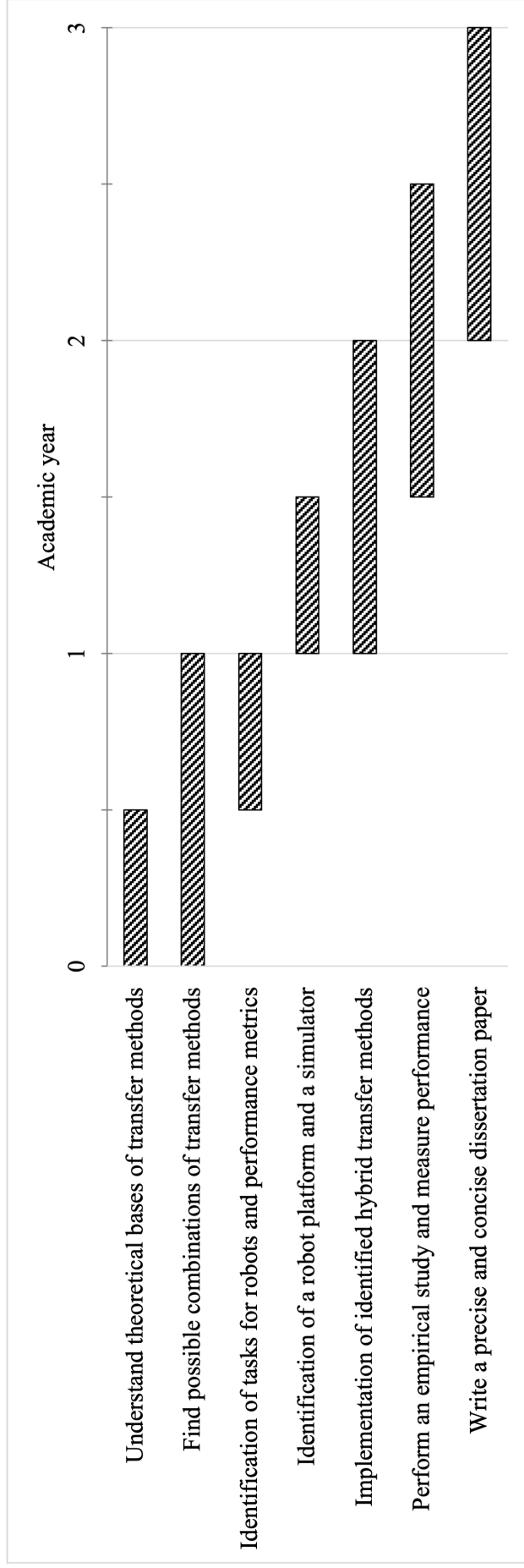
3.2 Research Tasks and Time Allocation

Figure 2: Gantt chart for time allocation of this project.

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