Sample-Based Motion planning for Soft Robot Manipulators Under Task Constraints

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***Abstract*— Random sampling-based methods for motion planning of constrained robot manipulators has been widely studied in recent years. The main problem to deal with is the lack of an explicit parametrization of the non linear submanifold in the Configuration Space ($\mathcal{CS}$), due to the constraints imposed by the system. Most of the proposed planning methods use projections to generate valid configurations of the system slowing the planning process.**

Recently, new robot mechanism includes compliance either in the structure or in the controllers. In this kind of robot most of the times the planned trajectories are not executed exactly by the robots due to uncertainties in the environment. Indeed, controller references are generated such that the constraint is violated to indirectly generate forces during interactions.

In this paper we take advantage of the compliance of the system to *relax* the geometric constraint imposed by the task, mainly to avoid projections. The relaxed constraint is then used in a state-of-the-art sub-optimal random sampling based technique to generate any-time paths for constrained robot manipulators. As a consequence of relaxation, contact forces acting on the constraint change from configuration to configuration during the planned path. Those forces can be regulated using a proper controller that takes advantage of the geometric decoupling of the subspaces describing constrained rigid-body motions of the mechanism and the controllable forces.

Fig. 1. The Motion planning method presented in this paper is developed for systems with compliance either in their structure of via the control loop. In this case the bimanual system includes the compliance in the qbmotors [9] composing the structure which is combined with mechanically embedded compliance of the PISA/IIT SofHands [10]. In this paper we consider that all compliance is in the contact points.

I. Introduction

In robot motion planning, interacting with the environment is normally considered a task to avoid, however in everyday tasks humans don't do that. Actually, simple tasks as opening a door, sliding an object on a table and moving an object consist on taking advantage of the objects and their constraints with the environment rather than avoiding touching them. In robotics solving the problem of generating motions is not simple mainly because we need to face two main problems: 1) working on high dimensional spaces, which make the problem NP-Hard to solve it optimally, and 2) working under constraints such as closed loop kinematic chains and force/torque limits. The first, is solved in an efficient way randomly sampling the configuration space ($\mathcal{CS}$) of the robot. This is possible thanks to the available explicit description of the $\mathcal{CS}$ of the robot. The second problem is harder due the fact that an explicit description of the admissible $\mathcal{CS}$ is not available. It means that not all random samples of the $\mathcal{CS}$ can be considered as a possible configuration to explore. There exist some approaches to generate motions for robots under environmental constraints, which are based either on the decomposition of the chain in a passive and an active chain [1], or in the projection of any random sample to the valid $\mathcal{CS}$ [2], [3].

In this paper we propose a new method to generate motions for kinematic chains under constraints. It is based on the relaxation of the constraint to be able to randomly sample an augmented valid $\mathcal{CS}$. Then, using state-of-the-art algorithms as RRT* [4], we guarantee the convergence of the algorithm to a path, connecting two points, which optimizes the distance to the constraint at each point on it.

A. Planning with Task Constraints - State of the Art

Since the introduction of random sampling techniques for path planning, a lot of advances have been made in this field. There exist two main approaches in this topic, the first is the Probabilistic Roadmap (PRM) and the second is the Rapidly-Exploring Random Tree (RRT) introduced in [5] and [6] respectively. These two approaches were designed to plan motions in high dimensional spaces, in fact they are normally applied in the $\mathcal{CS}$ of robot manipulators. The major advances have been focused in the improvement of these methods to mainly include heuristics to speed up the planning time and bias the solutions to get preferred behaviours. For example in [7] exploration and exploitation of $\mathcal{CS}$ is balanced for fast convergence of the planners. In [8] the authors propose to include different heuristics to bias the growth of the trees towards a preferred part in the $\mathcal{CS}$.

The last major contribution in probabilistic motion planing

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was presented in [4] where the authors studied the quality of the paths generated by randomized planners. They proposed a modification of the RRT and PRM algorithms, called RRT* and PRM*, to generate better quality paths. The completeness and sub-optimality of the solutions are guaranteed. Some improvements to speed up the solutions of this planner have been proposed in [11] and [12].

The inclusion of constraints in the model is another research line in the area, for example 1) *nonholonomic constraints* for mobile robots as summarized in [13], 2) *task constraints* where the end effector has to maintain a desired orientation over the whole planned path, [14], and 3) *close kinematic chains* for cooperative robots or parallel manipulators [15]. The latter is sometimes considered a particular case of 2). There is also a research line to include *dynamic constraints* such as joint torque limits. This planning techniques are called kinodynamic motion planning [16]. In this work we will focus the attention to motion planing for systems with tasks space constraints and close kinematic chains.

The main problem in motion planning for closed kinematic chains is that the $\mathcal{CS}$ of the robot is not all available to be explored but just a nonlinear submanifold $\mathbb{M}$, described by the constraint equations, living in it.

All randomized planners include a function called *Sample* where a random point in the configuration space is returned. In case of closed kinematic chains the function *Sample* must return a random point on the aforementioned submanifold. The practical probability of this is 0 because the manifold is a zero measure set in the configuration space.

The proposal presented in this paper is to relax the constraints by transforming this set into a volume so that the probability of sampling a point randomly on it is not null. This idea comes from the state of the art robots, see Fig. 1, which have a compliant rather than a rigid structure. From the point of view of path following for systems with compliance is traduced to control references which may or may not be followed by the real system but they are still valid. From this viewpoint, references can violate the constraints imposed by the system structure and by its interaction with the environment.

B. Path Execution

The path execution problem can be addressed with a suitable force/position controller using the theory presented in [17]. In that paper, the authors demonstrate that the object trajectories and the contact forces can be addressed as decoupled control problems. It implies that we can execute any object trajectory coming from planning phase and that contact forces can be steered so as to avoid violation of contact constraints, allowing to regulate a desired force during motion.

II. Organization

Section III formally defines the motion planning problem under task constraints and presents the main contribution of this work. In section IV the algorithm called $soft-RRT^*$ is presented, it describes the strategy implemented to find paths in the relaxed constraint. Section V addresses the problem of the practical implementations of the $soft-RRT^*$ algorithm and introduces a possible solution. After an example presented in section VI, section VII exposes the conclusions and future developments of this work.

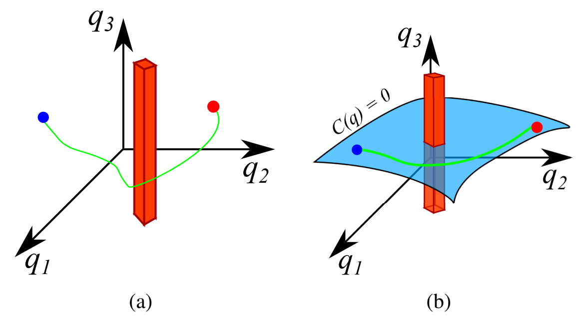


Fig. 2. Differences of motion planning problem without constraints (a) and with constraints (b). Initial position q_{init} in blue, final position q_{final} in red and Planned path in green. Constraint $C(q) = 0$ in baby blue.

III. Problem Definition

Random sampling-based methods for path planning have an excellent performance when they are able to explore the whole $\mathcal{CS}$ of robot manipulators. The good performance comes from the fact that manipulators are able to explore the whole environment performing any kind of motions in any directions in the $\mathcal{CS}$, so any point in it is a valid configuration and can be connected to any other one. However when the system is subject to constraints, such as closed kinematic chains, this fact is not true any more.

In this section we formally introduce the motion planning problem for systems subject to constraints.

A. Motion Planning Problem of Systems Under Constraints

Consider a configuration space $\mathcal{M} \in \mathbb{R}^d$ that is a compact set of configurations q. Let $\mathcal{O} \in \mathcal{M}$ be the obstacle region and $\mathcal{M}_{free} := \mathcal{M} \setminus \mathcal{O}$ the configuration set free of obstacles. Introducing a kinematic constraint $C(q) = 0$ that limits the robot configurations and hence motion, see Fig. 2(b), we define a nonlinear submanifold in $\mathcal{M}$ as $\mathcal{M}_v := \{q : q \in \mathcal{M}_{free}, C(q) = 0\}$ to describe all configuration where non of the links of the mechanism collide neither with objects in the environment not with other links, and satisfy the constraint. The motion planning problem is to find a continuous path $\sigma : [0, 1] \to \mathcal{M}_v$; with $\{\sigma(0) = q_{init},\ \sigma(1) = q_{final}\}$. As mentioned, the main challenge in applying sampling based motion planning algorithms to closed kinematic chains is that the probability of getting a random point laying on the submanifold is zero, see Fig. 2(b).

B. Relaxing Constraints

As mentioned in the introduction we consider systems with compliance. In this paper we introduce compliance in the planning phase as a parameter to relax the constraint, so $C(q) \leq \epsilon$, using this approach the rigid kinematic constraint is replaced with a compliant one. In the case in which the

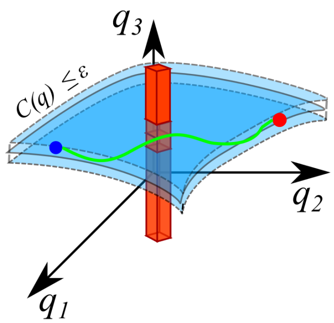
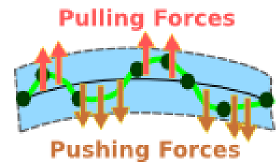
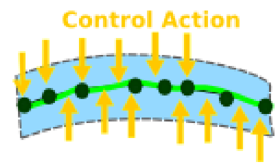


Fig. 3. Motion planning problem under relaxed constraints. Initial position q_{init} in blue. Final position q_{final} in red. Planned path in green. Constraint $C(q)$ in baby blue.

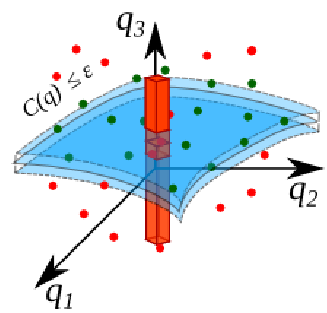


(a) Undesired forces arising from planning on the relaxed contraint

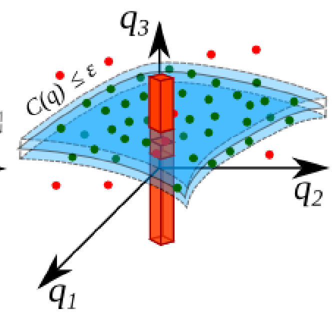


(b) The task of the controller is to project the undesired forces back to the manifod

Fig. 4. Lateral view of the relaxed constraint. In green are the pushing and pulling forces against the constraint. The black dots are the nodes extracted from the tree generated by the $soft - RRT^*$.



(a)



(b)

Fig. 5. Graphical explanation of the difference of using uniform distribution a) and applying the algorithms presesnted in [22] b) to get new random sampling configuration in $\mathcal{M}$.

tight constraint is violated a proportional force f_h arises between the two parts in contact. With this parameter the sub-manifold describing the relaxed constraint can be considered as a space with the same dimension of $\mathcal{CS}$. Thanks to this we can use rejection techniques to randomly sample the $\mathcal{CS}$ valid, now defined as $\mathcal{M}_r := \{q : q \in \mathcal{M}_{free}, C(q) = \epsilon\}$, and thus speed up the planning process. Now the planning problem is to find a continuous path $\sigma : [0,1] \rightarrow \mathcal{M}_r$, with, $\{\sigma(0) = q_{init},\ \sigma(1) = q_{final}\}$. This relaxed problem is graphically described in Fig. 3.

IV. Randomized Planning Algorithm

The random based-sampling algorithm used in this paper is the $soft-RRT^*$ reported in the algorithm 1. The difference with the original RRT* algorithm is that instead of just checking for collision we also check if the new configuration is inside the relaxed constraint. This is performed in the

Algorithm 1 $\mathcal{T} = (V, E) \leftarrow$ soft-RRT*(x_{init})

```
T ← InitTree();
for i = 1 to N do
    x_rand ← Sample(i);
    x_nearest ← Nearest(V, x_rand);
    x_new ← Steer(x_nearest, x_rand);
    if Constraints(X_nearesr, x_new) then
        X_near ← Near(T, x_new)
        x_min ← BestParent(X_near, x_new)
        T ← T ∪ (x_new, x_min)
        T ← Rewire(T, X_near, x_new)
    end if
end for
return G = (V, E).
```

Constraints function where the constrained optimization problem described in the subsection IV-B is solved. Notice that this function is also called inside the **BestParent** and **Rewire** functions, typical of RRT*.

A. Biased Random Sampling

The first step in randomized path planners is perfomed in the function **Sample** and it consists on generating a new sample in $\mathcal{M}$. Typically, random configurations are taken using a uniform distribution to explore equally all regions in $\mathcal{CS}$. Doing the same in our problem, the probability of getting a new point in $\mathcal{M}_r$ can be computed as

$$\rho = volume(\mathcal{M}_r)/volume(\mathcal{M}), \tag{1}$$

where the volume of $\mathcal{M}$ is defined by the mechanism, more precisely by the range of motion of all joints. In the other hand, the volume $\mathcal{M}_r$ is proportionally to the relaxing parameter ϵ. As a consequence, the probability of getting a new point goes to 0 as ϵ approaches 0, in other words it means that bigger is ϵ, higher the probability of getting a new configuration in $\mathcal{M}_r$.

It is evident that if ϵ is small most of the new samples will be rejected in the **Constraints** function because they are not in the relaxed constraint. To minimize the impact of this fact, in the $soft - RRT^*$ we used the algorithm presented in [22] to bias the random sampling procedure to converge to a uniform distribution not in $\mathcal{M}$ but in $\mathcal{M}_r$. This idea is graphically presented in the Fig. 5.

B. The Equilibrium Manifold

In order to guarantee the equilibrium of the object being manipulated by the multi-robot system we recall the kineostatic analysis presented in our previous work [18]. In that work we presented the equilibrium manifold of the multi-robot system subject to synergistic underactuation and variable stiffness in the joint actuation. Since we are performing motion planning in the $\mathcal{CS}$, we need a fully actuated system to allow to the system to follow the planned path. Thus, the main equations describing the equilibrium configuration of the system are:

$$
\begin{aligned}
w + G(u) f_h &= 0, && (2)\\
\tau - J^T(q,u) f_h &= 0, && (3)\\
f_h - K_c p_h &= 0, && (4)\\
\tau - K_q(q_r - q) &= 0, && (5)
\end{aligned}
$$

where $x \in \mathbb{R}^{2d+12}$ is an equilibrium residual vector containing the joint positions $q \in \mathbb{R}^d$, joint torques $\tau \in \mathbb{R}^d$, contact forces $f_h \in \mathbb{R}^6$ and object positions $u \in \mathbb{R}^6$. $\Phi(x) \in \mathbb{R}^{2d+12}$ includes the equations describing the equilibrium manifold. $G(u)$ is the so called grasp matrix of the system, $w \in \mathbb{R}^6$ is the external wrench in the object, $J^T \in \mathbb{R}^{c \times d}$ is the multi-robot Jacobian matrix, $K_{pc} \in \mathbb{R}^{c \times c}$ is the contact stiffness matrix and $K_q \in \mathbb{R}^{d \times d}$ is the joint stiffness matrix. Dimension c is the number of contact constraints.

Equations (2) to (5) describe the equilibrium manifold in the system that by adding quotes into the contact forces f_h becomes the same as the one used in the planning phase. In order to find equilibrium configurations we firstly get the random sampling configurations q_r and then we solve the following optimization problem to the get the rest of the variables

$$
\begin{aligned}
\min_{q,u,f_h,\tau} \quad & x^T \mathbf{W} x \\
\text{subject to} \quad & \Phi(x,q,u,f_h,\tau) = 0,
\end{aligned}
\tag{6}
$$

Once the planning problem is solved a proper controller able to let the robot follow the planned path must be determined. The main challenge comes from the fact that the closed kinematic constraint has been relaxed, so undesired contact forces arise from interactions, a graphical example is shown in Fig. 4(a). The real-time controller must ensure that the nominal constraint is satisfied during the whole execution, see Fig. 4(b). Indeed, if only the relaxed constraint is verified the object handled by the robot does not fall but can be damaged since high squeezing forces can appear. On the other hand, whenever the nominal closed kinematic constraint is verified this can not occur.

V. Execution of the Planned Path

The problem that arise when relaxing constraints is that from the point of view of implementation, the constraint violation can be dangerous, see Fig. 6, since undesirable interaction forces may be indirectly induced into the system. In this section we introduce a control to solve this problem.

A. Control

In order to address the problem of regulating contact forces and, at the same time, executing the planned path, a force/position controller can be implemented. There are many control approaches to do that, for example in [19] an adaptive hybrid control scheme for multiple geometric constraints based on the joint-space orthogonalization method (JSOM) is proposed, in [20] the authors propose a general framework for multi-contact motion/force control. In both

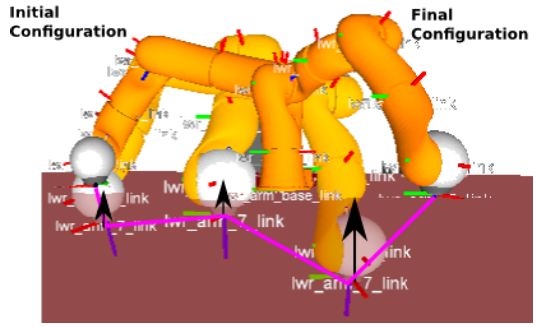


Fig. 6. In this example the kuka robot has to move from the initial to the final configuration maintaining the contact with the plane (red object). The resulting path from applying the $soft-RRT^*$ is shown in pink and the forces during motions in black arrows.

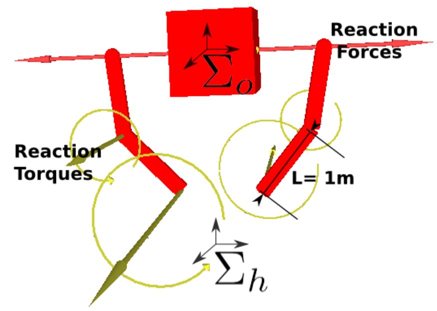


Fig. 7. The two finger hand used for the presented example. In this pictures the object position u, the fingers configurations q, the joint torques τ and contact forces f_h are expressed graphically.

cases the main considerations is that contacts are performed with rigid environments. However, new robot developments, like Soft Robots, are designed to work in uncertain environments and compliant task spaces. A general analysis of manipulation systems with general kinematics and compliant contact models is presented in [17] and complemented in [21], the main result of the last two contributions is a geometric description and an algorithm to provide a basis to describe the feasible motions that can be executed by the system, and forces that can be controlled to avoid violation of the contact constraints, both in a decoupled way. In practice it means that it is possible to control all object displacements given a fixed force reference and vice versa, where the first is useful to correct the relaxations in the planning phase.

VI. Simulations

In this section we show some simulations of the motion planning method presented in this paper. As an example we consider a two finger planar hand with two degrees of freedom in each finger, see Fig. 7.

This systems has 7 degrees of freedom in total but the $\mathcal{CS}$ for planning purposes is of dimension 4 since we are not sampling the object configurations. Algorithms have been implemented in C++ and use ROS for visualization purposes. All tests were performed in a 2.4Ghz quad-core computer with 3Gb of RAM memory and Ubuntu 14.04

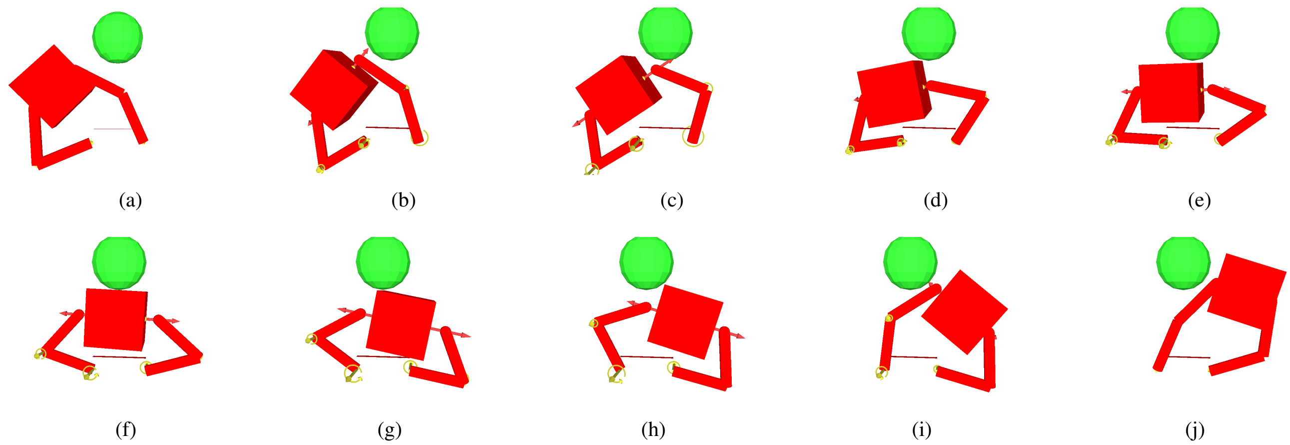


Fig. 9. Final path from the presented experiment. a) Initial position and b) final position.

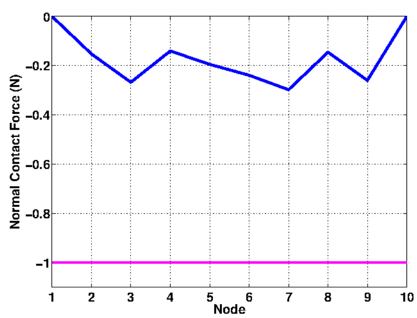


Fig. 8. Normal contact forces (blue) resulting from the relaxation of the constraint during planning. The maximum allowed forces ϵ are in magenta.

operative system. Fig. 9(a) shows the starting position and Fig. 9(j) shows goal position of the hand, the objective is to find a path connecting this two points avoiding the spherical obstacle in green and maintaining the contact forces within ϵ. Figs. 9(b) to 9(i) show some snapshots of the planned path resulting from the execution of algorithm 1, we can observe how the hand avoids the obstacle. Interaction forces arising from the planning phase, which in the case of the 2D example presented in this section are normal to the contact constraints and of magnitude proportional to ϵ, are shown in Fig. 8. Notice that the relaxation parameter ϵ is never overtaken.

VII. Conclusions

In this paper we propose a motion planning method for Soft Robots moving with task constraints. The approach consists in the combination of constraint relaxation and random sampling sub-optimal planner. The first one helps to speed up the planning phase considering the closed loop imposed in the system because of the interaction of the manipulators and the object. The second one allows us to explore the complete configuration space of the system and, at the same time, take into account optimality of the planned trajectories. Combining the first two strategies we are able to fast plan motions for multiple robot manipulators working cooperatively, however due to the constraint relaxation interaction forces my appear during executions of the planned path. To deal with this, as a future work we can implement a control strategy, as the ones presented in V, to online regulate the contact forces while executing trajectories coming from planning phase.

Acknowledgments

This work is supported by the EC under the CP-IP grant no. 600918 “PaCMan”, within the FP7-ICT-2011-9 program “Cognitive Systems”, ERC Advanced Grant no. 291166 “SoftHands” - A Theory of Soft Synergies for a New Generation of Artificial Hands-, under grant agreements no.611832 “Walk-Man” and by CONACYT through the scholarship 266745/215873.

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