Generating Realtime Motion Plans from Attribute-Based Natural Language Instructions Using Dynamic Constraint Mapping

Jae Sung Park, Biao Jia, Mohit Bansal, and Dinesh Manocha

Abstract—We present an algorithm for combining natural language processing (NLP) and realtime robot motion planning to automatically generate safe robot movements. Our formulation uses novel a Dynamic Constraint Mapping to transform the complex, attribute-based natural language instructions into appropriate cost functions and parametric constraints for optimization-based motion planning. We generate a factor graph called Dynamic Grounding Graph (DGG) from natural language instructions that takes into account the latent parameters. The coefficients of this factor graph are learned based on conditional random fields (CRFs) and are used to dynamically generate the constraints for motion planning. We directly map the cost function to the motion parameters of the planner and compute smooth trajectories in dynamic scenes. We highlight the performance of our approach in a simulated environment as well as via a human interacting with a 7-DOF Fetch robot using intricate language commands that include negation, orientation specification, and distance constraints.

I. INTRODUCTION

In the field of human-robot interaction (HRI), natural language has been used as an interface to communicate a human’s intent to a robot [1], [2], [3], [4]. Much of the work in this area is related to specifying simple tasks or commands for robot manipulation, such as picking and placing objects. As robots are increasingly used in complex scenarios and applications, it is important to develop a new generation of motion planning and robot movement techniques that can respond appropriately to diverse, attribute-based NLP instructions for HRI, e.g., those containing negation based phrases or references to position, velocity, and distance constraints. Furthermore, we need efficient techniques to automatically map the NLP instructions to such motion planners.

Humans frequently issue commands that include sentences with orientation-based or negation constraints such as “put a bottle on the table and keep it upright,” or “move the knife but don’t point it towards people,” or sentences with velocity-based constraints such as “move slowly when you get close to a human.” In order to generate robot actions and movements in response to such complex natural language instructions, we need to address two kinds of challenges: 1. Accurate interpretation of attribute-based natural language instructions and their grounded linguistic semantics, especially considering the environment and the context. For example, a human may say “move a little to the left,” or “do not move like this,” and the robot planner needs to learn the correct interpretation of these commands with spatial and motion-based adjectives, adverbs, and negation. 2. The realtime motion planner needs to generate appropriate trajectories based on these complex natural language instructions. This includes appropriately setting up the motion planning problem based on different motion constraints (e.g., orientation, velocity, smoothness, and avoidance) and computing smooth and collision-free paths.

At a high level, natural language instructions can be decomposed into task description and attributes. Task descriptions are usually verb or noun phrases that describe the underlying task performed by a robot. The attributes include various adjectives, adverbs, or prepositional phrases are used to specify additional conditions the robot must (or must not) satisfy. For example, these conditions may specify some information related to the speed, orientation, physical space characteristic, or the distances. Therefore, it is important to design motion planners that take into account these robotic task descriptions and robot motion constraints.

Main Results: We present an algorithm to generate parameterized constraints for optimization-based motion planning from complex, attribute-based natural language instructions. We use Dynamic Grounding Graphs (DGG) to parse and interpret the commands and generate the constraints. Moreover, our formulation includes the latent parameters in the grounding process and that allows us to model many continuous variables in our grounding graph. Furthermore, we present a new dynamic constraint mapping that takes DGG as the input and computes different constraints and parameters of the motion planner. The appropriate motion parameters correspond to the speed, orientation, position, smoothness, repulsion, and avoidance. The final trajectory of the robot is computed using a realtime constraint optimization solver. Overall, our approach can automatically handle complex

Jae Sung Park, Biao Jia, Mohit Bansal, and Dinesh Manocha are in University of North Carolina at Chapel Hill, USA \{jaesungp, biao, mbansal, dm\}@cs.unc.edu

Fig. 1. The Fetch robot is moving a soda can on a table based on NLP instructions. Initially the user gives the “pick and place” command. However, when the robot gets closer to the book, the person says “don’t put it there” (i.e. negation) and the robot avoids the book using our dynamic constraint mapping functions and optimization-based planning. Our approach can generate appropriate motion plans for such attributes.
natural language instructions corresponding to spatial and temporal adjectives, adverbs, superlative and comparative degrees, negations, etc. As compared to prior techniques, our overall approach offers the following benefits:

- The inclusion of latent parameters in the grounding graph allows us to model continuous variables that are used by our mapping algorithm. Our formulation computes the dynamic grounding graph based on conditional random fields.
- We present a novel dynamic constraint mapping which is used to compute different parametric constraints for optimization-based motion planning. We also present a novel algorithm to compute this dynamic constraint mapping in realtime.
- Our grounding graphs can handle more complex, attribute-based natural language instructions and our mapping algorithm uses appropriate cost functions as parameters over the continuous space. As compared to [2], [1], [4], [5], our approach is much faster and able to handle more complex and attribute-based natural language instructions.

We highlight the performance of our algorithms in a simulated environment as well as on a 7-DOF Fetch robot operating next to a human in a safe manner. Our approach can handle a rich set of natural language commands and can generate appropriate paths in realtime. These include complex commands such as picking (e.g., “pick up a red object near you”), correcting the motion (e.g., “don’t pick up that one”), and negation (e.g., “don’t put it on the book”).

II. Related Work

Most algorithms used to map natural language instruction to robot actions tend to separate the problem into two parts, the parsing part and the motion planning computation. In this section, we give a brief overview of prior work in these areas.

A. Natural Language Processing

Kollar et al. [1] present a probabilistic graphical learning model called Generalized Grounding Graphs or G^3, by which the robot interprets and grounds natural language commands to the physical world. The graph is defined based on the syntactic parse structure of the command, enabling the system to associate parts of the command with objects, events, and locations in the external world. Howard et al. [2] reduce the search space by modifying the G^3 graph structure by adding all possible grounding nodes (meanings of word phrases) and optimizing the correspondence variables (indicating the word phrase and the grounding match correctly). Duvallet et al. [7] used this algorithm on a ground vehicle for a navigation problem given natural language commands. Our approach extends the G^3 graph structure with respect to the linguistic parse structure, the probabilistic graphical model, and the use of optimization-based motion planning.

Other related work in language grounding of task instructions includes Branavan et al. [3], [8], which uses reinforcement learning to learn the mapping from natural language instructions and apply it to sequences of executable actions. Reinforcement learning-based methods require little annotated data, but the search space can be very large when applied to motion planning of a robot arm. Matuszek et al. [4] use a statistical machine translation model to map the natural language instructions to a path description language to follow the directions for robot navigation. Duvallet et al. [9] use imitation learning to train the model via demonstrations of humans following directions. Paul et al. [10] proposed the Adaptive Distributed Correspondence Graph (ADCG). It can handle abstract groundings, providing hierarchical meanings of word phrases from an abstract level to a concrete level. Arkin et al. [5] further extended DCG, proposing the Hierarchical Distributed Correspondence Graph (HDCG), which defines constraints as discrete inequalities and ground word phrases with corresponding inequalities. However, their method depends on discretized constraints in a continuous space (e.g., discretized distance constraints) and has not been evaluated on real robots. Chung et al. [11] use it on ground vehicles for navigation commands and demonstrated performance improvements over G^3 in terms of running time, factor evaluations and correctness. Oh et al. [12] integrate HDCG with their navigating robot system and measured performances in terms of completion rates and compared them with humans’ behaviors. Our approach is designed for general purpose tasks and NLP instructions.

B. Robot Motion Planning in Dynamic Environments

In order to generate collision-free motion plans in dynamic environments, many replanning algorithms have been suggested. Fox et al. [13] propose the dynamic window approach to compute the optimal velocity in a short time window. Optimization-based motion planners [14], [15], [16], [17] solve a constrained optimization problem to generate smooth and collision-free robot paths. These planners can be adapted to other tasks by adding cost functions and constraints in the optimization formulation. However, it can be difficult and tedious to manually tune many parameters. We present an automatic scheme to generate the motion planning problem from NLP instructions.

There is some work on integrating optimization-based motion planning with NLP in 2D workspaces. Silver et al. [18] developed an algorithm for learning navigation cost functions from demonstration. Howard et al. [2] use a probabilistic graphical model to generate motion planning constraints for a 2D navigation problem. Compared to these methods, our approach can handle 3D workspaces and high-dimensional configuration spaces to generate robot motions corresponding to complex NLP instructions. There is considerable work on generating safe motion plans for robots operating next to humans [19], [20], [21], though it is complimentary to our approach.

III. Overview

We first introduce the notation and terminology used in the paper and give an overview of our natural language processing and motion planning algorithms.
The grounding of each word phrase is the mapping from the word phrase to its meaning in the real world. Groundings can be objects, locations, motions, tasks or constraints. In our model, the grounding $\gamma_i$ depends on its work phrase $\lambda_i$ and children grounding nodes $\gamma_1, \cdots, \gamma_m$, where the tree structure of the grounding nodes follows the parse tree.

Correspondence node $\phi_i$ indicates the correct matching between the word phrase $\lambda_i$ and the grounding $\gamma_i$. It is a binary variable; $\phi_i$ is true if the word phrase and the grounding correctly matches and false if not.

B. Robot Configurations and Motion Plans

We denote a single configuration of the robot as a vector $q$ that consists of joint-angles or other degrees-of-freedom. A configuration at time $t$, where $t \in \mathbb{R}$, is denoted as $q(t)$. We assume $q(t)$ is twice differentiable, and its derivatives are denoted as $q'(t)$ and $q''(t)$. The $n$-dimensional space of configuration $q$ is the configuration space $\mathcal{C}$. We represent bounding boxes of each link of the robot as $B_i$. The bounding boxes at a configuration $q$ are denoted as $B_i(q)$.

For a planning task with a given start configuration $q_0$ and derivative $q_0'$, the robot’s trajectory is represented by a matrix $Q$, whose elements correspond to the waypoints [14], [15], [16], [17]. The robot trajectory passes through the $n + 1$ waypoints $q_0, \ldots, q_n$, which will be optimized by an objective function under constraints in the motion planning formulation. Robot configuration at time $t$ is interpolated from two waypoints. Formally, for $j$ such that $t_j \leq t \leq t_{j+1}$, the configuration $q(t)$ and derivative $q'(t)$ are cubically interpolated using $q_j, q_j', q_{j+1}$ and $q_{j+1}'$.

The $i$-th cost functions of the motion planner are $C_i(Q)$. The 6 different cost functions we used in this paper are listed in Section [V]. Our motion planner solves an optimization problem with non-linear cost functions and linear joint limit constraints to generate robot trajectories for time interval $[0, T]$.

\[
\begin{align*}
\text{minimize} & \quad \sum_i w_i C_i(Q) \\
\text{subject to} & \quad q_{\min} \leq q(t) \leq q_{\max}, \\
& \quad q_{\min} \leq q'(t) \leq q'_{\max}, \\
& \quad 0 \leq t \leq T.
\end{align*}
\]

In the optimization formulation, $C_i$ is the $i$-th cost function and $w_i$ is the weight of the cost function.

IV. DYNAMIC GROUNDING GRAPHS

In this section, we extend the ideas of the Generalized Grounding Graphs ($G^3$) model and the Distributed Correspondence Graph (DCG) model [2] by including the latent variables in the grounding graph and using them to compute the constraints for motion planning. We present dynamic grounding graphs and use an appropriate learning model to compute them. Our goal is to compute a mapping from a natural language sentence $\Lambda$ to the cost function parameters $H_i$, given the robotic environment $E$, where the robot is operating. $E$ is a representation of the environment composed of obstacle positions, orientations, and the robot’s configuration. Feature vectors are constructed in the factor graph from the
environment description. \( H \) is a real-valued vector that contains all cost function parameters used in the optimization-based motion planner. It also includes the weights of different types of cost functions used in the optimization formulation. For example, the end-effector position cost function (Eq. (5)) requires the 3D coordinates of the target position as parameters. The repulsion cost function (Eq. (4)) requires the repulsion source position and the constant in the exponential function.

A. Latent Parameters

A key novel component of our approach is inclusion of latent variables in the grounding graph. Our primary goal is to compute the best cost function parameters \( H \) that we can directly use for optimization-based motion planning. We denote \( H \in \mathbb{R}^h \), a real vector of size \( h \), as a collection of cost function parameters. In this case, the size \( h \) and the number of cost function parameters depend on the types of cost functions that are used.\(^1\) From the predicted groundings \( \gamma_i \), the cost function parameters in the motion planning formulation (Fig. 3(b)) is inferred through the latent variable \( H \). It contains all the cost function parameters (e.g., weights of cost functions, locations, and orientations). The details of the cost function parameters are explained in Section V.

In Fig. 3(b), the resulting constraint-based motion planning problems are shown. We use the collision avoidance cost function as the default, smoothness cost function and the target location cost function, though weights can vary. The target location, whose 3D coordinates are the cost function parameters, is set on the surface of the table. The cost function parameter node \( H \) contains the weights of the parameters and the 3D coordinates of the target location. In the bottom of Fig. 3(b), where a new “Don’t” command is given, a repulsion cost function is added. Thus, the cost function weight and the location of the repulsion source (below the robots end-effector position) are added to \( H \).

B. Probabilistic Model

We present a new probabilistic model to compute \( H, \Lambda \) and \( E \). We pose the problem of finding the best cost parameters as an optimization problem:

\[
\max_H p(H | \Lambda, E).
\]

However, modeling the probability function without decomposing the variables and some independence assumptions is difficult due to the high-dimensionality of \( H, \Lambda \) and \( E \) and the dependencies between them. To simplify the problem, the natural language sentence is decomposed into \( n \) word phrases based on a parse tree, i.e.

\[
p(H | \Lambda, E) = p(H | \lambda_1, \cdots, \lambda_n, E).
\]

Like \( G^3 \), we introduce the intermediate groundings \( \gamma \) of word phrases \( \lambda_i \), and correspondence variables \( \phi_i \). The correspondence variables \( \phi_i \) is a binary random variable. The value \( 1 \) indicates that the word phrase \( \lambda_i \) correctly corresponds to the grounding \( \gamma_i \). 0 means an incorrect correspondence.

We assume conditional independence of the probabilities to construct a factor graph (see Fig. 3(a)). With the independence assumptions, a single factor is connected to a word phrase node and its children grounding nodes which contain information about the sub-components. These independence assumptions simplify the problem and make it solvable by efficiently taking advantage of the tree structure of the probabilistic graphical learning model. Formally, the root grounding node \( \gamma \) contains all the information about a robot’s motion. The factor that connects \( \gamma_i \) and \( H \) implies that, from the root grounding node, the cost function parameters \( H \) are optimized without any consideration of other nodes. Other factors connect \( \gamma_i, \phi_i, \lambda_i \), children grounding nodes \( \gamma_j \), and the environment \( E \), where the parent-child relationship is based on a parse tree constructed from the natural language sentence. This graphical representation corresponds to the following equation:

\[
p(H | \lambda_1, \cdots, \lambda_n, E) = p(H | \gamma_i, E) \prod_i p(\gamma_i | \lambda_i, \phi_i, \gamma_1, \cdots, \gamma_m, E).
\]

For the root factor connecting \( H, \gamma_i \) and \( E \), we formulate the continuous domain of \( H \). We compute the Gaussian Mixture Model (GMM) on the probability distribution \( p(H | \gamma_i, E) \) and model our probability with non-root factors as follows:

\[
p(\gamma_i | \lambda_i, \phi_i, \gamma_1, \cdots, \gamma_m, E)
\]

\[
= \frac{1}{Z} \psi_{\gamma_i}(\gamma_i, \lambda_i, \phi_i, \gamma_1, \cdots, \gamma_m, E)
\]

\[
= \frac{1}{Z} \exp(-\theta^T f(\gamma_i, \lambda_i, \phi_i, \gamma_1, \cdots, \gamma_m, E)), \tag{2}
\]

where \( Z \) is the normalization factor, \( \psi_{\gamma_i} \) is the feature function, and \( \theta \) and \( f \) are the log-linearization of the feature function. The function \( f \) generates a feature vector, given a grounding \( \gamma_i \), a word phrase \( \lambda_i \), a correspondence \( \phi_i \), children groundings \( \gamma_j \) and the environment \( E \).

- **Word phrases.** The feature vector includes binary-valued vectors for the word and phrase occurrences, and Part of Speech (PoS) tags. In particular, there is a list of words that could be encountered in the training dataset such as \{put, pick, cap, up, there, \cdots \}. If the word phrase contains the word “put,” then the occurrence vector at the first index is set to 1 and others are set to 0. If the word phrase is “pick up,” then the occurrence values at the second, while the fourth is set to 1 and others are set to 0. It also includes real-valued word similarities between the word and the pre-defined seed words. The seed words are the pre-defined words that the users expect to encounter in the natural language instructions. We used Glove word2vec [23] to measure cosine-similarity (i.e. the inner product of two vectors divided by the lengths of the vectors) between the words. The measurement indicates that the words are similar if the similarity metric value is near 1, have opposite meanings if the similarity metric is near -1, and have a weak relationship if it is near 0. This
provides more flexibility to our model, especially when it encounters new words that are not trained during the training phase.

- **Robot states:** From the robot state, we collect the robot joint angles, velocities, the end-effector position, the end-effector velocity, etc. This information can affect the cost function parameters even while processing the same natural language commands. For example, if the robot is too close to a human under the current configuration, then the cost function for end-effector speed $C_{\text{speed}}$ or smoothness $C_{\text{smoothness}}$ will be adjusted so that the robot does not collide with the human. We also store information about the objects that are close to the robot. This information include object type, position, orientation, shape, dimension, etc.

### C. Factor Graph using Conditional Random Fields

We represent our dynamic grounding graph as a factor graph. We build a factor graph based on the probabilistic model described in Section IV-B and use that for training and inferring the meaning of given commands. In particular, we use Conditional Random Fields (CRF) [24] as a learning model for factor graphs, because CRFs are a good fit for applying machine learning to our probabilistic graph model with conditional probabilities. During the training step of CRF, we solve the optimization problem of maximizing the probability of the samples in the training dataset over the feature coefficients $\theta_i$ for every parse tree structure. By multiplying Eq. 4 for all training samples, the optimization problem becomes

$$
\text{maximize} \prod_k p(H^{(k)}|\gamma^{(k)}, E^{(k)}) \prod_i \frac{1}{Z} \exp(\theta_i^T f(\gamma^{(k)}, \hat{\alpha}_i^{(k)}, \phi^{(k)}, \gamma_1^{(k)}, \ldots, \gamma_{im}^{(k)}, E^{(k)}))
$$

where superscripts $(k) = 1 \cdots D$ mean the indices of the training samples. This is a tree-structured CRF problem.

At the inference step, we used the trained CRF factor graph models to find the best groundings $\Gamma$ and the cost function parameters $H$ by solving the CRF maximization problem

$$
\text{maximize} \prod_k p(H|\gamma, E) \prod_i \frac{1}{Z} \exp(\theta_i^T f(\gamma, \hat{\alpha}_i, \phi, \gamma_1, \cdots, \gamma_{im}, E)).
$$

Because the nodes $H, \gamma_1, \cdots, \gamma_n$ being optimized creates a tree structure in the factor graph, we can solve the optimization problem efficiently using dynamic programming. Each factor depends on its parent and children varying variables and other fixed variables connected to it. This implies that we can solve the sub-problems in a bottom-up manner and combine the results to solve the bigger problem corresponding to the root node.

### V. Dynamic Constraint Mapping With NLP Input

In this section, we present our mapping algorithm, Dynamic Constraint Mapping, which maps the word phrase groundings to proper cost function parameters that correspond to the natural language instructions. Our realtime optimization-based planning algorithm [17] solves the cost minimization problem, the function and constraints of which come from DGG, as explained in Sec. IV.

The overall optimization formulation is given in Eqn. 1 in Sec. III-B. In order to formulate the constraints, we use the following cost functions, which are design to account for various attributes in the NLP instructions.

#### A. Cost Functions

In our formulation we use many types of cost functions, such as collision avoidance, robot smoothness, robot end-effector speed, target positions and target orientations that are used to handle many attributes of the natural language instructions. Each cost function has its weight and other cost function parameters, if necessary. For example, the robot end-effector speed cost function has parameters corresponding to the direction and the magnitude of the speed, which impose a constraint on the final computed trajectory. If the weight of the end-effector speed cost function is higher than the others, then it contributes more to the overall objective function in the optimization formulation. If the weight is low, then the end-effector speed cost will be compromised and has lesser impact on the path planner. We want the robot to avoid collisions in any case, so we set the weight of collision avoidance cost to 1, and other cost function weights are normalized by this weight.

#### B. Parameterized Constraints

In order to handle various attributes, we use the following parameterized constraints in our optimization formulation.

**Collision avoidance:** By default, the robot should always avoid obstacles.

$$
C_{\text{collision}}(Q) = \int_0^T \sum_i \sum_j \text{dist}(B_i(t), O_j)^2 dt,
$$

where $\text{dist}(B_i(t), O_j)$ is the penetration depth between a robot bounding box $B_i(t)$ and an obstacle $O_j$. Because it is a default cost function, we set the weight of this cost function as 1 and change the weights of the other types of cost functions accordingly.

**Smoothness:** We penalize the magnitude of a robot’s joint angle speeds to make the trajectory smooth. This corresponds to the integral of the first derivative of joint angles over the trajectory duration. This function is useful when we need to control the speed of the robot. When the robot should operate at a low speed (e.g. when a human is too close), or we don’t want abrupt movements (e.g. for human safety), the smoothness cost can have high weights so that the robot moves slowly without jerky motions.

**End-effector position:** Usually, a user specifies the robot’s target position to make sure that the robot reaches its goal position. This cost function penalizes the squared distance...
between the robot’s end-effector position and the target position over the trajectory duration as

\[ C_{\text{position}}(Q) = \int_0^T \| \mathbf{p}_{\text{ee}}(t) - \mathbf{p}_{\text{target}} \|^2 dt, \quad (3) \]

where \( \mathbf{p}_{\text{ee}}(t) \) is the robot end-effector position at time \( t \), and \( \mathbf{p}_{\text{target}} \) is the target position. The target position \( \mathbf{p}_{\text{target}} \) is considered as a cost function parameter. In the mapping algorithm, a position grounding node encodes the target position parameter. It can be a 3D position or the current object position in the environment. Typically, the target position is specified by an object name in the sentence, such as “pick up the cup” or “move to the box”. In these cases, the grounding nodes for “the cup” and “the box” are interpreted as the current 3D coordinates of the target positions, which are the parameters of this cost function.

**End-effector orientation:** Robotic manipulation tasks are sometimes constrained by the end-effector orientation. This cost function penalizes the squared angular differences between the end-effector orientation and the target orientation over the trajectory duration.

\[ C_{\text{orientation}}(Q) = \int_0^T \text{angledist}(\mathbf{q}_{\text{ee}}(t), \mathbf{q}_{\text{target}})^2 dt \]

\[ C_{\text{upvector}}(Q) = \int_0^T \text{angledist}(\mathbf{n}_{\text{up}}(t), \mathbf{n}_{\text{target}})^2 dt, \]

where \( \mathbf{q}_{\text{ee}}(t) \) is the quaternion representation of the robot end-effector’s orientation at time \( t \), \( \mathbf{q}_{\text{target}} \) is the end-effector orientation that we want the robot to maintain, \( \mathbf{n}_{\text{up}} \) is the normal up-vector of the robot’s end-effector, and \( \mathbf{n}_{\text{target}} \) is the target up-vector. As with the end-effector position cost, the target orientation \( \mathbf{q}_{\text{target}} \) is the cost function parameter. The target orientation usually depends on the object the robot picked up. For example, when the robot is doing a peg-hole insertion task under the command “insert that into the hole,” the orientation of the robot’s end-effector \( \mathbf{q}_{\text{ee}} \) should be constrained near the hole.

**End-effector speed:** It penalizes the robot’s end effector speed and direction:

\[ C_{\text{speed}}(Q) = \int_0^T \| \mathbf{v}_{\text{ee}}(t) - \mathbf{v}_{\text{target}} \|^2 dt, \]

where \( \mathbf{v}_{\text{ee}}(t) \) is the robot’s end-effector speed at time \( t \), and \( \mathbf{v}_{\text{target}} \) is the target speed. The parameters of this cost function correspond to \( \mathbf{v}_{\text{target}} \). In some cases, we must restrict the robot’s end-effector velocity, e.g., if a user wants to pick up a cup filled with water and doesn’t want to spill it. Spilling can be prevented by limiting the end-effector speed, slowing it.

**Repulsion:** The repulsion functions are commonly represented as potential fields

\[ C_{\text{repulsion}}(Q) = \int_0^T \exp(-c \| \mathbf{p}_{\text{ee}}(t) - \mathbf{p}_r \|) dt, \quad (4) \]

where \( \mathbf{p}_r \) is the position to which we don’t want the robot to move. The coefficient \( c > 0 \) suggests how much the cost is affected by \( \| \mathbf{p}_{\text{ee}}(t) - \mathbf{p}_{\text{repulsive}} \| \), the distance between the end-effector position and the repulsion source. The cost function is maximized when the end-effector position is exactly at the repulsion source, and it decreases as the distance between the end-effector and the repulsion position increases. For example, if the command is “Don’t put the cup on the laptop,” we can define a repulsion cost with the laptop position as the repulsion source. The cost function is inversely proportional to the distance between the end-effector and the laptop.

**VI. IMPLEMENTATION AND RESULTS**

We have implemented our algorithm and evaluated its performance in a simulated environment and on a 7-DOF Fetch robot. All the timings are generated on a multi-core PC with Intel i7-4790 8-core 3.60GHz CPU and a 16GB RAM.

We have evaluated the performance in complex environments composed of multiple objects and local minima. Based on the NLP commands, the robot decides to pick an appropriate object or is steered towards the goal position in a complex scene. In particular, the user gives NLP commands such as “move right”, “move up”, “move left” or “move down” to guide the robot. For each such command, we compute the appropriate cost functions.

We also integrated our NLP-based planner with ROS and evaluated its performance on the 7-DOF Fetch robot. In a real-world setting, we tested its performance on different tasks corresponding to: (1) moving a soda can on the table from one position to another; (2) not moving the soda can over the book. With a noisy point cloud sensor on the robot, the thin book is not recognized as a separate obstacle by the robot, though the human user wants the robot to avoid it. All
the instructions used in these tasks have different attributes, which makes it hard for prior methods. In Fig. 6, the two sub-tasks are specified in one sentence at the beginning, as “move the can on the table, but don’t put it on the book”. The cost function is used to move the robot’s end-effector to the surface of the table. Another cost function penalizes the distance between the book and the end-effector. In Fig. 6, the two only the first sub-task is given at the beginning. This results in the robot moving the can on the book. As the robot gets too close to the book, the person says “stop,” then says “don’t put it there.” The robot recomputes the cost functions and avoids the region around the book.

A. Analysis

We evaluated the performance based on the following metrics:

- **Success Rate**: The ratio of successful task completion among all trials. Failure includes colliding with the obstacles due to incorrect mapping of cost function parameters, violating constraints specified by natural language commands, and not completing the task due to some other reason.
- **Trajectory Duration**: The duration between the time the first NLP command is given and the robot’s successful completion of the task after trajectory computation. A shorter duration implies higher performance.
- **Trajectory Smoothness Cost**: A cost based on evaluating the trajectory smoothness based on standard metrics and dividing by the trajectory duration. A lower cost implies a smoother and more stable trajectory.

Table I shows the results on our benchmarks with varying numbers of training data samples on the simulation environment shown in Fig. 6. When the number of training data samples increases, the success rate also increases, and

| # Training Data | Success Rate | Duration | Smoothness Cost |
|-----------------|--------------|----------|-----------------|
| 1,000           | 5/10         | 23.46s (5.86s) | 8.72 (5.56) |
| 3,000           | 9/10         | 16.02s (3.28s) | 2.56 (0.64) |
| 10,000          | 10/10        | 13.16s (1.24s) | 1.21 (0.32) |
| 30,000          | 10/10        | 12.81s (0.99s) | 0.78 (0.12) |
| 100,000         | 10/10        | 12.57s (0.97s) | 0.72 (0.10) |

Table II highlights the number of natural language instructions (input) in these scenarios, number of cost function parameters |H| (used by our algorithm), and realtime performance.

| Scenarios                  | Instructions | |H| | DGG Time | Planning Time |
|----------------------------|--------------|-----|-----|---------|-------------|
| Pick up an object (Fig. 4) | 10           | 12 | 32ms | 93ms    |
| Don’t put on laptop (Fig. 5)| 20           | 13 | 16ms | 98ms    |
| Move around obstacle       | 45           | 9  | 16ms | 95ms    |
| Static Instructions (Fig. 6)| 20           | 18 | 73ms | 482ms   |
| Dynamic Instructions (Fig. 1)|21            |18  |58ms |427ms    |

In this section, we compare our approach with prior methods and highlight the benefits in terms of handling attribute-based NLP instructions. Most prior methods that combine NLP and motion planning have focused on understanding natural language instructions to compute robot motion for simple environments and constraints. Most of these methods are limited to navigation applications [12], [11], [7] or used in simple settings [8] or not evaluated on real robots [5]. In our approach, the goal is to generate appropriate high-DOF motion trajectories in response to attribute-based natural language instructions like negation, distance or orientation constraints, etc.

Our algorithm demonstrates many advantages over Howard et al. [2]. They use a discrete set of constraints and their planning algorithm determines whether those constraints are activated or not. In the worst case, the complexity of their search space can grow exponentially as more constraints are added. On the other hand, we use appropriate cost functions as parameters over the continuous domain. Our constraint setup algorithm based on dynamic constraint mapping is different and our formulation can easily handle complex dynamic environments. As a result, we can handle complex instructions with attributes in realtime (see Table II).

It may be possible to extend prior methods [1], [2] to handle attribute-based NLP instructions. For example, distance attributes require a number of constraints in the motion planning formulation. Lets consider natural language instructions such as: “Pick up the blue block and put it 20 cm to the left of the red block” or “Pick up one of the two blocks on the rightmost, and place it 10 inches away from the block on the leftmost,” where the exact distance specifications are the distance attributes. Prior methods that use G3, DCG and the Hybrid G3-DCG models have only been evaluated with a

2These are based on NLP instructions for manipulation tasks available at [https://github.com/tmhoward/h2sl] We added distance attributes to the original instructions to evaluate the performance.
small number of attributes (distance, orientation and contact) to solve constrained motion planning problems. These prior techniques use discretized constraints [2], each of which can be active (i.e., \( f(x) > 0 \)), inverted (\( f(x) < 0 \)) or ignored (i.e. not included). Therefore, it is not possible to exactly represent an explicit constraint corresponding to the value of the continuous variable distance in their formulation. One workaround is to discretize the continuous distance and to create multiple constraints for each discretized values. However, a large number of constraints increases the runtime overhead of their planner. However, our model can represent this distance attribute precisely with only one constraint using the latent parameter \( H \) and the corresponding cost function.

VIII. LIMITATIONS, CONCLUSIONS AND FUTURE WORK

We presented a real-time motion planning algorithm that computes appropriate motion trajectories for a robot based on complex NLP instructions. Our formulation is based on two novel concepts: dynamic grounding graphs and dynamic constraint mapping. We highlight the performance in simulated and real-world scenes with a 7-DOF manipulator operating next to humans. The preliminary results are promising and our approach can handle more complex scenarios than prior methods.

We use a trajectory optimization algorithm to compute the high-DOF robot trajectory. It is a high-dimensional optimization problem and the solver may get stuck in local minima. As a result, it is difficult to provide rigorous guarantees in terms of satisfying all the constraints or following the intent of the user. Furthermore, the accuracy of the mapping algorithm varies as a function of the training data.

As future work, we would like to overcome these limitations and evaluate the approach in challenging scenarios with moving obstacles while performing complex robot tasks. More work is needed to handle the full diversity of a natural language, especially for rare words, complicated grammar styles, and hidden intention or emotion in human speech. We plan to incorporate stronger natural language processing and machine learning methods such as those based on semantic parsing, neural sequence-to-sequence models, reinforcement learning, and speech-based emotion analysis, and to compute the appropriate optimization-based planning formulations.

REFERENCES

[1] T. Kollar, S. Tellex, M. R. Walter, A. Huang, A. Bachrach, S. Hemachandra, E. Brunskill, A. Banerjee, D. Roy, S. Teller, et al., “Generalized grounding graphs: A probabilistic framework for understanding grounded language,” JAIR, 2013.

[2] T. M. Howard, S. Tellex, and N. Roy, “A natural language planner interface for mobile manipulators,” in Robotics and Automation (ICRA), 2014 IEEE International Conference on. IEEE, 2014, pp. 6652–6659.

[3] S. R. Branavan, H. Chen, L. S. Zettlemoyer, and R. Barzilay, “Reinforcement learning for mapping instructions to actions,” in Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1-Volume 1. Association for Computational Linguistics, 2009, pp. 82–90.

[4] C. Matuszek, D. Fox, and K. Koscher, “Following directions using statistical machine translation,” in Human-Robot Interaction (HRI), 2010 5th ACM/IEEE International Conference on. IEEE, 2010, pp. 251–258.

[5] J. Arkin and T. M. Howard, “Towards learning efficient models for natural language understanding of quantifiable spatial relationships,” in RSS 2015 Workshop on Model Learning for Human-Robot Communication, 2015.

[6] A. D. Dragan, K. C. Lee, and S. S. Srinivasa, “Legibility and predictability of robot motion,” in Human-Robot Interaction (HRI), 2013 8th ACM/IEEE International Conference on. IEEE, 2013, pp. 301–308.

[7] F. Duvallet, M. R. Walter, T. Howard, S. Hemachandra, J. Oh, S. Teller, N. Roy, and A. Stentz, “Inferring maps and behaviors from natural language instructions,” in Experimental Robotics. Springer, 2016, pp. 373–388.

[8] S. Branavan, N. Kushman, T. Lei, and R. Barzilay, “Learning high-level planning from text,” in Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1. Association for Computational Linguistics, 2012, pp. 126–135.

[9] F. Duvallet, T. Kollar, and A. Stentz, “Imitation learning for natural language direction following through unknown environments,” in Robotics and Automation (ICRA), 2013 IEEE International Conference on. IEEE, 2013, pp. 1047–1053.

[10] R. Paul, J. Arkin, N. Roy, and T. M. Howard, “Efficient grounding of abstract spatial concepts for natural language interaction with robot manipulators,” in Robotics: Science and Systems, 2016.

[11] L. W. Chung, O. Propp, R. Walter, and T. M. Howard, “On the performance of hierarchically distributed correspondence graphs for efficient symbol grounding of robot instructions,” in Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on. IEEE, 2015, pp. 5247–5252.

[12] J. Oh, T. M. Howard, M. R. Walter, D. Barber, M. Zhu, S. Park, A. Suppe, L. Navarro-Serment, F. Duvallet, A. Boularias, et al., “Integrated intelligence for human-robot teams,” in International Symposium on Experimental Robotics. Springer, 2016, pp. 309–322.

[13] D. Fox, W. Burgard, and S. Thrun, “The dynamic window approach to collision avoidance,” IEEE Robotics & Automation Magazine, vol. 4, no. 1, pp. 23–33, 1997.

[14] M. Zucker, N. Ratliff, A. D. Dragan, M. Pivtoraiko, M. Klingensmith, C. M. Dellin, J. A. Bagnell, and S. S. Srinivasa, “CHOMP: Covariant hamiltonian optimization for motion planning,” International Journal of Robotics Research, 2012.

[15] M. Kalakrishnan, S. Chitta, E. Theodorou, P. Pastor, and S. Schaal, “STOMP: Stochastic trajectory optimization for motion planning,” in Proceedings of IEEE International Conference on Robotics and Automation, 2011, pp. 4569–4574.

[16] M. Zucker, N. Ratliff, A. D. Dragan, M. Pivtoraiko, M. Klingensmith, C. M. Dellin, J. A. Bagnell, and S. S. Srinivasa, “Chomp: Covariant hamiltonian optimization for motion planning,” The International Journal of Robotics Research, vol. 32, no. 9-10, pp. 1164–1193, 2013.

[17] C. Park, J. Pan, and D. Minocha, “FTOMP: Incremental trajectory optimization for real-time replanning in dynamic environments,” in Proceedings of International Conference on Automated Planning and Scheduling, 2012.

[18] D. Silver, J. A. Bagnell, and A. Stentz, “Learning autonomous driving styles and maneuvers from expert demonstration,” in Experimental Robotics, Springer, 2013, pp. 371–386.

[19] A. D. Dragan, S. Bauman, J. Forlizzi, and S. S. Srinivasa, “Effects of robot motion on human-robot collaboration,” in Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction. ACM, 2015, pp. 51–58.

[20] J. Mainprice and D. Berenson, “Human-robot collaborative manipulation planning using early prediction of human motion,” in Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on. IEEE, 2013, pp. 299–306.

[21] H. S. Koppula, A. Jain, and A. Saxena, “Anticipatory planning for human-robot teams,” in Human-Robot Interaction. Springer, 2016, pp. 453–470.

[22] S. Bird, “Nltk: the natural language toolkit,” in Proceedings of the COLING/ACL on Interactive presentation sessions. Association for Computational Linguistics, 2006, pp. 69–72.

[23] J. Pennington, R. Socher, and C. D. Manning, “Glove: Global vectors for word representation,” in Empirical Methods in Natural Language Processing (EMNLP), 2014, pp. 1532–1543. [Online]. Available: http://www.aclweb.org/anthology/D14-1162

[24] C. Sutton, A. McCallum, et al., “An introduction to conditional random fields,” Foundations and Trends® in Machine Learning, vol. 4, no. 4, pp. 267–373, 2012.