Constructing Dynamic Knowledge Graph for Visual Semantic Understanding and Applications in Autonomous Robotics

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Abstract—Interpreting semantic knowledge describing entities, relations and attributes explicitly with visuals and implicitly with behind-scene common senses gain more attention in autonomous robotics. By incorporating vision and language modeling with common-sense knowledge, we can provide rich features indicating strong semantic meanings for human and robot action relationships, which can be utilized further in autonomous robotic controls. In this paper, we propose a systematic scheme to generate high-conceptual dynamic knowledge graphs representing Entity-Relation-Entity (E-R-E) and Entity-Attribute-Value (E-A-V) knowledges by “watching” a video clip. A combination of Vision-Language model and static ontology tree is used to illustrate workspace, configurations, functions and usages for both human and robot. The proposed method is flexible and well-versed. It will serve as our first positioning investigation for further research in various applications for autonomous robots.

I. INTRODUCTION

Recent advances in computer vision have enabled research in autonomous robots including smart service robots. The core of autonomous robots lies in its capability to semantically understand and process information on demand from a task scene. Semantic understanding for smart robotic control requires the decoding of the visual and literal inputs and the representing of explicit and implicit semantic knowledge, which are still open problems among computer vision, natural language processing and information theory research.

Traditionally, robots are controlled on motion paths pre-defined by coordinate-based programming or teach-in demonstration modules. Robots present smarter and more flexible behaviors through methods including SLAM, visual servoing, deep learning, and etc. However, decomposing and analyzing the semantic concepts involve the understanding over a variety of human manipulation tasks which are challenging even before transiting into robotic knowledge representation and design. Effective semantic context processing should tackle into the fact that human shares the ability to highly capture and express the dynamics of visual contents and to summarize them into transferrable semantic concepts. And knowledge representations should take caution over the fact that human is able to logically fill in both explicit and implicit common-sense knowledge through learning experience of any forms. As such, an expressive and instructive mechanism to decompose and analyze the semantic contexts in activities is required. A unified modeling of vision, language and knowledge is needed over the fact that information is connected, convertible and accessible.

On the basis of the open problems above, in this paper, we are interested in the fundamental problem of perceiving dynamic semantic knowledge graph and utilizing collective world semantic knowledge bank to mimic the phenomenon of common senses in human brain. We first investigate in the scheme to process presented visual inputs into dynamic knowledge graph in forms of Entity-Relation-Entity (E-R-E) given a set of discrete time observations over the manipulation task videos. We then investigate in the parsing and completion of a complex dynamic knowledge graph with common-sense knowledge and attributes using Entity-Attribute-Value (E-A-V) through the searching of a collective static semantic knowledge bank using ontology tree. We start with the experiments in our specifically collected semantics dataset before incorporating a larger system design for the overall semantic understanding procedure. Our main contributions are:

• A scheme to generate high-conceptual, dynamic semantic knowledge graph with E-R-E and E-A-V knowledge through Vision-Language model and static knowledge representation.
• An initial collection for Robot Semantics Dataset with contextual knowledge tokens and collective world knowledge ontology tree annotations.
• A system framework to parse and utilize semantic knowledge in smart robotic applications.

The rest of the paper is organized as follows: Section II involves the summarization over the recent advances in semantic understanding topics. Section III discusses the fundamental formulation for our semantic knowledge representations and Section IV proposes the system framework with use cases. Experiment details and analysis are conducted in Section V. We draw the final conclusion and summarize the possible future improvements in Section VI.

II. RELATED WORK

Semantics in Vision-Language Problems Earlier research in semantic understanding problems under Vision-Language settings starts with the exploration of attributes, or semantic concepts. Wu et al. [1-5] argues the importance of those semantic concepts for various Vision-Language based applications. The proposal of datasets like Visual Gnome Dataset [6] and GQA [7] push the learning of captioning sentences into the learning of Entity-Relation-Entity (E-R-E) graphs, and more studies [8-15] follow the idea of learning E-R-E graphs as ways of composing semantic context features into the captioning model design.

Semantics in Robotic Vision Problems Unlike captioning problems, earlier research over semantics under robotic vision
settings originates from human task taxonomy and action recognition. Aksoy et al. [16] and Kruger et al. [17] prove the importance of understanding hierarchy structure of human activities for robotic design. Complex system designs using deep learning methods enable the uses of semantic attributes on various applications, including composing language commands or grammar trees [18-24] for robotic action captivation, decoding human language instructions to boost grasping precision [25-27] for visual grounding problems, and parsing description for robot navigation problems [28], etc.

**Semantics in Robot Automation** Successful robot automation demands considerations not only over action physical knowledge, but over the executions for future actions and policies. Multiple studies have considered the physical knowledge in robot automation, including the usage of gel to capture pressure and touch force information [29], the usage of GAN to synthesis visually indistinguishable yet more physically difficult grasping objects [30], etc. Action planning modules and policy learning methods have also benefited from direct human semantic knowledge learning [31-33].

In summary, research over semantics lies in pieces, yet has a strong impact in robot automation. The in-behind attributes of the knowledge are either studied through explicit categorizations or processed and ignored implicitly by human operators. Representing a universal collective knowledge to mimic human common senses still needs more time to mature.

### III. Semantic Knowledge Representation

In this section, we first review the basic concepts for knowledge representations involving Entity-Relation-Entity (E-R-E) and Entity-Attribute-Value (E-A-V). We then propose our representation scheme for semantic knowledge through our proposed Robot Semantics Dataset and the corresponding modeling scheme using video captioning. We then introduce our representation for common sense knowledge using ontology tree, before we finally introduce the fundamental structure for our dynamic knowledge graph.

**A. Entity-Relation-Entity and Entity-Attribute-Value**

Individual knowledge components are usually first considered before understanding a whole domain of knowledge. Human uses individual knowledge to explicitly and implicitly describe entities representing objects, actions and many other things. There are two ways to represent knowledge for any perceived entities in a relational, object-oriented language: (a) Entity-Relation-Entity (E-R-E) tuple and (b) Entity-Attribute-Value (E-A-V) tuple.

**Entity-Relation-Entity** The E-R-E tuple explicitly describes things and their probable relationships. Entities are denoted as classes of objects, or concepts in a domain, while relations denote typically the connections, or hierarchies between entities. Various relations can exist among entities.

**Entity-Attribute-Value** The E-A-V tuple describes the properties of the assigned entities with user-specified values. E-A-V tuple allows us to capture and distinguish the properties of the entities and to assert certain restrictions given different attribute values. Those attributes can be perceived directly through visual inputs or can be logically deduced and filled in later through common senses.

**B. Robot Semantics Dataset and Video Captioning**

We introduce our fundamental process to represent E-R-E knowledge in manipulation task settings by defining two important factors: (a) We first define the entities and relations knowledge through the collection of our Robot Semantics Dataset, and (b) We define the learning and modeling process over the E-R-E knowledge using video captioning.

**B.1. Constructing Robot Semantics Dataset**

![Figure 1. An example of pouring context with RGB and colorized depth images in Robot Semantics Dataset. "Manipulator" E-R-E tuple describes the entities observed in the video clips and the corresponding action relations, and "Static" E-R-E graphs describe the entities presented in scene.](image)

While many datasets have been proposed in the fields of video captioning study, only few of those datasets deal with detailed and precise semantic contexts presented in object and task manipulations, and the learning experience is hardly transferrable to robot automation. Although semantic concepts have been proven critical in assist of robot task manipulation, it is still difficult to construct a unified collective knowledge representation to be used for knowledge extraction and acquisition procedure, and data has also been limited in those areas. Motivated by these limitations, we propose our collection scheme for Robot Semantics Dataset, which are composed of Egocentric manipulation task videos with contexts and manipulation context knowledge tuples. The videos are collected using Intel RealSense D435i RGB-D camera, which provides visual inputs both in RGB data and depth data. Activities of Daily Living (ADL) tasks in kitchens are collected with the coverage of different manipulation task settings, including pouring, cutting, moving, and compositional tasks, etc.

The dataset annotations are composed as semantic language contexts in E-R-E from. Figure 1 shows an example of the pouring context with colorized depth images and the E-R-E description tuples. Semantic context annotations of the dataset are denoted as E-R-E language command tokens. The E-R-E semantic annotations of the video consist of:

- **"Manipulator"** descriptions, where a manipulator imposing a certain action on the object of interests and command sentence in E-R-E format over the current action is captioned. The entities are represented by the categorizing describing word tokens of the presented objects and items without naming specifically for individual items. **“Manipulator”** descriptions are further separated by manipulator orientation, which for human manipulation videos are separated by “lefthand” and “righthand” orientation.

- **“Static”** descriptions, where we do not consider any manipulator-oriented actions and only caption the
static semantic contexts describing the visually available entities. The static descriptions aim to capture visual changes in concepts through multiple dense command sentences.

The manipulation tasks are currently performed only with human subjects, and we are addressing robot manipulators in the future collection tasks. We currently have the full semantic annotations on pouring tasks, as such, we have only acquired and experimented with the pouring contexts for now. 31 individual items are presented in the pouring contexts. The pouring context consists of 24 videos with 9649 numbers of RGB image frames. 417 manipulator descriptions and 1172 static descriptions are provided. The semantic annotations for the rest of the manipulation contexts are still ongoing.

B.2. Training Video Captioning Model for E-R-E Knowledge

We propose to train an End-to-End video captioning model to process E-R-E knowledge presented in the manipulation video stream. Figure 2 shows the detailed architecture for our neural caption parser to model language command tokens. We adapt the video2command architecture proposed in [23]. Given a discrete observation video clip at time $t$ consisting of $n$ frames $F_t = (F_1, F_2, \ldots, F_n)$, the objective is to caption the given observation into a caption $S_t = (S_1, S_2, \ldots, S_k)$ of $k$ word tokens. We set the limit to observation into $n$ numbers of frames. If the video clip does not have enough $n$ frames, an artificial video frame using mean image from ImageNet dataset is padded into the inputting video clip to reach the maximum $n$ frames.

During the process of image feature extraction, the video clip $F_t$ is inputted into a convolutional neural network (CNN) pretrained on ImageNet classification task. The extracted CNN features are further processed consecutively by an LSTM into $V_t$ to provide better visual feature representations given the time continuity and temporal motion properties of videos.

The language generation is formulated and optimized by maximizing the probability of the correct describing word token given the current observations. The log-likelihood of the generated words given the current context words and the current visual image input can be expressed as:

$$\log p(S_t|V_t; \theta) = \sum_{i=1}^{n} \log p(S_{t+i}|S_{t+i-1}, V_t; \theta)$$ (1)

where $p(S_{t+i}|S_{t+i-1}, V_t)$ is the conditional probability of generating word $S_{t+i}$ given visual feature $V_t$, previous words $S_{t+i-1}$ and the parameters of the model $\theta$. The maximum likelihood objective can be expressed as:

$$\theta^* = \arg \max_{\theta} \sum_{(F_t,S_t)} \log p(S_t|V_t; \theta)$$ (2)

C. Common Senses Representation with Ontology Tree

Describing entities only through the visually available relations among entities is not enough. Human perceives entity knowledge in a way to mind-map and complete entity knowledge through previously accumulated common senses in life. As such, representing common senses in the form of collective knowledge and combining search methods are important to fully describe entities and implicit knowledge behind. The ontology tree is constructed to serve as the robotic ways of human-like common-sense thinking under the task manipulation contexts for the purposes including logical reasoning and knowledge attribute completion. It represents both knowledge over the entities presented in workspace, and specifications regarding the robot configurations, functions and usages. Figure 3 shows an example of the ontology tree for Robot Semantics Dataset using Protégé [34].

The constructed ontology tree consists of 3 major classes: (a) “ManipulationContext”, where different manipulation scenarios like “PourContext”, “CutContext”, and etc, are presented. (b) “KitchenObject”, where kitchen objects presented in different manipulation contexts like “containers”, “food”, and etc, are presented. (c) “Manipulators”, where physical manipulators used to perform actions, like “HumanManipulators” and “RobotManipulators”, are presented.

Static object attributes are additionally considered to capture detailed characteristics and domain knowledge over the manipulation contexts for a family of entities. There are two categorizations of which we treat attributes. Attributes that are visually perceived, such as “Material”, “Color”, are annotated as visual object attributes through direct observation over the object appearance. Attributes that are difficult to perceive through direct visual inputs yet known to human knowledge due to prior manipulation experience, are annotated as implicit object attributes through robotic trails and experiments. We currently provide three such properties: (a) “GraspingForce”, where we denote the grasping force that can be safely applied on the object grasp area without causing appearance changes or damaging the object. Objects that are unsafe to apply large force is annotated “ForceSmall”, otherwise “ForceMedium” if consecutively applying larger force on gripper does not change the object appearance. (b) “HoldTemperature”, where we annotate “Container” object sets with knowledge whether the container is able to safely hold hot, medium warm or cold pouring liquid and substance or not. (c) “GraspDifficulty”, where we set up robotic trails using Kinova gripper to grasp and lift objects in a given amount of time. Objects that are hard for gripper to lift stably is considered “GraspDifficult”, otherwise “GraspEasy”.

Figure 2. Architecture for the visual context captioning network using the adapted video2command network.

Figure 3. Visualization of world knowledge ontology in Protege for Robot Semantics Dataset, majorly composed of classes in pouring context.
D. Structure for Dynamic Knowledge Graph

While ontology tree represents the static understanding over the semantic knowledge, it is inadequate to integrate purely in a static manner, since the changes of entities presented in visual inputs are dynamic. It is also incomplete to parse only the visually available properties over the entities as human tends to complete entity knowledge through prior experience and common senses. As such, combining dynamic entity parsing and static knowledge searching will provide a more complete local knowledge over the visual contexts.

Figure 4 presents a logic structure of our dynamically generated knowledge graph. Entities and their relation actions are treated as the main graph body while external attributes branch out for each individual entity with attributes and constraints in static knowledge ontology. E-R-E knowledge is structured and regularized through Vision-Language model using video captioning and natural language processing, while E-A-V knowledge is filled in through searching and querying by any entity available. Additional attribute properties over the action relations can also be parsed statically through querying over the ontology reasoning or produced dynamically through models by utilizing all presented entities and attributes.

Figure 4. A logic structure of the dynamic knowledge graph with Entity-Relation-Entity and Entity-Attribute-Value pairs.

IV. SYSTEM FRAMEWORK

Figure 5 presents the overall conceptual flow for the semantic understanding procedure. The key of visual high-conceptual semantic understanding lies in the stage of constructing a dynamic knowledge graph through the combination of dynamic Entity-Relation-Entity (E-R-E) models and collective static common-sense knowledge. The generated dynamic knowledge graph enlists explicit and implicit knowledge attributes presented in the current visual context and is subjugated by the domain knowledge constraints pre-existent in ontology tree. In the following sections, we discuss in detail over the generation process of the dynamic knowledge graph. We then discuss some typical use cases in robotic applications.

A. Generation of Dynamic Knowledge Graph

A.1. Visual Context Parsing

Given a sequence of discrete observation of video frames, we first need to caption the entities and their relation actions presented. The pre-trained video captioning model with neural language generator is used first to caption the command sentence of the inputted discrete video observation. A sentence parsing and tagging model is then followed to process the generated command sentence and then parses the sentence into E-R-E relation graph, which serves as our foundation E-R-E knowledge graph. To parse from captioning command sentence into E-R-E graph form, we invoke simple Part-of-Speech tagging with hard-coded rules. Entities, including objects and manipulators, presented in command sentence are associated with speech tag \(<{\text{NN}}>\), while action relations are associated with speech tag \(<{\text{VBP}}>\). Extra word tokens like “to” and “from” which indicate directional logics are associated with speech tags \(<{\text{TO}}>\) and \(<{\text{IN}}>\), accordingly. We use NLTK to process and annotate POS tags. In regards of the hard rules, for manipulator command sentences, manipulator entities are by default the start entities, with action and directional logical relations pointing to the object entities that are being manipulated. For static command sentences, object entities are served as the start entities, with action and directional logical relations pointing to the object entities that are being manipulated.
start entities with most relations being directional logics.

A.2. Static Knowledge Completion

The foundation E-R-E knowledge graph modelled from direct visual inputs is incomplete to describe the implicit knowledge that human is able to reason with. The next step to complete a full dynamic knowledge graph with implicit knowledge is to search for the useful implicit knowledge in the common-sense knowledge collection. The static ontology tree is provided and queried with each individual entity we perceived from the visual model as a search key. Knowledge attributes are parentally inherited backwards in the ontology tree structure, and static constraints between entities and relations pre-defined in the ontology tree are imposed to further complete the searching over contexts. The implicit knowledge search is complete when all entities presented in the dynamic E-R-E graph are parsed and processed with their corresponding attributes and values from the static ontology. The final output will be a dynamic knowledge graph with both entities perceived from dynamic models and attributes parsed from static ontology.

The dynamic knowledge graph is completed after the entities inherit attributes from the querying results. Compared to the static ontology, the generated knowledge graph is dynamic due to the fact that the entities are dynamically inquired and processed by the context-oriented modeling methods. The generated knowledge graph is complete due to the fact that it inherits a family of restrictions imposed in the static ontology tree, which serves as the general common-sense knowledge we have already known over the entities. Yet it is simpler since we only pay attention to the highlighted local entities presented instead of considering every detail in the static ontology. We present some examples of the generated dynamic knowledge graph in Figure 6.

![Figure 6. Examples of the generated dynamic knowledge graphs.](image)

B. Dynamic Knowledge Graph Driven Uses in Robotics

Given the proposed framework to generate dynamic knowledge graph, we theorize and plan to apply the framework in the following applications in robotics.

B.1. Human-Robot Visual Dialogue

The goal of language-oriented Human-Robot interaction (HRI) is to generate logically reasonable instructions for future robotic controls through a series of knowledge inherited from both visuals and human instructions. For example, under the settings of visual grounding for robotic grasping, the robot initiates the conversation to ask which object to be grasped. Human can instruct the robot to grasp an object with certain attribute properties, whether the attributes are explicit visual knowledge or implicit in-behind common-sense knowledge. The dynamic knowledge graph, in this case, is more beneficial to object grasping, since when robot perceives an object and its presenting scene, the generated dynamic knowledge graph provides detailed attributes coming from both visual knowledge through models and in-behind knowledge through static ontology. The explicit visual attribute is easier to acquire compared to most encoding-based learning methods, and the implicit in-behind knowledge inside the dynamic knowledge graph cannot be specifically processed and learned through only visual training samples. The ontology language additionally provides native support for reasoning and logical deduction, and under the domain knowledge constraints, the dynamic knowledge graph also inherits a large portion of those constraints, introducing more flexibilities for advanced visual dialogue problem.

B.2. Semantic-based Smart Automation in Service Robot

One of our key arguments for Robot Semantics Dataset in exploiting contexts as domain static ontology is that, certain entities, relations and attributes are only presented under certain manipulation task contexts. Given those task-driven entities, we can deduce manipulation action contexts in a probabilistic manner and plan manipulation action ahead for future. Given dynamic knowledge graph with $\sum (E, R, E)$ and $\sum (E, A, V)$, attribute values, entities and action relations are all collected and sorted into a tensor. A Naïve Bayes classifier is then applied to generate the probability distribution over all possible manipulation contexts, and the contexts with the largest probability is selected as the most possible manipulation context for the action relation.

Identifying manipulation context is critical for future action decision making. For example, given the current visual clip input and the dynamic knowledge graph that the water kettle and an empty mug are presented in front of the manipulator, since the mug is empty and the water kettle is filled with water, a logical reasoning for possible manipulation context is pouring context, which strongly suggests that “pour” is one of the actions that is most likely to occur in the following action decision making. Combining with dynamic knowledge graph, a service robot can choose to perform the grasping and pouring actions not because it receives command controls from human, but because it is expected to perform those actions with the acknowledged context. The idea of utilizing semantic knowledge is critical in intelligent Human-Robot interaction, and we plan to have further future investigation in this.

B.3. Semantic-based Experience Transfer in Learning from Demonstration (LfD)

For general LfD tasks, the trajectory in each action is
assumed to be known, and the robot is required to perform trajectory-oriented learning in order to acquire useful knowledge in specific tasks. Given RGB-D videos, the manipulation trajectories can be acquired through processing over camera parameters and depth information. And motion path planning can be achieved and simulated in 3D space. When learning multiple trajectories for related tasks, demonstrations share high similarity in semantic level, and thus learning semantically similar trajectory is beneficial for learning and performing other semantically similar tasks. Dynamic knowledge graph can serve as an explanatory model to semantically categorize trajectories and motions by entities and the action relations among. By generating dynamic knowledge graph, we look explicitly and implicitly deeper into the current visual inputs and we can, on semantic level, locate the semantically important stage of motion for LfD learning. Identifying key motions is critical to structure domestic manipulation tasks and perform hierarchical learning between trajectories.

V. EXPERIMENTS AND ANALYSIS

A. Evaluation with Video Captioning Model

Training The adapted video2command network is trained in an end-to-end fashion. Teacher-student forcing is used where the next ground truth word token will always be used as the training target. We randomly sampled 752 video clips using the “Manipulator” descriptions only and evaluate our model through cross validation. We experiment with different CNN backbones, including ResNet50, VGG16, VGG19, and InceptionV3, for frame image feature extraction. The word embeddings and the weights for LSTM are randomly initialized and the states of LSTM are zero initialized. All the models are trained with Adam for 100 epochs with a learning rate of 0.0001.

Evaluation The LSTM language generator is initialized into zero states. The generation process will terminate until the language generator predicts end token “<eos>” or the maximum sentence generating length, which we choose as 10, is reached. We report the experimental results with the baseline architecture settings using the standard machine translation and language generation metrics: BLEU 1-4, METEOR, ROUGE-L, and CIDEr, which all provide quantity measures over the grammar structures and the semantic meanings of the generated sentences. All scores are computed with the coco-evaluation code [35]. Table I shows the mean experiment scores with different backbones on the pouring task using 5-cross validation. The results from cross validation are comparable among backbones, with VGG19 serving as a seemingly stronger semantic feature extractor.

| Name          | B-1 | B-2 | B-3 | B-4 | C | M | R      |
|---------------|-----|-----|-----|-----|---|---|--------|
| v2c-ResNet50  | 0.637 | 0.502 | 0.389 | 0.336 | 0.36 | 0.679 | 3.279 |
| v2c-InceptionV3 | 0.619 | 0.486 | 0.375 | 0.322 | 0.33 | 0.646 | 3.215 |
| v2c-VGG16     | 0.634 | 0.497 | 0.382 | 0.323 | 0.34 | 0.686 | 3.355 |
| v2c-VGG19     | 0.644 | 0.507 | 0.395 | 0.339 | 0.34 | 0.688 | 3.43  |

B. Analysis of Dynamic Knowledge Graph

We present some examples of our dynamically generated knowledge graphs in Figure 6. In general, the dynamic knowledge graph shows promising details in regards of inputted manipulation tasks. However, searching details of static knowledge are extremely susceptible to the quality of dynamic entities being produced by video captioning model. Due to the fact that we currently do not consider in great details over the direct visual annotations, attributes like color and material are ill-searched through parental inheritance only and visually wrong and useless values can also be parsed. We are working to address this issue by providing more detailed visual annotations and investigating methods to process those visual details for the overall system architecture.

On the other hand, due to the fact that multiple E-R-E knowledges, for example both static descriptions and manipulator descriptions in the case for Robot Semantics Dataset, can co-exist to describe a presented video clip, the neural language generation model should consider a topic-oriented solution and guard its initial states by the topic of interests. And the standard caption evaluation metrics should also be modified to complement this.

VI. CONCLUSION

In this paper, we propose a method to represent collective knowledge in task manipulation and generate dynamic knowledge graph through a combination of vision and language model. The preliminary experiments and analysis show promising results over knowledge representation for smart autonomous robots. The proposed scheme is compatible and adaptive in numerous applying scene requiring semantic understanding, although more strategies can be adapted to provide better processes over the entire framework.

The experiments conducted for dynamic knowledge graph generation so far are still open for further investigation and improvements. One direction is to investigate in the capability for vision and language models, including from discrete observing to continuous observing video stream, and from captioning one command E-R-E sentence to captioning multiple E-R-E sentence given topic orientation. The current Robot Semantics Dataset and ontology tree are basic and still need further extensions. We plan to expand and complete our collection into robot-oriented manipulation with more contexts. And we plan to construct deeper ontology tree given more complicated manipulation and service domain. Applications in robotics have potential to contribute in various stages for robot automation, and we plan to exploit our system framework for relevant robotic experiments in future works. More future investigation will also be done in combination of robotic manipulation controls and semantic action decision plan.

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