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Interactive Natural Motion Planning for Robot Systems Based on Representation Space

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Abstract
Endowing robot with interactive natural motion planning is of great importance, since user has to get more and more involved for better realization with versatile tasks under increasingly complicated environments. In this paper, studies on interactive natural motion planning are summarized and a general theoretic framework for which is presented in triple-folds. Firstly, the motion planning model is formulated based on representation space, and essential guidelines on planning algorithm selection are also proposed. Then user intention inference, which consists of grid-based intention model and Bayesian filtering based inferring algorithm, is investigated to mitigate the impact of network induced imperfections during human–robot interaction. Finally, for further rejecting various uncertainties, $\mathcal{H}_\infty$ control theory based disturbance observer is proposed. All three algorithmic design procedures are stated in detail and the efficiency of which are presented via existing results, followed by discussions on the future directions.

Keywords Robot · Interactive natural motion planning · Representation space · Intention inference · Bayesian filtering · Disturbance observer

1 Introduction

Robotic research has been stepping into a brand new era over the last decades [1]. Robot has to accomplish more and more complicated and versatile tasks. On the other hand, it usually works in dynamic uncertain environments. Furthermore, robot taking part in human beings' daily life has now become inevitable. Under this circumstance, conventional motion planning schemes are no longer capable of acquiring feasible trajectories for task realization [2]. Thus, it is essential to seek solutions by resorting to interactions between human and robot. Additional information and guidelines might be embedded, so that robot could purposely be able to understand environments, task prescribed, self-states, as well as behavior and intentions from human operators [3,4]. Therefore, it is imperative to endow robot with the capability of interactive natural motion planning, for it being able to accomplish the prescribed task while interacting with human beings. Thus robot can enter the human society more naturally and adapt to various complicated environments more smoothly.

Interactive natural motion planning concentrates on active decision making while interacting with users, rather than passive planning in steady environment for invariant task [5,6]. This planning method can adjust robot's behaviors according to the instantaneous information obtained through human–robot interaction. Obviously, such flexible framework can plan more rapidly and effectively, since it can take full advantage of various information during interacting. In order to realize acceptable behaviors, it should effectively reject various disturbances in the process of task realization. Consequently, the core components of interactive natural motion planning are active interaction, motion planning and disturbance rejection, in which motion planning are the most essential capability that robot should own.

The central problem of robotic motion planning is how to plan an optimal trajectory for the specific task under constraints, while satisfying performance requirements [7,8]. Conventionally, motion planning algorithms are conducted either in configuration space (C-space) [9], or in task space (T-space) [10]. C-space based algorithm can directly obtain

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the robot's control signal, thus real time performance is guaranteed. However, it is not so intuitive and flexible for task realization, different C-spaces are needed for different type of robots. While for T-space based methods, one can directly map the task to system state, thus the process of motion planning can be observed intuitively. However, when applying to real robot, huge amounts of inverse kinematics are needed, which lead to heavily computational burden and jeopardize real time performance.

The aforementioned motion planning methods have already had a wide range of applications. However, they are only applicable to the tasks that are implicitly realizable. What kind of tasks could be achieved and how to handle those unachievable tasks, by a specifically configured robot system, have seldom been addressed so far. To deal with this problem, Hsieh [11] proposed "constraints relaxation". Based on this, OlfatiSabe [12] thought that it was more reasonable to consider the constraints with higher weighting coefficient with more priority. While Hauser [13] dealt with the problem by gradually removing some constraints till an acceptable one obtained. However, these methods have difficulty in scaling to more general cases. On the other hand, robot may be subjected to various constraints, such as task constraints, physical constraints and obstacle constraints. It has been becoming very difficult for one to determine whether the task can be realized in advance, due to the increasingly complicated environments, versatile tasks and unpredictable disturbances.

Therefore, for a given task and a robot system of definite configuration, two important issues should first be considered: (1) whether the given task can be realized by the system, designing task-oriented motion planning and coordination strategies is meaningful only if the task is realizable; (2) if a prescribed task cannot be accomplished by the robot system of definite configuration, how to make it accomplishable via task adjustment and/or system reconfiguration. Namely, it is essential to find a strategy to transform an unrealizable task to be a realizable one with the available system capability. The transformation condition should be figured out before designing the concrete realization schemes. Following this idea, Su and Xie [14,15] proposed representation space (R-space) model for robotic task planning, the core idea of R-space is that by extending the conventional T-space and C-space, and taking all the constraints and variables during task realization into account, a new strategy with completely representing the robot task realization can be obtained. Henceforth, one can develop theories and practical algorithms to deal with task planning problem accordingly.

Robot should have to interact with users while accomplishing the task. With the developing of communication network, human–robot interaction (HRI) can further be improved in its flexibility and reliability [16], with various communication networks such as wired or wireless Ethernet, or even the Internet. However, the introducing of network will induce imperfections from different hierarchies, such as time delays, time-varying transmission/sampling intervals, packet losses and disorder, competition of multiple nodes accessing network, data quantization, clock asynchronization among local and remote network as well as network security and safety etc.. The existing of network induced imperfections will deteriorate the performance of HRI, or even endanger its stability [17,18]. Therefore, network based HRI may cause many unexpected bad behaviors during task realization.

During the past decades, extensive studies on network-induced imperfections have been carried out by both the control and the communication communities assuming different scenarios. It is shown that, for a particular networked control systems, different types of imperfections listed above may not occur simultaneously in practice. Moreover, the effects of some imperfections in certain network may be minor, e.g., the time delay can be ignored in a real-time network, and the quantization errors are negligible in high bandwidth Ethernet. Thus, most researchers focus on only a part of imperfections aforementioned. Walsh et al. [19] divided the time delays into different types, such as, constant delay, time-varying delay, deterministic delay and stochastic delay, then specific technique was proposed. Quevedo et al. [20] mainly dealt with packet losses and disorder. Sinopoli et al. [21] studied on competition of multiple nodes accessing network. Furthermore, bilateral control [22,23] and sliding mode based impedance control [24,25] have also been used to tackle the network induced imperfections. Although network induced imperfections have been addressed widely in the last decades, unfortunately, it is not yet clear what the best control scheme is. For these methods, only a part of network induced imperfections are taken into account. However, it is hard to guarantee the performance for just taking only a part of network induced imperfections into account for real robot system. Since, generally, various types of imperfections lead to the results jointly. What is worse is that we cannot even figure out which kind of imperfections leads to the undesired results. In addition, the above methods aim to control the robot directly following user commands, which usually need intensive interactions. Thus, the impact of network induced imperfections may be aggravated due to the huge amounts of data transmission. Under this circumstance, we argue that the impact of network induced imperfections could be relieved by resorting to the autonomy of the robot. Additional specially assigned intelligence might be embedded into the robot, so that the robot could understand the user command and execute the assigned task autonomously without frequently interacting with user. Hence, communication between the robot and the user is minimized, so is the impact of network induced imperfections upon system performance. Following this idea, Su [26] proposed user intention inference based networked robot control scheme, in which user inten-

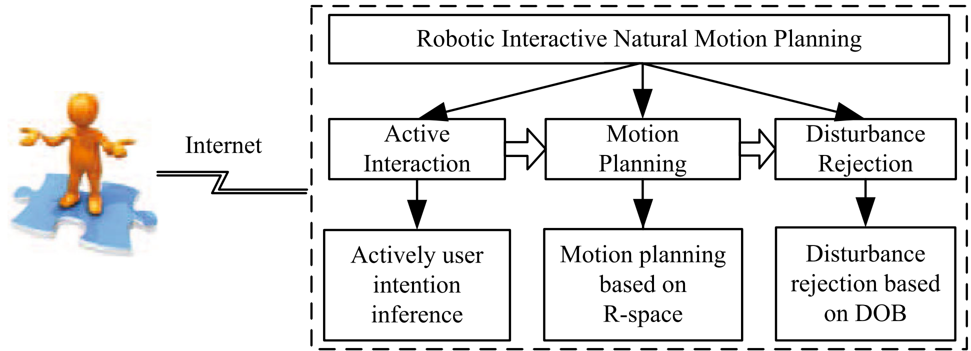

Fig. 1 General theoretic framework for robotic interactive natural motion planning

tion has been modelled by grid model, then Bayesian filtering technique has been applied to infer the user intention. The scheme presents novel method for robot control subjected to network induced imperfections.

As is known to all, how to model robot in its dynamics or kinematics is a long-standing open problem that perplex researchers from both robotics and control theory society [27,28]. On the other hand, we cannot consider all uncertainties into the conventional model based control schemes. Furthermore, all the uncertainties, including unmodeled dynamics, couplings, fractions, and external disturbances etc., will reduce the high-speed, high-accuracy position and tracking performance severely. Therefore, how to reject the uncertainties effectively in practice is one of the key issues in modern control theory [29–31]. In fact, most existing control methods, such as PID [32], robust control [33], stochastic control [34], adaptive control [35], sliding model control [36] as well as intelligent control methods [37,38], can eliminate the disturbance in some extent, but many issues are still open. For example, it is difficult to analyze the stability of PID based control system. Robust control owns innate strong conservatism. The general premise for stochastic control, that all disturbances are Gaussian, can not be fulfilled in practice. The chattering phenomenon existing in sliding mode control limits its application largely. Intelligent control methods usually lead to extensive computation burden and slow convergence process.

In recent years, disturbance rejection based robotic control schemes have attracted extensive attention, in which active disturbance rejection control (ADRC) [39] and disturbance observer (DOB) [40] based control methods have been attracting a large number of researchers from both academia and industry, due to their easy implementation and excellent disturbance rejection capability in practice. Generally, in both control schemes, the disturbance rejection ability and robustness of the system have been improved by using an observer based mechanism, extended state observer (ESO) in ADRC or Q-filer in DOB, to estimate the unknown external disturbances and unmodeled dynamics in real-time. Then disturbance rejection mechanism is designed to compensate for those unknown signals. It is shown that ADRC is a promising approach for robotic calibration-free visual servoing [41]. DOB has been widely used in robotic control due to its flexible design methods and the ability of sufficiently taking advantage of domain knowledge.

In conclusion, robotic interactive natural motion planning can plan an optimal path in R-space with constraints and performance satisfied, on the basis of actively inferring user intention and rejecting various uncertainties during task realization. To realize this, firstly, one has to construct the R-space and design planning algorithm. Then, actively inferring user intention to mitigate imperfections caused by the introduction of network during HRI. Finally, DOB based control scheme can improve control performance by actively eliminating various uncertainties. Therefore, we will establish a general theoretic framework for robotic interactive natural motion planning which contains three components (as shown in Fig. 1), i.e., R-space for general representation of motion planning, active user intention inference to mitigate the impact of network induced imperfections and DOB based disturbance rejection control for performance guarantee by eliminating various uncertainties.

2 R-space Model

For general robotic motion planning, the R-space based motion planning scheme consists of two iterative levels: task level and motion level (as shown in Fig. 2). In task level, one obtains the task objective and corresponding constraints. In motion level, one has to firstly construct R-space by selecting representation variables that are most related to task

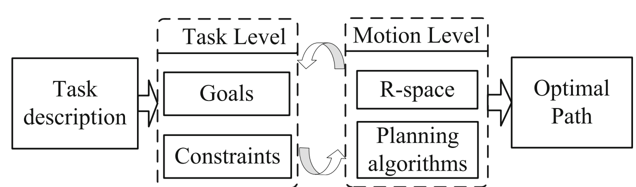

Fig. 2 The framework of hierarchical motion planning in R-space

objectives, then the optimal path can be obtain by motion planning algorithms conducting on R-space. If there does not exist an acceptable path, one may resort to task adjustment and/or system reconfiguration by returning to the task level, then these two levels iteratively conducted until an optimal path obtained. Thus, R-space based motion planning can be reduced to construction of R-space and designing of planning algorithms.

2.1 Construction of R-space

Constructing a R-space with all representation variables will lead to a model suffer from the curse of dimensionality. Therefore, we will only include those variables that are directly related to the task requirements and system characteristics, ignoring those of less interest. There are many ways to formalize R-space, so long as the system attributes and task definitions can be revealed by the chosen representation variables. For a given planning task, a n-dimensional R-space $\Omega = \left(\xi_1\ \xi_2\ \cdots\ \xi_n\right) \subseteq \mathcal{R}^n$ can be established, with constraints on each variable,

$$\xi_{i_{\min}} \le \xi_i \le \xi_{i_{\max}}, \quad i = 1, \cdots, n. \tag{1}$$

The initial representation ξ^0 of the robot system and the goal ξ^g when the robot system has accomplished the given task are specified, respectively, as

$$\begin{cases} \xi^0 = \left(\xi_1^0, \xi_2^0, \cdots, \xi_n^0\right) \\ \xi^g = \left(\xi_1^g, \xi_2^g, \cdots, \xi_n^g\right). \end{cases} \tag{2}$$

Generally, a robot system may be subjected to three kinds of constraints: physical constraints $\bar{\Psi}_p$, obstacle constraints $\bar{\Psi}_o$, and task constraints $\bar{\Psi}_t$. Mechanical restriction and motion capability of the robot are physical constraints, such as moving ranges of joints or the size and shape of a mobile robot etc.. Obstacles in the robot workspace will limit its activity. In addition, the task to be achieved may impose constraints on the robots. For example, the gripper or joints of a manipulator is required to move along a predefined path. Physical constraints are inherent in the robot system and are regarded as internal constraints, while obstacle and task constraints are regarded as external constraints. Thus, the unreachable subspace $\bar{\Psi}$ of R-space can be represented as,

$$\bar{\Psi} = \bar{\Psi}_p \bigcup \bar{\Psi}_o \bigcup \bar{\Psi}_t = \sum_i \bar{\Psi}_{pi} \bigcup \sum_j \bar{\Psi}_{oj} \bigcup \sum_k \bar{\Psi}_{tk}. \tag{3}$$

Let Ψ denotes the reachable subspace of R-space, we have $\Omega = \Psi \bigcup \bar{\Psi}$. Thus, the R-space generalizes the T-space and C-space of the robot system. The pose and position of the robot concerned in the T-space, as well as the joint variable concerned in the C-space, are all possible representations of the robot system related to a specific task realization.

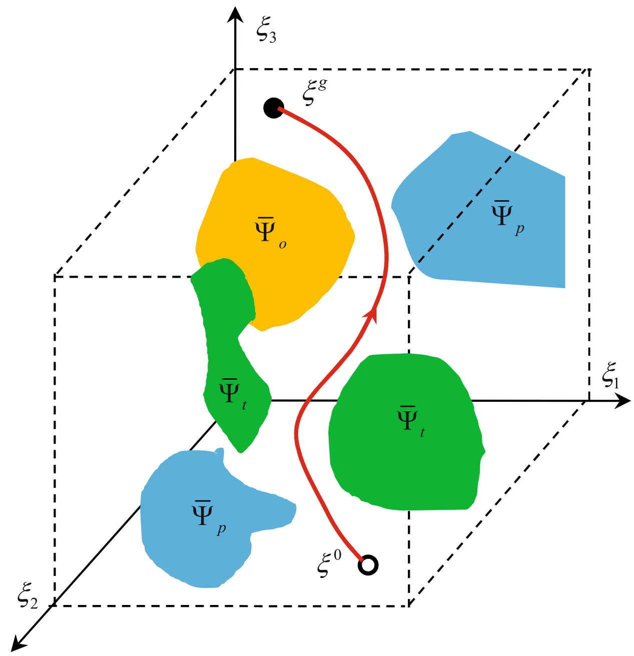

Fig. 3 Example of the R-space with $n = 3$

Then, the objective of motion planning is to design appropriate algorithms for searching a sequence of trajectories from ξ^0 to ξ^g within the reachable area Ψ (as shown in Fig. 3 with $n = 3$ as an example [14]),

$$\begin{cases} \left(\xi^0 \in \Psi\right) \cap \left(\xi^g \in \Psi\right), \\ \exists P \subset \Psi,\ P = \left\{\xi^0, \cdots, \xi^g\right\}, \end{cases} \tag{4}$$

where P is the optimal path. The core of R-space based motion planning is that transforming a planning task to a trajectory searching and optimization problem. Hence, the task can be realized only if there at least exists one path P connecting ξ^0 and ξ^g and locating in the reachable subspace Ψ totally.

2.2 Trajectory Searching in R-space

As long as the R-space for a given task is established, one obtains the corresponding representation transitions in R-space, which reflect the process of task realization. Therefore, R-space based hierarchical motion planning must be of completeness, i.e., for the given task, an optimal path will be obtained if the task is solvable, otherwise return guidelines for transitions from the infeasible one into a feasible one.

Commonly used motion planning methods are listed in Table 1. When solving a given task with specific requirements, one has to select appropriate planning algorithms

Table 1 Performance comparisons of common motion planning methods

Algorithms	Completeness	Optimality	Applicability in high dimensional space
Naive potential	No	Yes	No
Visibility graph	Yes	Yes	No
Grid-A*	Resolution ratio	Grid	No
Grid-D*	Resolution ratio	Grid	No
RRT	Probability	No	Yes
PRM	Probability	Graph	Yes
RRT*	Probability	Asymptotical	Yes
PRM*	Probability	Asymptotical	Yes

according to the characteristics and the dimension and precision of R-space. Algorithms with restrict completeness are rarely used in practice since they usually suffer from huge computation burden for complex tasks. Grid based A^* and D^* are widely applied to solve low dimensional planning tasks, but there are difficulties for scaling to those with high dimensions, since its resolution ratio completeness limited by the dimensions and precision of the grids largely. Sampling based planning algorithms, such as probabilistic road map (PRM) and rapidly-exploring random tree (RRT), attracts more and more interests in recent years, due to its probabilistic completeness and high performance when applied to solving high dimensional tasks. RRT* and PRM* improve RRT and PRM with asymptotic optimality.

As shown in Eq. 4, the task can not be realized if any condition in Eq. 4 can not be fulfilled, i.e., $\xi^0 \notin \Psi$, $\xi^g \notin \Psi$ or there does not exist a feasible path in the reachable subspace. Under this circumstance, one can modify some attributes of R-space by reselecting representations, increasing the dimensions of R-space through adding new representation variables, or redefining the unreachable space by relaxing some constraints appropriately. Following this idea, Su et al. [14] applied R-space based motion planning algorithms to deal with manipulator planning, mobile robot planning and multi-robots formation etc., they also list detailed guidelines for selecting representation variables. More specifically, for 2-DOF robot manipulator, both the position of end effector and pose components of each axes are used to build the R-space, the inherent physical constraints and the obstacles in the workspace are further considered, then a feasible trajectory was obtained with trajectory searching in the R-space. Furthermore, transforming an unrealizable task into a realizable one are given by re-building the R-space, which cannot be dealt with in conventional T-space and C-space based method. Moreover, the example of multi-robot formation movement also verifies the flexibility of R-space based motion planning scheme.

R-space is a general task planning model of completeness, which takes all internal and environment constraints related to task realizability into account. R-space transforms the task planning for a specific robot into optimal trajectory searching in its reachable subspace, on the basis of task realizability evaluation. Furthermore, it optimizes the process of task realization dynamically by observing the instantaneous stage of task execution. Compared with conventional methods, R-pace is more general for robotic task planning. On the other hand, interactive natural motion planning request that users and robot should have to interact with each other frequently for accelerating task realization. With the developing of network technique, the interaction should be based on networks. Therefore, interactive natural motion planning must research on how to mitigate the unexpected effects caused by network induced imperfections.

3 User Intention Inference for Networked Robot

Network induced imperfections will degenerate the performance of task realization largely. Actively inferring user intention may reduce the effects of network induced imperfections at its most fundamental. So how to build the intention model and how to infer the intention are core issues in this scheme. Su [26] proposed grid based intention model inspired by the fact that grid representation has been successfully applied in robotic localization and navigation. In addition, Bayesian filtering has been widely used to deal with many problems in robotics due to its excellent capabilities of information representation, inference and prediction in uncertain environment.

3.1 Grid-Based User Intention Representation

Grid based representation was firstly proposed by Efles et al. [42] to tackle robotic localization and navigation. Its main idea is that dividing the continuous map into small grids, then localization realized by inferring on these grids based map. Inspired by this, Su represented the continuous intention space by building discrete intention grids. Intention grids represent robot state as stochastic probability grids, with each

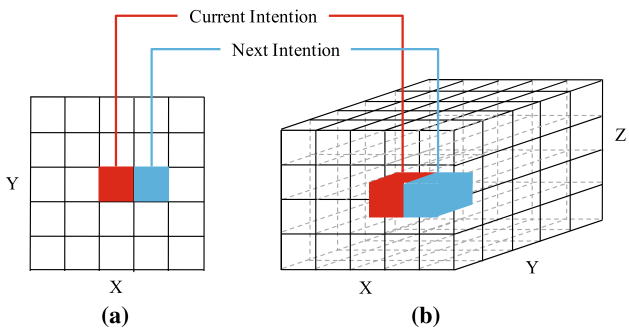

Fig. 4 Grid-based user intention representation, **a** Planar grids, **b** Spatial grids

grid describes one kind of user intentions. At every moment of task execution, the value of each grid represents the probability of specific intention. During the task realization, the grids will be updated by detecting robot states and user commands. As show in Fig. 4, X, Y and Z are states, each grid represents one possible intention, the red grid is the current intention, while the blue one is the next probable intention. After training using some samples, one can infer user intention and obtain the transition trajectories in the intention grids. Thus, robot can autonomously realize the given task with no need or just very little additional interactions as long as the true intention is captured.

Denoting $d_i (0 \leq i \leq t)$ as observations at i including user commands and system states, then the observations up to time t are,

$$D_t = \left\{ d_0 \cdots d_i \cdots d_t \right\}. \tag{5}$$

User intention, i.e., control commands for the robot to conduct a task or the state that the robot is going to be in, is denoted by a variable u. Suppose u_t is the user intention at time moment t, and U_t is the corresponding variable set. Typically, robot does not know the exact user intention; instead, it has a probability distribution of what the user might be willing to do. Let $P(U_t|D_t)$ denote the probability distribution of user intention at the moment t. For example, $P(U_t|D_t)$ is the probability density conditioned on all observations D_t, with which the robot is assigned the possibility describing the user intention u_t at time t. Thus, one can infer user intention at time $t+1$, based on current intention distribution $P(U_t|D_t)$, which is the one with most transition probability.

In general, the complexity of computing such posterior grows drastically over time since the amount of all measurements increases exponentially over time. To make the computing tractable, the dynamics is assumed to be Markovian,

$$\begin{aligned} &P\left(d_{t+1}, d_{t+2}, \cdots |U_t = u_t, d_0, \cdots, d_t\right) \\ &\quad = P\left(d_{t+1}, d_{t+2}, \cdots |U_t = u_t\right). \end{aligned} \tag{6}$$

which means all relevant information is contained in the current state u_t.

3.2 Bayesian Filtering for User Intention Inference

For obtaining the user intention, one can recursively compute the density $P(U_t = u_t|D_t)$ at time t, with two stages involved.

Predictive stage In this stage, the user current intention is predicted by taking only the robot sensor information into account. Assuming that the current sensor information is only dependent on the previous state u_{t-1} and an available sensor measurement v_{t-1}. Then the predicted current intention can be obtained,

$$\begin{aligned} P\left(U_t = u_t|\, D_{t-1}\right) = \int & P\left(U_t = u_t|\, v_{i-1},\ U_{t-1} = u_{t-1}\right) \\ & \cdot P\left(U_{t-1} = u_{t-1}|\, D_{t-1}\right) du_{t-1}. \end{aligned} \tag{7}$$

Following the Bayesian rule,

$$P\left(u_t\ |v_{t-1},\ u_{t-1}\right) = \frac{P\left(v_{t-1}\ |u_t,\ u_{t-1}\right) P\left(u_t\ |u_{t-1}\right)}{P\left(v_{t-1}\ |u_{t-1}\right)}. \tag{8}$$

Since $P(v_t|u_{t-1})$ is independent of u_t, Eq. 7 can be simplified as,

$$P\left(u_t\ |v_{t-1},\ u_{t-1}\right) \propto P\left(v_{t-1}\ |u_t,\ u_{t-1}\right) P\left(u_t\ |u_{t-1}\right). \tag{9}$$

Correction stage In this stage, the commands received from user, denote as c_t, are incorporated to compute the posterior $P(U_t|D_t)$, while the new input is used to modify the predicted distribution in Eq. 7. Accordingly, the posterior is achieved by using the Bayesian rule,

$$P\left(U_t = u_t\ |D_t\right) = \eta P\left(c_t\ |U_t = u_t\right) P\left(U_t = u_t\ |D_{t-1}\right), \tag{10}$$

where η is the normalization constant. It is reasonable to assume that user current intention is consistent with his past intention. So $P(c_t|u_t)$ is expanded by integrating over the state u_{t-1} using marginalization principle,

$$P\left(c_t\ |u_t\right) = \int P\left(c_t\ |u_t,\ u_{t-1}\right) P\left(u_{t-1}\ |u_t\right) du_{t-1}. \tag{11}$$

Therefore, the user intention inference procedure goes as follows. Firstly, one represents the user intention by taking advantage of grid-based model as shown in Fig. 4. Secondly, the user current intention is predicted by taking only the robot sensor information into account then computing Eq. 9. Thirdly, the prediction is corrected according the received user command by computing Eq. 10. At the learning stage, we alternatively exploit the second and third step until the algorithm converges, and we could obtain an inference grid model. At implementation stage, we implement the inference model to factor the user intention $P(u_{t+1}|v_t, u_t)$ on-line according to current observation. During the implementation stage, no further interactions are needed. Therefore, the interactions between the robot and the users are minimized, so as the impact of network induced imperfections. Su et al. [26] applied above method to control a Internet based office robot remotely, and compared many pairs of time-varying delays. The results show that, the interaction frequencies between users and robot are definitely decreased, so as the time and real path length for task execution.

User intention inference based control scheme for networked robot can endow robot with intelligence and autonomous capability, and also presents a novel approach for task realization under network induced imperfections. Furthermore, robot will inevitably suffer from various internal/external uncertainties, therefore, it should have to reject disturbances for accomplishing the given task effectively.

4 DOB-Based Disturbance Rejection Control for Robot

High performance motion control is a basic requirement for accomplishing the given task effectively, while the existing model uncertainty, couplings, frictions between joints and unknown external disturbances deteriorate the motion control performance severely. The disturbance observer (DOB) based control methodologies (as shown in Fig. 5), since its initiative in 1980s, have been widely used due to its excellent disturbance rejection ability. The DOB consists of an inverse nominal model and a low-pass filter, where the low-pass filter is of great importance since it has to make sure the realizability for the inverse nominal model and disturbance rejection ability. Therefore, how to construct the evaluation function for low-pass filter design and how to formulate a systematically parametric scheme are the key issues in the research of DOB. With this consideration, Yin and Su [43,44] proposed a DOB design algorithm with closed loop robustness guaranteed and with relative order constraint and internal model order constraint satisfied, by taking advantage of $\mathcal{H}_\infty$ control theory.

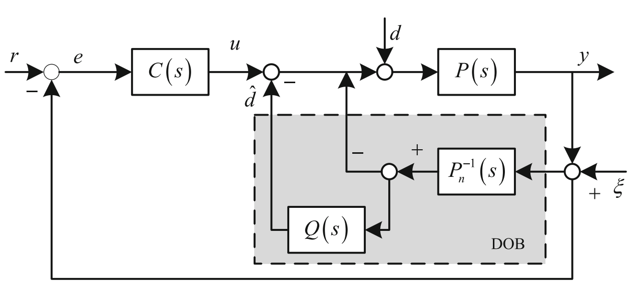

Fig. 5 DOB based control framework

4.1 Disturbance Rejection Performance Analysis for DOB-Based Robot System

In Fig. 5, when one considers only the inner loop, i.e., without taking the outer loop controller $C(s)$ into account, the transfer function of output y can be represented as,

$$y(s) = G_{yu}(s)\,u(s) + G_{yd}(s)\,d(s) - G_{y\xi}(s)\,\xi(s), \tag{12}$$

where $G_{yu}(s) = \frac{P_n P}{P_n + (P - P_n)Q}$, $G_{yd}(s) = \frac{P P_n (1-Q)}{P_n + (P - P_n)Q}$, $G_{y\xi}(s) = \frac{PQ}{P_n + (P - P_n)Q}$. $Q(s)$ should be a low-pass filter, and make it physically implementable of the module $Q(s)P_n^{-1}(s)$. From Eq. 12, if $Q(s)$ satisfies $Q(s) \approx 1$ at low frequency range, and $Q(s) \approx 0$ at high frequency range, one obtains,

$$y(s) = P_n(s)\,u(s). \tag{13}$$

Equation 13 indicates that the introducing DOB loop into the original system leads to desired nominal performance $P_n(s)$, regardless of the existing of modeling errors ($P_n \neq P$), input disturbances $d(t)$ or noises $\xi(t)$. Furthermore, the introducing of DOB does not affect the nominal performance when the model is accurate ($P_n = P$), $d(t) = 0$ or $\xi = 0$. In other words, DOB is added into the system like a "patching" and leads to desired nominal performance. On the other hand, the system owns low conservatism since it is not designed for the "worst" cases. Most importantly, DOB can actively eliminate various disturbances with high performance guaranteed. Thus, how to designed desired $Q(s)$ is of great significance for practical applications.

4.2 Parameter Optimization for DOB Based on $\mathcal{H}_\infty$ Control Technique

The key for parameters optimization of DOB is that optimization of the low-pass filter $Q(s)$. The desired performance is that improving its disturbance rejection capability, i.e., make $1 - Q(s)$ small as far as one can in the corresponding frequency range, with robustness, dynamics performance and sensitivity to noises guaranteed.

By taking advantage of $\mathcal{H}_\infty$ control methods, defining the following optimization problem,

$$\begin{aligned} \max \quad & \gamma, \\ s.t. \quad & \min_{\substack{Q(s)\in\Omega_k \\ Q(s)\in\mathcal{R}H_\infty}} \left\| \begin{bmatrix} \gamma W_1(s)(1-Q(s)) \\ W_2(s)Q(s) \end{bmatrix} \right\|_\infty < 1, \end{aligned} \tag{14}$$

where $W_1(s)$ is the weighting function reflecting prior information of disturbances, while $W_2(s)$ is the one reflecting model uncertainties and frequency characteristics of noises. Ω_k is the set for $Q(s)$ that satisfies relative order constraints, internal model order constraints and stability of the closed loop system.

Defining a virtual loop transfer function $\tilde{L}(s) = \tilde{P}(s)\tilde{K}(s) \triangleq \frac{Q(s)}{(1-Q(s))}$ and substitutes into Eq. 14, one can obtain an equivalent mixed sensitivity optimization problem as,

$$\begin{aligned} &\max \ \gamma, \\ &s.t. \ \min \left\| \begin{bmatrix} \gamma W_1(s)(1+\tilde{P}(s)\tilde{K}(s))^{-1} \\ W_2(s)\tilde{P}(s)\tilde{K}(s)(1+\tilde{P}(s)\tilde{K}(s))^{-1} \end{bmatrix} \right\|_\infty < 1. \end{aligned} \tag{15}$$

Solving the above problem obtains the low-pass filter,

$$Q(s) = \frac{\tilde{P}(s)\tilde{K}(s)}{1+\tilde{P}(s)\tilde{K}(s)}. \tag{16}$$

Thus, the parametric optimization procedure of $Q(s)$ is concluded as,

Step 1: Selecting weighting functions $W_1(s)$ according to the frequency characteristics of external disturbances. In general, $W_1(s)$ should contain all modes of disturbances.

Step 2: Selecting weight functions $W_2(s)$ according to relative order constrains and high frequency performance requirements. Generally, $W_2(s)$ should reflect the upper bound of system uncertainties in the high frequency range and characteristics of noises, its order should be less than that of relative order of $Q(s)$.

Step 3: Designing virtual control plant $\tilde{P}(s)$. $\tilde{P}(s)$ should be stable and its order should be equal to that of $W_2(s)$.

Step 4: Solving the mixed sensitivity optimization problem Eq. 15 and obtaining the optimal virtual controller $\tilde{K}(s)$ through 2-Riccati algorithm, then one obtains $Q(s)$ from Eq. 16.

Yin et al. [44,45] applied the aforementioned methodology to control a two-inertia system with closed loop robust stability guaranteed, and to solve the decoupling control of a two degrees-of-freedom flexible manipulator. Wang et al. [46] scaled to nonlinear system by integrating $\mathcal{H}_\infty$ control theory and backstepping based nonlinear control methods, the result was applied to deal with a attitude control of the Unmanned Aerial Vehicles (UAVs). Ma et al. [47] proposed a novel solution for robotics uncalibrated visual servoing control, by compensating for the uncertainties in image Jacobian matrix online through the $\mathcal{H}_\infty$ control theory based DOB. In addition, some works analyse the DOB based control system from time domain, or by singular perturbation theory [48,49], or are used to deal with unmatched uncertainties [50]. These works flourish the theory and applications of DOB in different directions. In comparison with other disturbance rejection control methods, such as ADRC, DOB could take full advantage of the known knowledge of the given system. Therefore, more system-specific disturbance rejection method could be developed. However, how much uncertainty could be dealt with under the framework of DOB based method is still an open problem.

DOB based control system has been widely used in real robotic motion control for its flexible architecture and supreme disturbance rejection ability. The $\mathcal{H}_\infty$ control theory based DOB design methods provide a systematic scheme for DOB design with robust stability guaranteed, as well as satisfying relative order constraint and internal model order constraint, which make it more suitable for practical applications.

5 Conclusions

We establish a general theoretic framework for robotic interactive natural motion planning from three levels. Firstly, we build R-space based robotic task planning framework on the basis of clarifying the importance and key issues of robotic motion planning. We also compare commonly used trajectory searching algorithms from completeness, optimality and adaptation to high dimensional problems, which gives guidelines for trajectory searching in R-space. Secondly, we present user intention inference based networked robot control scheme, by observing that most human–robot interaction are conducted via network. It provides a novel solution to deal with network induced imperfections. Finally, to deal with the widely existing internal/external disturbances, we propose DOB based disturbance rejection approach. The presented general framework of robotic interactive natural motion planning is of great importance not just for dealing with task planning with satisfied requirements and improved performance, but also for improving its human intelligence imitation. Although the proposed theory has shown some promising applications, there are still many open problems,

1. Constructing R-space based on complete set theory. In R-space, the procedure of task realization can be directly represented as sates evolving in it. Every operation in R-space can be reflected by the changing of states. Thus there must exist a feature set that can represent different stages and conditions of task execution, the set is just the task oriented complete set. Therefore, how to design algorithms to make sure evolve from current incomplete R-space to a complete one, and efficient planning

algorithms based on the complete R-space is of great importance. Existing works show that deep neural network (DNN) [51], with its capability to approximate any nonlinear functions, can deal with very complex tasks. Therefore, research on DNN based R-space can unify the construction of R-space and planning algorithm, which provide a new approach for the construction of R-space.
2. Developing efficient user intention inference algorithm. We definitely hope that robot can successfully understand user intention just based on as few samples as possible. However, the network induced imperfections will introduce uncertainties for robot task realization, which lead to sample inefficiency. Thus, developing efficient inference algorithms is of great importance. Bayesian program learning [52] can accomplish human cognitive imitation just by very little samples. Thus, one can apply Bayesian program learning to user intention inference for reducing the frequency of human–robot interactions.
3. Studying on robust DOB schemes under big data conditions. As is known to all, it is very hard to build an acceptable model for ever increasingly complex robot systems. However, various mounted sensors have collected huge amounts of data related to the system. Therefore, how to develop data-driven [53] disturbance rejection control methods, while with system robust stability guaranteed, is of great significance for improving performance continuously during system operation.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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