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Intent-Uncertainty-Aware Grasp Planning for Robust Robot Assistance in Telemanipulation

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Abstract— **Promoting a robot agent's autonomy level, which allows it to understand the human operator's intent and provide motion assistance to achieve it, has demonstrated great advantages to the operator's intent in teleoperation. However, the research has been limited to the target approaching process. We advance the shared control technique one step further to deal with the more challenging object manipulation task. Appropriately manipulating an object is challenging as it requires fine motion constraints for a certain manipulation task. Although these motion constraints are critical for task success, they are subtle to observe from ambiguous human motion. The disembodiment problem and physical discrepancy between the human and robot hands bring additional uncertainty, make the object manipulation task more challenging. Moreover, there is a lack of modeling and planning techniques that can effectively combine the human motion input and robot agent's motion input while accounting for the ambiguity of the human intent. To overcome this challenge, we built a multi-task robot grasping model and developed an intent-uncertainty-aware grasp planner to generate robust grasp poses given the ambiguous human intent inference inputs. With this validated modeling and planning techniques, it is expected to extend teleoperated robots' functionality and adoption in practical telemanipulation scenarios.**

I. Introduction

A. Need of Robot Assistance in Telemanipulation

Teleoperating a robot allows operators to carry out tasks remotely with the robot as a medium. This indirect interaction brings in many advantages including increased motion precision and strength, and remote access to work fields that might be inaccessible or hazardous to the operator. However, successfully teleoperating the robot for a task is often difficult and complex due to indirect manipulation and physical discrepancy between a human hand and robot hand[1][2]. To reduce the control difficulty of teleoperated robots and the operation workload of the operators, the robot agent is being designed to have more intelligence and autonomy, thus, to understand the operator's intent and assist in achieving it. Research has demonstrated that in a target approaching process, the robot agent can infer the target location by observing the operator's motion trajectory and provide motion assistance in approaching the target [3][4]. Much research has been documented on how to precisely infer the target location and how to effectively blend the human input trajectory and robot agent's input.

Even though the approaching process is one of the major components that consist of the teleoperation, the object manipulation task after approaching is essential and challenging but has not received enough research attention. Successfully manipulating an object requires fine motions (i.e., motion constraints for task success [17]), such as approaching the object in a specific angle, grasping the object at a particular part, and applying the force in a certain manner [18]. To satisfy the certain constraints for a task, the operator has to use his/her own mental and physical capability to adjust the robot hand, beyond suffering from the general disembodiment problem and physical discrepancy of teleoperation. Thus, there is a great need of technologies that can enable the robot agents to proactively assist the operator in successfully tele-manipulating objects for various tasks.

B. Influence of Uncertainty in Robot-Assisted Telemanipulation

One of the main barriers in intent-based robot assistance is the uncertainty of intent inference could cause inappropriate robot assistance. If the robot's modeling and planning process does not consider the uncertainty of intent inference, it can cause incorrect assistance, or task failure [9]. Uncertainty exists due to natural ambiguity of human motion. For instance, when a human grabs the body of a cup with a specific grasp pose in teleoperation, it is difficult to determine the manipulation intent for the grasp pose, although the pose itself could be for drinking for one user or for transferring the cup to another location for another user. In addition, indirect interaction of human hands with remote objects further increase the ambiguity of human motion and increase the uncertainty in intent inference.

For those ambiguous human motions, there are indeed subtle unique differences for different tasks, which could provide better context to humans in predicting the intended action [11]. These subtle differences are critical to ensure the success of the task such as 1) a "drinking" task requires sufficient room on the top and grasping poses may dominate the handle, 2) a "transfer to another location" task requires sufficient room on the bottom to place the object safely, and 3) a "handover" task requires sufficient room for another person to grab which tends to create a finger dominated grasp. These subtleties vary between different people; however, they are still key components to discern the task. Usually, these subtle differences are difficult to observe, which makes it hard for models to infer the appropriate

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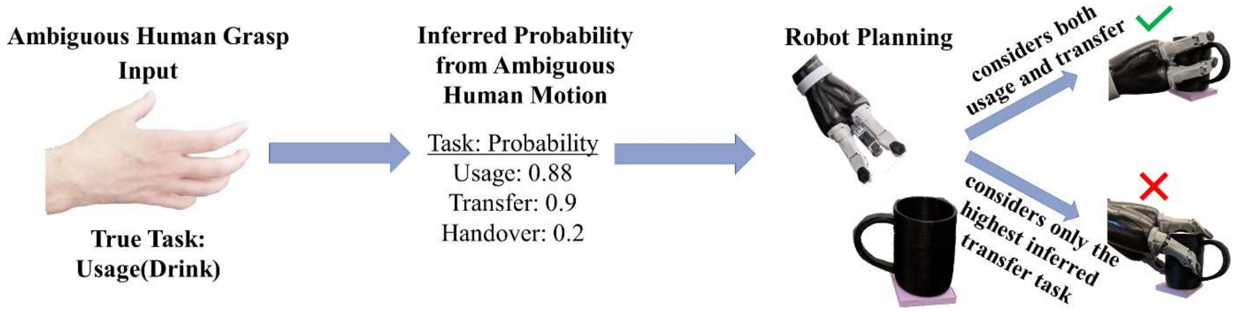

Figure 1: Intent interpretation from an ambiguous grasp lead to different solutions based upon the planning procedure. If the ambiguity in the intent is not considered it can lead to unsuccessful grasp configurations which result in the failure of the task. Considering ambiguity allows for subtle adjustments to be made to the grasp configuration to accommodate the task requirements which are close in intent and ensure the robustness of motion planning. Interpretation of ambiguous inputs, and uncertainty in model outputs is crucial for the planning procedures success.

classification for a task, and consequently provide inappropriate assistance.

To solve these open issues, an intent-uncertainty-aware grasp planning method is developed for robot-assisted telemanipulation. This approach enables robot-assisted telemanipulation in which the robot infers the human operator's manipulation intent and provides grasping motion assistance to achieve the operator's intended task. The contributions of this work are two-fold:

1) Multi-Task Grasp Modeling. The modeling considers the ambiguity of human motion. Instead of building independent task models, some grasp poses share common features which result in satisfying multiple tasks. The models, therefore, contain overlap between features and poses. Additionally, non-overlapping areas are of special interest since they carry fundamentally different features from other tasks. Although these fundamental differences are often subtle, they are of critical need for the robust grasp planning model. Therefore, we developed a multi-task grasp modeling method to allow robots to understand the common features as well as subtle unique features which distinguish tasks.
2) Intent-Uncertainty-Aware Grasp Planning. We developed an intent-uncertainty-aware planner to handle the uncertainty in human intent inference. Given the intent inference probability input, the planner first interprets the ambiguity level of human motion, then generates the grasp based on this ambiguity level. Highly ambiguous input may need a grasp pose that compromises features from all possible tasks. Input with low ambiguity generate a grasp pose that emphasize features for the higher inferred task.

II. Methods

A. Framework Overview

The overall framework process to handle this can be seen in Fig. 2. The three main components discussed in this section will be the multi-task robot model, the human intent ambiguity interpreter, and the intent-uncertainty-aware grasp planner. The multi-task robot model will consider the overlapping nature of different tasks due to common motion features shared by their grasp poses and allows the robot to understand the fundamental different features of these tasks. Grasping objects is ambiguous without a clear discrete difference between satisfying specific tasks because of the inherent nature of the manipulation problem where this varies between users. So, the interpretation of human intent inference provides a descriptor for the ambiguity level among the tasks the robot can satisfy. The planner will attempt to find a robot pose which will pull characteristics from different tasks depending upon the ambiguity levels among tasks.

B. Multi-Task Robot Modeling

Unlike more traditional models the model structure we propose uses common poses in conjunction with probability distribution. Traditional Bayesian structures [5][6], as shown on the left in Fig. 3, do not consider ambiguity[12] of task distinctions, where our method on the right shows the consideration for overlapping tasks. Current robot models

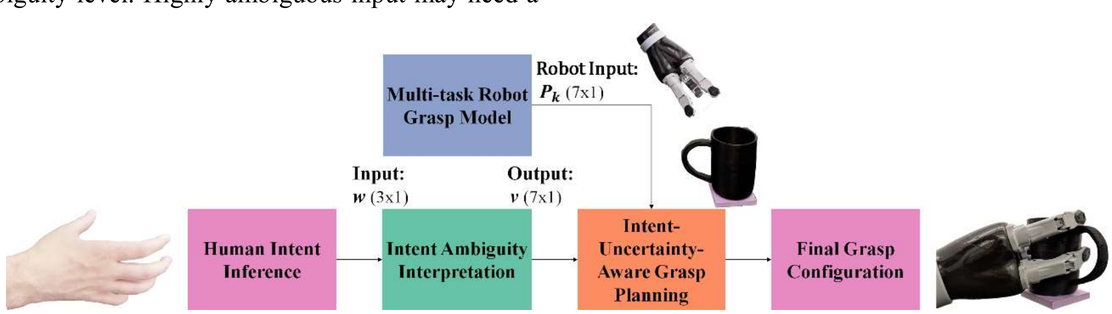

Figure 2: This overview demonstrates the framework used to achieve an intent-uncertainty-aware grasp planning. The initial human grasp creates a probability for each principle task, w. To account for ambiguity the intersection of each principle task is considered, v. The robot model will also account for the intersection of tasks by using common poses. Both of these produce probability vectors which are used for the intent-uncertainty-aware grasp planning. A final grasp pose is then obtained from the planning process.

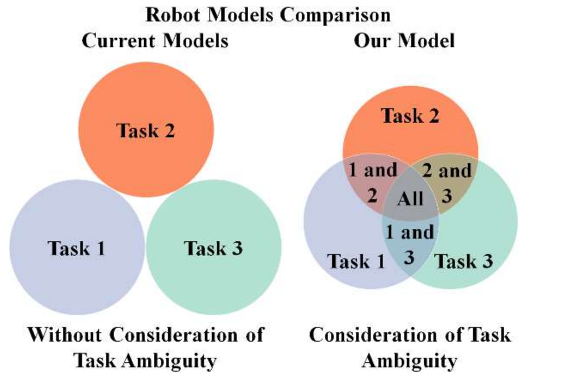

Figure 3: Robot models need to consider task ambiguity. Current models(left) do not consider ambiguity or where multiple tasks may be satisfied simultaneously. An alternative model(right) considers tasks being concurrently fulfilled by common poses.

create task models separately from one another—to create clear, independent distinctions between tasks—and lack consideration of common poses. This causes difficulties to find continuous features between poses. Common poses have a unique ability to satisfy multiple tasks, however, they may be sub-optimal to satisfying a single principle task and less transparent to independent models. However, traditional Bayesian structures can obtain probability rather easily [10]. To ensure the probability obtained for our model is correct it is imperative the training data is labeled appropriately and reflects the right side of Fig. 3.

1) *Inclusive Task Labeling*

Common poses do add a degree of ambiguity compared to those of independent model strategies. Although, our approach takes into consideration the ambiguity by creating a multi-class Bayesian structure [13][14]. Our model considers this by giving an inclusive aspect where poses which satisfy more specific situations should be included in the more general cases. For instance, in Fig. 3, all tasks within the Task 1 circle should be considered within the Task 1 class. The example model created was for grasping a cup—as shown in Table I in conjunction with Fig. 3—for principle tasks which include: task 1, usage or drinking from a cup, task 2, transfer of a cup to another location, and task 3, handover of the cup to a person.

Compared with traditional grasp modeling techniques, the

TABLE II. INCLUSIVE LABELING FOR PRINCIPLE TASKS WITH CONSIDERATION OF COMMON POSES

H T U	Class k	1: U	2: T	3: H	4: U∩T	5: U∩H	6: T∩H	7: U∩T∩H
0 0 1		1	0	0	0	0	0	0
0 1 0		0	1	0	0	0	0	0
1 0 0		0	0	1	0	0	0	0
0 1 1		1	1	0	1	0	0	0
1 0 1		1	0	1	0	1	0	0
1 1 0		0	1	1	0	0	1	0
1 1 1		1	1	1	1	1	1	1

Principle Tasks: U = Usage, T = Transfer, H = Handover

classes and labeling of our modeling method will not be the three principle tasks, exclusively, rather they will contain seven classes in which the robot can satisfy. To label these classes correctly, the assumption made is a robot pose which satisfies more principle tasks than necessary is admissible to a more general class because it satisfies the necessary principle task. By creating an inclusive class structure, the model can begin to understand the subtle and unique differences among tasks. For instance, when looking at Table I, we observe a group labeled for the class "Usage and Transfer". Poses falling under this label satisfy not only the class "Usage and Transfer", but also "Usage" and "Transfer", thus the pose should be considered into the training sets for "Usage" and "Transfer" tasks. This duplication, or information sharing, of training sets allows the more inclusive class (such as Task 1, Task 2, and Task 3) to identify the distinctions between unique and common features. Table II shows how to appropriately label and consider the training set for the model created by the right of Fig. 3 in conjunction with Table I. The letters U, T, and H stands for the principle tasks, "Usage", "Transfer", and "Handover" respectively. The columns represent each class the robot model knows, while the rows are the strict subset of events which make up each class. A pose which is used for "Usage and Transfer only" (row 4), can satisfy both "Usage"(column 1) and "Transfer"(column 2) alone as well as "Usage and Transfer"(column 4). Additionally, for instance, all poses which could be used to satisfy a "Usage" task (column 1) include, "Usage only"(row 1), "Usage and Transfer only"(row 4), "Usage and Handover only"(row 5), and "All Tasks"(row 7).

TABLE I. SUBTLE FEATURE COMPARISON OF DIFFERENT COMMON POSES WITHIN A MULTI-TASK MODEL

Task	Usage	Transfer	Handover	Usage and Transfer	Usage and Handover	Transfer and Handover	All
Top View Left View							
Subtle Detail	More fingers to dominate handle space. Lower palm to leave sufficient room on top to drink.	Prefers to be perpendicular to table and higher on cup to ensure space on bottom to place cup.	Lower palm, leaves room for another user to grasp handle (180˚rotation of wrist).	Fingers dominate the handle. Palm position allows room to drink and place cup.	Few fingers in handle space but occupies more of it. Lower palm to leave room to drink.	Few fingers in the handle space for user. Higher palm to ensure space on bottom.	Few fingers in the handle space for user. Enough space to drink and place.

When observing Table I, we notice between the classes the pose features are subtle, yet they are critical. By labeling the training poses in this manner, we train the model to identify subtle differences and common poses for the principle tasks as well as unique specific cases within the principle tasks. Subtle features can be difficult to observe and determine, however, they provide better context to a human user. Table I includes the subtle features used for our model including high level concepts such as palm contact, clearance from the top of the cup, and sufficient room for a user to grasp. These subtleties are further discussed in the table.

2) *Multi-Task Modeling*

The goal of the Bayesian model is to obtain the posterior probability, or the probability of each class given a continuous pose[15][16]. Each pose contains continuous features, x, which can include position, orientation, force, and object features. Our model included palm center, and palm orientation as well as finger force. The model is a Naïve Bayes classifier (NB), but uses the features to create a multivariate normal distribution as shown in (1). The key parameters from the model for each classification zone, k, include: the mean value of each feature, μ_k, the covariance matrix, $\sum_k$, and the prior probability, P(k). These parameters are learned from the training set by using the Expectation Maximization Algorithm. In (1), it shows the conditional probability of x given k, where d is the length of x.

$$\mathrm{P}(\mathbf{x}|\mathrm{k}) = \frac{1}{\sqrt{\det(\Sigma_\mathrm{k})*(2\pi)^\mathrm{d}}} \mathrm{e}^{-\frac{1}{2}*(\mathbf{x}-\mu_\mathrm{k})^\mathrm{T}*\Sigma_\mathrm{k}{}^{-1}*(\mathbf{x}-\mu_\mathrm{k})} \quad (1)$$

With this equation, Bayesian models obtain the posterior probability of the class k given x with (2), where the class with the highest probability is the label for x.

$$\mathrm{P}(\mathrm{k}|\mathbf{x}) = \frac{\mathrm{P}(\mathbf{x}|\mathrm{k})*\mathrm{P}(\mathrm{k})}{\Sigma_\mathrm{k}^\mathrm{K}\mathrm{P}(\mathbf{x}|\mathrm{k})*\mathrm{P}(\mathrm{k})} \quad (2)$$

Each probability of a class is then put into what is referred to as the *robot probability vector, P_k*. The model we created from Fig. 3 and Tables I and II, mean there are seven classes and the probability for one pose to satisfy all seven classes must sum to one.

C. Intent Ambiguity Interpretation

To handle the ambiguity, the modeling of human manipulation intent follows a concept of multi-label classification, where two, three, or m principle task classification model outputs could be satisfied at the same time, shown in Fig. 1. Each classification model produces a probability and is put into a vector of mx1 size, where this is referred as the *classification input vector, w*. Since each model output is independently obtained, we can identify each joint probability case. This will generate a vector of size 2^m where m is the number of principle tasks. This vector of possible events with their subsequent probability will be referred to as the *human probability vector, u*, shown in (3), where $\psi(\mathrm{m})$ is the power set from 1 to m task classification models, and Y is each subset of $\psi(\mathrm{m})$.

$$P\left(\cap_{i\in Y} w_i \cap_{j\notin Y, j\in m} \neg w_j\right) = \prod_{i\in Y} P(w_i) \prod_{j\notin Y, j\in m} 1 - P(w_j), Y \subset \psi(m) \quad (3)$$

For example, consider when m=3 as shown in Fig. 1. The classification probability vector (0.88,0.9,0.2) produces a vector where each combination of the principle tasks is considered true and false. So when event U∩¬T∩¬H occurs, the probability is 0.88*(1-0.9)*(1-0.2) = 0.07, while when the event U∩T∩¬H occurs, the probability is 0.88*0.9*(1-0.2)=0.63.

Since the robot model is unaware of the event where inaction should be taken(¬U∩¬T∩¬H), it is important to eliminate this action and normalize the rest of the probability vector where at least one principle task m is satisfied. This is to ensure the robot classes, k, is equal to 2^m-1. This new vector is known as the *target probability vector*, v, and is shown in (4). The target probability vector now has a scenario associated with each class of the robot model previously discussed in Table I and II.

$$v_i = \frac{u_i}{\Sigma_j^{2^m-1}|u_j|} \ \forall\ i < 2^m \quad (4)$$

Alternatively, a designer could force the robot to ask for clarification if the inaction task is sufficiently high. The human probability vector has a distinct advantage over using the classification intent by allowing more descriptive behavior of the type of features the robot model should use. For instance, Fig. 1 shows if the classification intents for grasping a cup for Usage and Transfer are similar and high while the Handover task is low, then the decision process should carry features which demonstrate and use features from both higher intents. Additionally, the human probability vector inherently accounts for uncertainty in human intent by allowing for the system to consider multiple classes at once as well as the varying degree the multiple classes may influence the outcome of chosen features.

D. Intent-Uncertainty-Aware Grasp Planning

The planning process involves taking the ambiguity levels developed in the intent interpretation section and using them as a basis for the determining characteristics needed. Whether the ambiguity levels are high or low will determine which set of features should predominantly be used from the robot model classes developed earlier. The planning process will start from a known pose, which is closest to the ambiguity levels, then continue to refine the features of the pose until a more reflective pose is created. The refining step is iterative and will attempt to use both unique and subtle characteristics from all classes as it needs until convergence.

The planning process includes using a Bayesian structure to best fit the target probability vector. Traditional Bayesian models attempt to maximize the probability of one region or class over all others, since these models are based on independent model strategies, rather than minimize the difference between the current and target probability vectors. By matching the probability vectors, the subtle and unique features of the robot model should reflect the best combination of intent to make it predictable to the user. The first step is to identify the grasp class out of the defined 7 and select an initial grasp pose from the training set of this class, since this is currently the best approximation the robot model can make. This best approximation is done by taking the highest class of the human probability vector and choosing the best pose which is reflected in the class of the robot model. Determining the best pose within the class can be done by using the objective function as shown in (5). The objective function is a least square regression which will attempt to match the robot probability vector to the target probability vector.

$$min \frac{1}{2} \sum_k (v_k - P_k)^2 \quad (5)$$

By mimicking the probability, the unique and subtle features of the robot model will reflect those most similarly to the human intent. This is due to the robot model classes containing both the unique and subtle features which the planner takes characteristics. The next step is to refine this initial approximation and determine how the features need to be adjusted. To determine the amount of adjustments the planner will take, from a unique feature to a more common feature or vice versa, a gradient descent method was applied as shown in (6).

$$\frac{\partial P_k}{\partial x}(v_k - P_k)\ \forall k \quad (6)$$

This can be solved using finite-difference methods [7] or analytically using matrix calculus [8]. This approach will use the ambiguity levels as a guide to determine which subtle or unique features are more critical, or influential in ensuring a successful grasp pose. Afterwards, constraint equations will be applied—which are robot and case dependent based upon features selected thus will be left to the reader's discrepancy—and the objective function will be evaluated once again. The overall algorithm can be seen in Algorithm 1. All together these pieces will provide the best features to match the human intent.

Algorithm 1: Intent-Uncertainty-Aware Grasp Planning
Input: Multi-task Robot Model *NB,* Classification Intent Vector $\boldsymbol{w}$
Output: $\boldsymbol{x}$, $\boldsymbol{P_k}$
Evaluate $\boldsymbol{w}$ to find ambiguity levels, $\boldsymbol{v}$
Obtain starting pose $\boldsymbol{x}$, by choosing closest to known level to $\boldsymbol{v}$ from *NB*
while iter < iteration_max or obj < tolerance **do**
    $\boldsymbol{P_k} = NB(\boldsymbol{x})$
    obj = $\frac{1}{2}\sum_k(\boldsymbol{v_k} - \boldsymbol{P_k})^2$
    dobj = $\frac{\partial \boldsymbol{P_k}}{\partial x}(\boldsymbol{v_k} - \boldsymbol{P_k})$
    $\boldsymbol{x}$ = updateVariables($\boldsymbol{x}$,*BN,obj,**dobj***)
    $iter \leftarrow iter + 1$
end while
Return $\boldsymbol{x}$, $\boldsymbol{P_k}$

III. Experiment and Results

A. Experimental Setup

The experimental setup included using a Kinova Mico arm as well as a mug for the object of interaction. The robot model was gathered for three tasks: drinking/using the cup, handing the cup over to a person, and transferring the cup to another location. The robot model only considered features for the final grasp configuration and did not include trajectory or temporal features, however, the force in which the fingers applied was considered. The robot model was created by developing expert analysis of rules to determine which task could be satisfied. The rules developed express extreme cases where there are certain cases of no overlap between principle tasks. The robot was then manually moved to obtain the training data. Additionally, the optimization algorithm used was fmincon [7] available in MATLAB, however, other optimization algorithms may be used to achieve quicker convergence. The classification intent was simulated for the experiment to represent where one task is dominant, two tasks are codominant, and all three tasks are equal. Two different types of analysis were done to verify the method. The first was an objective result by comparing the initial intent inference and probability distribution with those created by the final pose configuration. The other analysis was the subjectivity and predictability of the pose by a human user.

B. Objective Results

Due to the planning framework, the resulting poses and solutions are deterministic. The results shown are for three separate cases which include: a single task where the target intent is for usage, a task which holds two likely intents for usage and transfer, and lastly a task where the intent for all tasks are equally likely. Table III shows the comparison of the target probability vector, v, and robot probability vector, P_k. These results show when the individual task is the target task it primarily takes features from this population, while mostly disregarding other populations. This coincides to how independent model strategies exist. It is shown the more ambiguity, or the closer the task intents are to one another, the better the optimization can handle pulling features from the separate populations to achieve a solution. We can also observe how close the final intent inference of the three principle tasks we get to compared to the initial intent inference, w, in Table IV below.

TABLE III. Posterior Probability Vector comparison

H T U	Single Task Target	Single Task Final	Two Task Target	Two Task Final	Three Task Target	Three Task Final
0 0 1	**0.7933**	**0.8156**	0.0817	0.0998	0.0090	0.0143
0 1 0	0.0098	0.0336	0.0817	0.1003	0.0090	0.0102
1 0 0	0.0098	0.0347	0.0010	0.0197	0.0090	0.0044
0 1 1	0.0881	0.1108	**0.7356**	**0.7533**	0.0811	0.0801
1 0 1	0.0881	0.0000	0.0091	0.0000	0.0811	0.0809
1 1 0	0.0011	0.0053	0.0091	0.0269	0.0811	0.0805
1 1 1	0.0098	0.0000	0.0817	0.0000	**0.7297**	**0.7295**

TABLE IV. Principle Intent Inference Comparison

Initial Intent	Single Task Target	Single Task Final	Two Task Target	Two Task Final	Three Task Target	Three Task Final
Usage	0.9	0.9265	0.9	0.8531	0.9	0.9049
Transfer	0.1	0.1497	0.9	0.8805	0.9	0.9004
Handover	0.1	0.04	0.1	0.0465	0.9	0.8953

Table IV shows the comparison of the initial target intent and the final intent given by the final pose. This shows the more ambiguous the initial intent the better the pose can satisfy it. In addition to checking the objective posterior probability and intent of the poses, it is also imperative to observe the grasp pose to determine if it could satisfy the given tasks.

C. Subjective Results

For the subjective analysis, there are two main properties to identify. The first, is to determine if poses can satisfy true tasks, while the second is observe the subtle features of the final pose configurations. To analyze both properties, observe Fig. 5. It shows the comparison between two ambiguous

Figure 5: There are three separate grasp poses a) represents the pose which satisfies the transfer task and not the other two tasks as seen by the intent provided on the top. This grasp dominates the top of the cup to leave room to place and it is unsuitable for usage. b) is the pose which our model generated which carries the subtleties to satisfy both usage and transfer while not satisfying handover. The robot hand dominates the handle by having a majority of fingers around it, while leaving sufficient room to drink from the top. The palm is higher on the cup. c) is the pose for which satisfies the usage task. The fingers dominate the handle space by having a majority of fingers near the handle, sufficient room on the top for drinking.

intents between the transfer and usage task. This figure shows the issues where independent models may fail or possibly be lucky to succeed. The intent for grasp pose *b)* is (0.9,0.9,0.1), so it is difficult to determine which to task to follow. For instance, if the true task is usage and the independent model method incorrectly infers the task is transfer, it will produce the grasp pose *a)* shown on the left. This grasp has subtle differences which fails for usage, such as a finger covering the top of the cup and leaving insufficient room to drink. While grasp *c)* appears to be an optimal grasp for drinking a cup, although it is not optimal for transferring the object because it lacks palm contact with the cup and is a finger dominated grab which may not be a stable hand configuration for a transfer task. Grasp *b)* takes features from both usage and transfer populations, which generate poses *a)* and *c)*, to produce a pose which is better equipped to handle both tasks. The palm is close to the cup, which can satisfy a stable grasp, while also leaving sufficient room on the top to drink from. The subtle differences allow a change in the finger placement, sufficient room to drink, and palm contact for a more stable grasp. These subtle differences of features within a pose allow for a smoother transition of tasks which reduce the risk for inferring the wrong intent. Humans are keen on picking up these subtle differences, so it is critical to account for the vagueness of intent and create models which are more flexible towards it.

Additionally, human predictability was also an important factor to consider when analyzing the poses the robot distinguished. The human expert was to identify 50 poses generated by the model and correctly label the pose for which tasks it could satisfy. The expert was able to distinguish 80% of the poses as the correctly labeled ones. The human subject often appeared to believe the pose could satisfy more tasks than it could which may be a result of the user seeing features from the other minor tasks which the optimization may have incorporated as part of the posterior probability vector. This shows the importance of creating continuous models since it is difficult to determine the vague intent presented by grasp configurations.

IV. Discussion

The ambiguity of distinctions between the different grasp configurations requires robot models to become continuous rather than discrete models. The methods provided demonstrate an effective way to consider and convert the robot models into a more appropriate framework. It is important to understand there are optimal poses which can satisfy a specific task, and there are also sub optimal poses which can satisfy all tasks. The goal of this work is to find sub optimal poses which are better solutions than a default preplanned grasps which can satisfy all tasks by transforming the problem into a continuous system. This is done by interpreting the human intent as independent and transforming the probability to a more descriptive representation. The results also show the subtle feature changes can have an impact in influencing predictability. Obtaining human intent and creating effective human inferencing models creates uncertainty which needs to be accounted for when having a robot system make decisions. This makes it difficult to confidently use independent model strategies compared to probability distribution strategies. All together this system accounts for uncertainty by creating a continuous Bayesian structure from which the final intent distribution can closely mimic the human intent.

V. Conclusion

The overall method proves effective due its practicability compared to other modeling methods. However, it can still be improved before being used for true telemanipulation. The evaluation for different levels of overlap between principle tasks is a necessary next step. It is also critical to analyze models for other objects. Lastly, more human subjects are needed to further validate the predictability.

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