Response to Reviewers – Paper Submission (AURO-D-17-00250)
Title: Disambiguation of Human Intent Through Control Space Selection

We sincerely thank all the reviewers for taking the time to provide us with useful feedback and insight. We will be responding to all the major concerns raised by each reviewer separately and will discuss the relevant changes that have been incorporated in the revised version of the document. All minor comments (e.g. grammar typos) have been incorporated into the text. Please also find attached to this letter a version of the article with all changes marked in blue.

The summary of our major changes are as follows. (1) We have made significant changes to the text that aim to improve the clarity and rigor of our writing, and to motivate the problem more clearly. (2) We have clarified the intuition behind our approach and choice of disambiguation metric. (3) We have presented new results, that compare our dynamic field theory based intent inference approach to a Bayesian inference approach used widely in shared autonomy settings. (4) We have included previously omitted survey results from our subject study, highlighting users' perception of our disambiguation system. We believe these changes to have significantly improved the quality of the paper. We again thank the reviewers, and look forward to their feedback.

<u>Response to Guest Editor:</u>

(1) Improve clarity and rigor

Throughout the text, we have made significant changes with the aim of addressing clarity, rigor and motivation. (To help spot these changes, all modifications to the text are marked in the version of the article attached to this letter.) We have also provided more explanation as to the intuition behind our approach, thereby addressing some of the concerns raised by Reviewers #1 and #3 (Section 3.1).

(2) Baseline comparison

In this version of the article, we have implemented a Bayesian inference approach often used in the shared autonomy literature, and provide a qualitative comparison to our dynamic field theory based intent inference approach. We provide intuition on under what conditions the approaches perform similarly and differently, and provide data on an illustrative example (Section 4.2).

Regarding information gain, we agree that an information theoretic notion of entropy could also be used to solve the disambiguation problem---and towards this end, we have added text to this revision on the topic of information theory. In this article we introduce the idea of control subspace selection for the purpose of intent disambiguation. As a first exploration of this idea, we took the approach of investigating what features of shape of the probability distribution over goals can be most beneficial for intent disambiguation purposes. We note that a change in entropy of a distribution is typically accompanied by a change in the contour/shape of the distribution. Therefore, by designing a disambiguation heuristic such as the one presented in this paper, we get to have a closer look at which low-level features of the distribution contribute the most to the intent disambiguation. Using information theoretic ideas would be the next step in our work.

(3) Intuition and clarity

We have added and revised text with the aim of providing more intuition for our choice of metrics and approach (Section 3.1). (Again, this text is marked in blue in the attached document.)

(4) Discussion addressing Reviewer #2's concerns regarding the experimental validation.

We have presented clarifications for Reviewer #2's concerns regarding the experimental validations, especially with respect to baseline comparison of our intent inference approach to Bayesian schemes (Section 4.2). We have also included survey results that support some of our claims regarding how the disambiguation system helped in easier task execution (Section 7.4).

Reviewer #1

a. *Further analysis is required*

In the current version of the paper, we have supplemented our analysis by including previously omitted user survey results, which indicate that the users generally found task execution to be easier when controlling the robot in the disambiguating control modes that the algorithm selected (Section 7.4). In the revised version, we also supplement our analysis of the efficacy of the intent inference algorithm by presenting some baseline comparisons to a standard Bayesian approach found used commonly in shared-control domain (Section 4.2).

b. Detailed analysis for intent inference

In this revised version, we have included a baseline comparison of our dynamic field theory based intent inference approach to a standard Bayesian inference scheme (Dragan et al., 2013) widely used in the shared autonomy literature (Section 4.2). This comparison includes both a qualitative discussion, as well as an illustrative example in which there are three discrete goals and the user teleoperates and moves the robot to each one of the objects sequentially. In general, we found performance between the two approaches to be similar, except in scenarios where the Bayesian approach's delta function collapsed (as in the figure shown in the paper). We were unable to uncover any scenarios in which our DFT approach performed worse than the Bayesian appoach.

c. User perception of disambiguation system

We have included the results of a user survey from our subject study, highlighting users' perception of our disambiguation system. Subjects were asked to fill out a questionnaire after each task in which they evaluated the system and reported how much they liked to operate the robot in the control modes selected by the algorithm (section 7.4).

d. The paper states that "a higher value [of the mode of the probability distribution] implies that the robot has a good idea," however this is not always true.

We agree with the reviewer, and believe that there in fact has been a misinterpretation due to a lack of clarity on our part, which we hope has been resolved in the current revision of the text. Our claim is that higher probability indicates a higher confidence in the robot's prediction (and not that a higher distribution mode will result in better disambiguation). It is precisely because of the reasons mentioned by the reviewer that we consider other features (the remaining 3 components/features) of the probability distribution as well, to determine which control mode has higher *disambiguation* capabilities. In the current version of the text we have clarified the intuition behind the choice of the different features that inform the disambiguation metric (Section 3.5).

(In short, a single feature by itself is unlikely to disambiguate the goals. But by considering multiple features in a combined fashion, it adds to the disambiguation power.)

e. In Fig. 3..., One way to improve it might be to visualize only one goal and illustrate the change of confidence for one goal.

We thank the reviewer for this suggestion. After careful consideration however, in the present version of the document have decided to retain the three goals, because disambiguation is more relevant when there are multiple goals (or else there is nothing to disambiguate between). The shaded bars indicate how the probabilities vary for robot motion along each dimension. For this illustration we use a simple directedness-based heuristic to determine the probabilities.

f. Fig. 4 is not clear; why is best control dimension x in the right column? I suggest simplifying it using only two goals. Also, how are the C1 and C2 specified? It appears that some information was omitted from the RSS version of this work.

Our reason for choosing four goals is to illustrate the robustness of the disambiguation algorithm in identifying disambiguating control dimensions effectively in a scene with higher number of goals. Intent disambiguation typically becomes harder as the number of potential goals in the scene increase. With two goals, the disambiguation problem in many cases becomes trivial. As mentioned in the figure caption, the right column shows those parts of the workspace in which the best disambiguating control dimension is **Z.** Due to space constraints we have referred our readers to our original RSS paper for detailed specifications of what the two confidence functions (C1 and C2) are. However, the figure caption does mention that C1 and C2 correspond to an instantaneous proximity-based and directedness-based heuristic confidence function.

g. I suggest that the authors extend their related work section with recent studies on shared autonomy (see recent survey by Javdani et al., "Shared Autonomy via Hindsight Optimization for Teleoperation and Teaming").

We have taken this into account and revised our related work section accordingly.

Reviewer #2

a. Why not Information Theoretic alternatives?

We agree with the reviewer about the utility of information theoretic concepts in relation to the problem posed in our article, and have expanded the discussion information theoretic concepts for the purposes of active learning and information gathering actions in the related work section.

In this article we introduce the idea of control subspace selection for the purpose of intent disambiguation. As a first exploration of this idea, our motivation is to investigate what aspects/features of the probability distribution over goals (more precisely, the shape of the distribution) inform intent disambiguation the most. A change in entropy is typically accompanied by a change in the shape of the probability distribution over goals. We take a bottom-up approach wherein we investigate how the shape of the probability distribution evolves as the user operates the robot and moves it in space. We hand-engineer four different features (components) that characterize different aspects of the shape of the distribution based on empirical insights we had during our algorithm design phase. The combination of these individual components into a single disambiguation metric is also a design decision, but carefully done in such a way that higher values of the disambiguation metric would imply greater disambiguation capability. Using information theoretic ideas would be the next step in our work.

b. Erroneous claims regarding the metric?

We respectfully disagree with the statement that this is erroneous. By virtue of design, a higher value of the metric indeed corresponds to better intent disambiguation and therefore the intent inference mechanism will be able to infer the human's intent unambiguously and accurately. We have made this aspect clear in the revised text to avoid any potential misunderstanding in interpretation (Section 3.5 – 5)).

c. Why not Bayesian?

We agree that a clear motivation for the development of our new intent inference approach was missing from the article, and thank the reviewer for pointing this out. The proposed dynamic field theory based system for intent inference is an alternative to Bayesian and other heuristic approaches. We have added text to the beginning of Section 4.1 that motivates our development of this alternative, as well as a comparison in Section 4.2 to a Bayesian approach from the shared control literature.

In addition to the new text in Section 4.1, we note that while it is true that if a process is truly finite-order Markovian then the state is a 'sufficient statistic', for human-robot interaction in the context of assistive robotics this assumption is not always correct. Furthermore, in a Bayesian scheme, if at any time-step the likelihood is peaked (a delta function), it can result in the collapse of the posterior to a single value, thereby eliminating any memory trace.
By framing the evolution of the probability distribution as a dynamical system, our method is similar to approaches in which recurrent neural nets are used for intent inference purposes (except in our case we hand-engineer the features that drive the dynamical system).

d. Benchmarking of proposed work.

In the revised version we have provided baseline comparison of our intent inference mechanism and a Bayesian approach that is widely used in shared autonomy setting (proposed by Dragan et al. (2013)).
We have provided a qualitative comparison through an illustrative example, and discussion of the mathematical underpinings of each approach (Section 4.2).

In essence, our approach, relies on the features of the raw input to determine how the probability distribution should evolve in time and does not assume that the human behaves optimally. This is crucial in the setting of assistive robotic manipulation, in which subjects have inherent motor limitations that make optimal behavior an unrealistic assumption.

e. Experimental Validation

In the present version of the work, we have included previously omitted user survey results from our subject study (Section 7.4). The survey results indicate that the subjects did find task execution to be easier when operating the robot in disambiguating control modes.

Reviewer #3

a. There are a few run-on sentences throughout the work. Please make sure all sentences are clear and concise. Similarly, there are a few very long paragraphs that could be broken up to best present one idea at a time. There are a few widows and orphans (hanging words or phrases). For aesthetic purposes, please watch for unnecessary white space.

Thank you for the suggestions. We have taken them into consideration and have revised our work accordingly.

b. Mathematical Notation

We have clarified our math notation to avoid ambiguity.

c. *There are a lot of equations that were selected to fit the task / goals of this work, but it might be nice to add a little intuition about how you selected these parameters (and maybe what didn't work) so readers can get useful insight from your work.*

We have included text throughout the article with the aim of providing more intuition. Please see in particular Sections 3.5, and also Section 8 for a discussion of what did not work well.

(d) Can you compare your methods to some baseline techniques for intent / goal inference? The results show how well your approach works, but doesn't give compare to baselines.

We have provided a baseline comparison to a standard heuristic Bayesian approach (Dragan et al. (2013)). A qualitative comparison through an illustrative example, and discussion of the mathematical underpinings of each approach, can now be found in Section 4.2.

(e) Please discuss how this would be useful in other applications (e.g. how would this extend to cases where there are less discrete goals) so readers can gain insight and use it in their work.

We thank the reviewer for the suggestion, and have included the discussion in Section 8.