# Grasp Point Optimization for Unknown Object Manipulation in Hand Task

Qiang Li, Robert Haschke, Bram Bolder and Helge Ritter

***Abstract*— In order to realize in-hand manipulation of unknown objects, we introduce an extension to our previously developed manipulation framework, such that long manipulation sequences, involving finger regrasping, become feasible. To this end, we propose a novel feedback controller, which searches for locally optimal contact points (suitable for regrasping), employing an online exploration process on the unknown object surface. The method autonomously estimates and follows the gradient of a smooth objective function. More concretely, we propose to dynamically switch between manipulability and grasp stability depending on the grasp stability level.**

**Physics-based simulation experiments involving artificial noise to model real-world sensor readings, prove the feasibility of our approach, rotating an object while multiply readjusting the grasp configuration with all fingers in turn.**

***Index Terms*— Dexterous Manipulation, Multi-fingered Hand, Exploration Learning**

## I. Introduction

A major challenge to exploit the potential of multifingered robot hands for carrying out manual actions that so far are restricted to human dexterity is the ability to enable large-range in-hand manipulation.

Roughly, there are three different lines of research to cope with this dexterous manipulation problem. The first line of research follows an analytic approach, requiring rather strong assumptions and detailed knowledge about the interaction model[7]. The second line of research is based on the idea of forward control, using a physics-based simulation of the object-hand interaction[5] to model the grasping and manipulation processes, then using motion planning methods like RRT or PRM to plan manipulation sequences based on offline calculated grasp posture. The third line of research uses feedback as a central mechanism[8].

Our unknown object manipulation in hand method falls in the third research strategy and goes beyond the state of art of this research line. We divide the object manipulation process into two stages: a local manipulation controller and a global finger gait planner. While the local controller manipulates the object by a small amount[2], the global planner supervises this motion and determines an appropriate sequence of finger gaits for regrasping in order to eventually continue the object motion. In our previous work we used a set of local controllers from a "manipulation control basis"[4] which were sequenced using a static Finite State Machine to realize large-scale rotation in-hand movements of an rotary object[3]. However, for more general object shapes we require a more elaborate search process to find suitable new grasp point during the couse of manipulation in order to continue the object manipulation, which is the focus of this paper.

We highlight a novel approach by integrating active exploration into the determination of a regrasp sequence: regrasping is split into successive repositionings of a "free" finger that identifies a suitable next contact point by small exploratory movements across the object's surface in the vicinity of its current contact while simultaneously monitoring a quality measure that combines grasp stability and manipulability in such a way that it can be evaluated under very weak information requirements.

## II. Finding Optimal Regrasp Points

We formalize the grasp point selection as an optimization problem by considering two quality criteria–the grasp stability[7] and the manipulability[6] as an objective function to be maximized in an exploratory search process. Both criteria are complementary, we employ manipulability as the primary criterion except grasp stability criterion is less than a given minimal threshold because of the *in hand manipulation* task requirement. We do not try to find a closed-form solution of the gradient, but aim for its online estimation because of the objective function $\phi$ strong nonlinear.

The gradient estimation and exploration motion planning algorithm is summarized in Alg. 1. In line 6, the gradient is estimated according to the calculated objective function and contact point motion. In line 8 we apply a sliding average ($\lambda$=0.9) to update the estimated gradient. In line 11, motion plan at next step is calculated according to the updated gradient , which will be the command to the hybrid controller[4].

**Algorithm 1** Object surface exploration, maximizing $\phi$

1: $i = 0$ {initialize cycle count}
2: $\tilde{\nabla}\phi^r \propto \mathcal{N}(0, \sigma = 0.15)$ {randomly initialize gradient}
3: **while** $++i \leq N_{\max}$ **and** $\|P \cdot (T_c^r)^{-1} \cdot \tilde{\nabla}\phi^r\| \nleq \varepsilon$ **do**
4: **if** $i \mod n = 0$ **then** {update $\tilde{\nabla}\phi^r$ every $n$ cycles}
5: $\Delta\mathbf{c}_c = P(\mathbf{c}) \cdot T_r^c \cdot (\mathbf{c}'_r - \mathbf{c}_r)$
6: $\nabla\phi^c = [\frac{\phi'-\phi}{\Delta\mathbf{c}_x^c}, \frac{\phi'-\phi}{\Delta\mathbf{c}_y^c}, 0]^t$
7: limit norm of $\nabla\phi^c$ to $\nabla_{\max}$
8: $\tilde{\nabla}\phi^r \leftarrow \lambda \cdot \tilde{\nabla}\phi^r + (1-\lambda) \cdot T_c^r \cdot \nabla\phi^c$
9: $\phi' \leftarrow \phi\ , \quad \mathbf{c}' \leftarrow \mathbf{c}$
10: **end if**
11: $\dot{\mathbf{c}}^r \leftarrow \eta \cdot T_c^r \cdot P(\mathbf{c}) \cdot (T_c^r)^{-1} \cdot \tilde{\nabla}\phi^r$
12: **end while**

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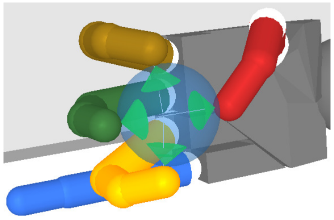
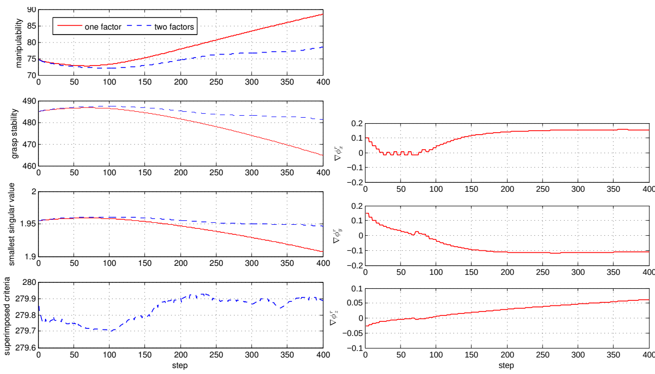


Fig. 1: Simulation scenario




(a) Quality criteria (b) Estimated gradient $\nabla\phi^r$

Fig. 2: Ring finger exploring the object surface.

## III. Simulation and discussion

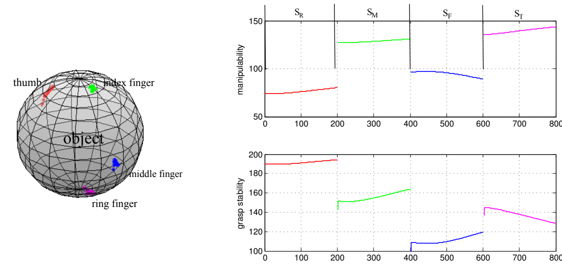
We use the Vortex physics engine to obtain real-time contact information (contact position and normal force magnitude) and the object's pose (position and orientation). Artificial white noise is superimposed on the feedback provided by the physics engine to model noisy real-world sensors. We use the noise standard deviations following the real tactile sensor spatial distribution accuracy. We test one exemplary object – a sphere of 5cm diameter(property unknown for the robot hand), which has to be rotated in place by a 22-DoF Shadow Hand model (see Fig. 1). All simulation video can be download at ASEMIS project website[1].

*a) Object surface exploration:* Fig. 2 shows the evolution of the quality measures during two different exploratory motions of the ring finger: The red solid lines consider manipulability as criteria, while the blue dotted lines result from linear superimposed two quality criteria. Both motions start from the same initial configuration.

As can be seen from the stability graphs, the grasp is stable during the course of manipulation, although stability may decrease. Repeating the exploratory motion 50 times using different initial gradient directions, always leads to a successful maximization of the objective function.

*b) Continuous Object Manipulation:* Finally, Fig. 3 shows the evolution of the contact points w.r.t. the object frame (a) and the corresponding quality criteria (b) during a continuous rotation of the object following the finger gait pattern.

From Fig. 3b, the algorithm always maximizes the manipulability of the exploring finger – except in state $S_F$, where the grasp stability is chosen as the objective function. In this state, the grasp stability drops to a low value, because




(a) Contact point cloud (b) Evolution of manipulability and grasp stability

Fig. 3: Results of complete manipulation sequence

the thumb will become active in the final phase and is thus excluded from the holding task.

Please notice, that the exploration process also reveals valuable shape information of the object as illustrated by the contact point cloud in Fig. 3a.

## IV. Summary and Outlook

The proposed, novel control algorithm to search the maximum of a given smooth objective function in an exploratory motion process, sliding a fingertip over an unknown object surface, provides another missing puzzle piece to realize complex in-hand manipulation. It eventually allows to find suitable contact points for regrasping in order to facilitate long-distance object-in-hand motions, which otherwise would be restricted by joint limits or other task space constraints.

In future, we will apply the algorithm to more complex object shapes, which is easily possible, because only smoothness constraints have to be fulfilled.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