EKF-based inhand object localization using tactile sensing

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INTRODUCTION

Technological advancements in the last few decades allowed the design and development of robotic manipulators to mature from simple grippers to anthropomorphic hands, like the DLR Hand Arm System (Fig. 1, left). While the mechanical capabilities of these hands have almost caught up with those of humans, the intelligence when it comes to grasping and manipulation still leaves much to be desired. One of the main problems, which makes complex tasks like inhand manipulation so challenging, is the lack of reliable information about the state of the object at any time. Imagine the difficulty of writing with a pen or tightening a screw with a screwdriver without knowing the exact position and relative motion of these tools in your hand. Usually, robotic applications rely on the use of visual localization techniques to determine the pose of an object [1]. However, after grasping the object, these approaches may be hindered by occlusions of the object by the fingers. While there has been extensive research on visual localization, the problem of localizing a grasped object has rarely been addressed in literature. The estimation of the object pose from contact information was introduced in [2]. In [3] the hand-object configuration was tracked from tactile sensing using particle filtering. Previously, we proposed a localization method based on a particle filter that used kinematic data and tactile sensing to online estimate the object pose [4].

The method that is proposed in this paper aims to solve the localization problem of a manipulated object by using a minimal set of tactile sensor information. Using only position and torque measurement of the fingers, this method is applicable to a wide range of robotic hand systems without requiring specialized hardware like artificial skin or contact sensors. Additionally, by using an extended Kalman filter (EKF), the presented algorithm is able to explicitly account for any uncertainties in the measurements and the state of the localization.

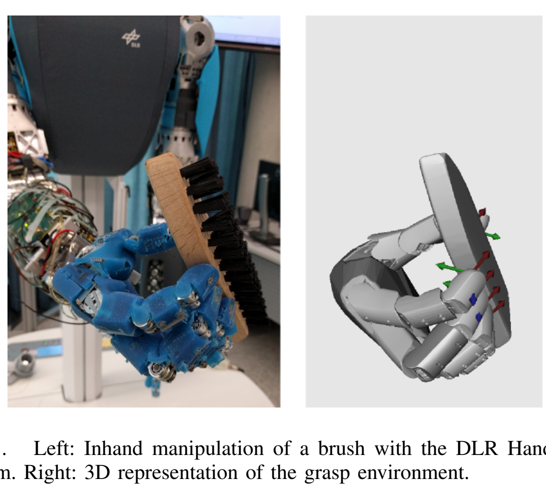

Fig. 1. Left: Inhand manipulation of a brush with the DLR Hand Arm System. Right: 3D representation of the grasp environment.

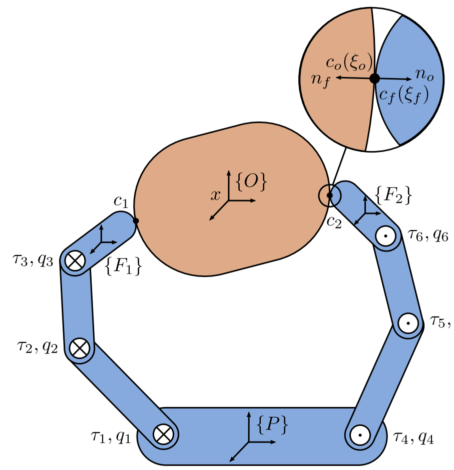

Fig. 2. Illustration of the grasp of an object with two fingers.

LOCALIZATION ALGORITHM

Fig. 2 illustrates the main quantities of an object that is manipulated by a robotic hand. The pose $x \in \mathbb{R}^6$ of the object is described by the translation and rotation of an object fixed frame $\{O\}$ w.r.t. a palm fixed frame $\{P\}$. While the purpose of any object localization algorithm is the determination of x, the grasp of the object is also described by the contacts between the object and the fingers. Each of these contacts is defined by its position $c_i(\xi_i) \in \mathbb{R}^3$, where $\xi_i \in \mathbb{R}^2$ is the position on the surface of the object, as well as a scalar force f_i in the direction of the surface normal n_i. Therefore, the current state of the estimation y is described by the pose of the object and a set of contact positions and forces at time t:

$$y_t = \{x_t, \xi_{1,t}, \ldots, \xi_{n,t}, f_{1,t}, \ldots, f_{n,t}\} \ , \tag{1}$$

where n is the number of contacts. The set of all joint positions q and of all joint torques τ build the measurement vector z:

$$z_t = \{q_{1,t}, \ldots, q_{m,t}, \tau_{1,t}, \ldots, \tau_{m,t}\} \ , \tag{2}$$

where m is the number of joints. Lastly, the control vector shall be given by the joint velocities of the fingers $\dot{q}$:

$$u_t = \{\dot{q}_{1,t}, \ldots, \dot{q}_{m,t}\} \ . \tag{3}$$

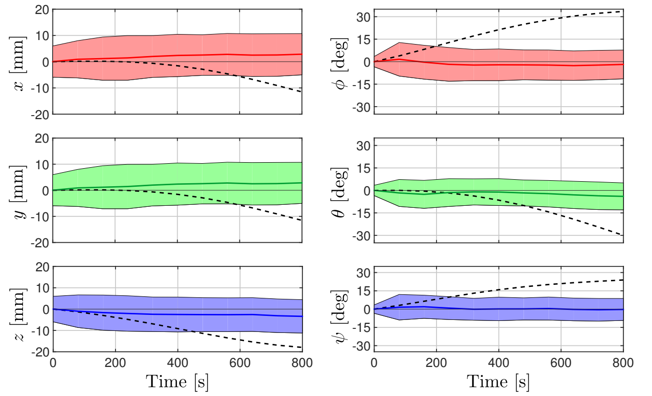

Fig. 3. Error in position (left) and orientation (right) of the manipulated brush from pose prediction (dashed, black line) and EKF estimation (colored, solid line), including 3σ uncertainty range (colored area).

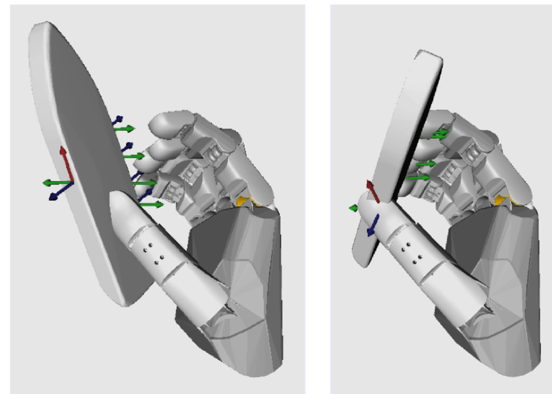

Fig. 4. Estimated object pose at the end of the manipulation from pose prediction (left) and EKF estimation (right).

The state, measurement and control vectors are utilized in the EKF framework as outline in [5]. In order to estimate the state and uncertainty of the object, a motion model and a measurement model of the system a required, for the prediction and update of the EKF respectively. The models are based on digital representation of the kinematics and geometry of the hand and the object, which are then locally linearized at each step for the EKF. Therefore, the algorithm utilizes 3D meshes of the fingers and the object to describe the contact surfaces (see Fig. 4). The main contribution of this papers lies in the formulation of these models that allow for an analytic solution to this highly nonlinear problem. The motion model $f(y_{t-1}, u_t)$ is given by:

$$f(y_{t-1}, u_t) = y_{t-1} + \begin{pmatrix} \widetilde{G}^{+} \widetilde{J} u_t \Delta t \\ 0^{3n \times 1} \end{pmatrix}, \tag{4}$$

where $\widetilde{G}$ and $\widetilde{J}$ are the grasp matrix and hand Jacobian as defined in [6]. Δt is the time between two steps.

The proposed motion model $h(y_t, u_t)$ is described as follows:

$$h(y_t) = \begin{pmatrix} h_q(y_t) \\ h_\tau(y_t) \end{pmatrix}, \tag{5}$$

$$h_q(y_t) = h_q(y_{t-1}) + J^{+}(c_o - c_f), \tag{6}$$

$$h_\tau(y_t) = J^{\mathrm{T}} \lambda_t, \tag{7}$$

where J is the reduced hand Jacobian for hard-finger contacts (see [6]). c_o is the vector of all contact positions on the object, $c_{o,i}(x_t, \xi_i)$, and c_f is the vector of all contact positions on the fingers, $c_{f,i}(h_q(y_{t-1}), \xi_{f,i})$. λ_t is the vector of the n contact forces $\lambda_{i,t} \in \mathbb{R}^3$, with:

$$\lambda_{i,t} = n_{o,i} f_{i,t}. \tag{8}$$

$\xi_{i,f} \in \mathbb{R}^2$ is the position on the surface of the finger, and is recalculated in each step to satisfy that:

$$n_{o,i} = n_{f,i}, \tag{9}$$

where $n_{o,i}$ is the contact normal on the object and $n_{f,i}$ is the contact normal on the finger.

Validation

The proposed algorithm was evaluated using the DLR Hand Arm System. Fig. 1 illustrates the experimental setup where a brush was inhand manipulated by the robotic hand. The 3D representation of the scene is shown on the right side of the figure. During the manipulation, the torque and position measurements of the fingers where recorded and later processed. The main purpose of the experiment was to validate the algorithm, showing its ability to estimate a feasible object pose that satisfies all constraints given by the measurements. This is in contrast to the traditional pose prediction using the grasp and Jacoby matrices, which assumes fixed contacts and merely integrate pose increments over time (see. [6])

Fig. 3 shows the results of the experiment. It illustrates the error in the position and orientation of the object. The plots show both the quality of the pose prediction (black, dashed line) and for the full estimation using joint measurements (colored, solid line). For the estimation algorithm, it also shows the 3σ uncertainty range (colored area). Fig. 4 further illustrates the quality of the respective localization methods at the end of the experiment. While the error from the pose prediction increases without constraint, the proposed algorithm manages to maintain a rather small error and conservative uncertainty at all times.

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