Sequential Improvement of Grasp based on Sensitivity Analysis

Christoforos I. Mavrogiannis, Charalampos P. Bechlioulis and Kostas J. Kyriakopoulos

***Abstract*— In this work, we present a novel concept in the area of optimal grasp synthesis, confronting both geometric and mechanical constraints. Initializing from a locally optimal force distribution on some predefined feasible contact points, our method improves gradually the grasp quality avoiding simultaneously singularities and mechanical limitations. The proposed scheme implements sequential perturbations on the contact points and the wrist's position/orientation incorporating a post-optimality method in an iterative process to derive the consecutive optimal states. The main novelty of this work lies in the fact that only local information of the object's surface is required, which can be provided for instance by an appropriate tactile sensor suite. Finally, a simulation study on the DLR/HIT Hand II clarifies and verifies the efficiency of the approach.**

Index Terms: Grasping Force Optimization, Nonlinear Optimization, Sensitivity Analysis, Grasp Synthesis, Grasp Planning.

I. INTRODUCTION

Over the last decades, there has been a tremendous progress in the field of robot hands [1]. Simple grippers have been replaced by complex human-like hands, built to grasp and manipulate a wide range of every-day-life objects. However, to perform successfully, efficient algorithms, that guarantee certain quality criteria concerning the desired grasp properties for the task to be executed, have to be employed. As a result, a lot of research has been conducted in the field of grasp quality, which is defined by metrics that quantify the performance of a grasp. A fundamental and widely accepted quality criterion for a grasp is force closure [2]. It ensures both that the grasped object's weight is compensated as well as that the contact friction constraints are not violated. However, force closure is quite a wide criterion. Therefore and owing to the increasing needs for precise and human-like grasps, several other quality measures have been presented. Ferrari and Canny in [3] addressed the problem of minimizing contact forces and proposed two different optimality criteria. Based on [3], Miller and Allen in [4], implemented 3D grasp quality computations for the Barrett and the DLR hands. Moreover, Mishra, in [5] compared various metrics and presented a corresponding mathematical analysis. A useful review on various grasp quality measures can be found in [6].

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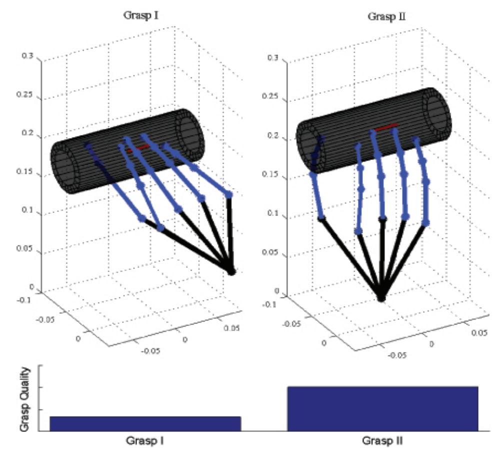

Fig. 1. The effect of different contact points and configurations to the grasp quality.

A lot of grasp synthesis algorithms have been proposed combining different quality measures. Various approaches have been presented both empirical and analytical. The empirical approaches use mainly learning techniques in order to mimic human grasping (see for example [7]). On the other hand, the analytical techniques use mathematical formulations considering the kinematics and the dynamics in order to determine optimal grasps regarding certain criteria [8]. In [9], a grasp optimization algorithm wrt (with respect to) an uncertainty grasp index as well as a task compatibility index is proposed. Particular emphasis has also been devoted to the grasping force optimization (GFO) problem (i.e., the problem of finding the minimal forces that satisfy the force closure sufficient conditions); many algorithms have been proposed in this direction (a complete and thorough overview of grasp synthesis algorithms concerning force optimization but also other grasp quality metrics and different approaches can be found in [8]). The problem of optimizing the maximum external wrench that a multifingered robot hand can withstand is studied in [10]. Finally the force limitations due to hardware and the increasing needs for real time computations have also been taken into consideration in the ongoing research [11].

The force distribution but also other aspects of grasp quality can be severely affected by the selection of contact points. Fig. 1 illustrates how different contact points and configurations affect the grasp quality. Optimality criteria for the selection of contact points were proposed in [12] and

[13]. A study on how infinitesimal perturbations of contact points would affect a class of grasp quality functions was presented in [14]. In [15], it is shown how different contact locations can affect the optimal force distribution wrt various quality measures.

The main goal of all these studies is to be incorporated as part of an algorithm for planning optimal grasps. In [16] a multi-criteria optimization algorithm regarding the fingers ability for force and velocity exertion was presented and was applied specifically for the case of the NASA-JSC robonaut hand. In [17], a strategy of moving fingers to neighboring joint positions to produce optimal force distribution is proposed, whereas in [18], a complete grasp improvement strategy is presented for objects of known geometry. It takes into consideration not only the force minimization requirement, but also the ability of the hand mechanism to exert forces while satisfying the mechanical limits of the finger joints. However, the grasp optimization is implemented through an evolutionary algorithm, which searches for contact points all over the object geometry, thus requiring global knowledge of the object geometry and consequently large number of operations and high computational time. Such an issue is the main drawback of the analytical approaches; they require global knowledge of the object's geometry, which in general is difficult to be acquired accurately in everyday life grasp problems [19].

In our paper, we propose a new concept in the area of optimal grasp synthesis, confronting both geometric and mechanical constraints. Starting from a locally optimal force distribution on some prespecified feasible contact points, our algorithm leads gradually to grasps with lower minimal forces, avoiding singularities and joint limitations. It is implemented sequentially, through perturbations (small changes) of the contact points and the wrist's position/orientation. The key idea behind this work lies in applying sensitivity analysis [20] in an iterative process to derive the sequential optimal solutions. The main advantage of the proposed method is that it needs only local information of the object's surface. Hence, it can be generalized for objects of unknown geometry with the use of suitable tactile sensors [21]. In this respect, the robot hand will be able to perceive the local geometry of the object and based on the proposed algorithm, it will adjust appropriately its configuration to improve the grasp.

The rest of the paper is organized as follows: Section II formulates the problem; Section III presents the methodology and the main algorithm and Section IV verifies the efficiency of our method using simulated paradigms for the DLR/HIT Hand II. Finally, Section V concludes the paper.

II. Problem Formulation

Consider the case of an n_c-fingered robot hand, consisting of n_q rotational joints in total, grasping an object with n_c fingertip contacts. Let us denote the contact wrench of the grasp by $\boldsymbol{f} = \left[\boldsymbol{f_1}^T \quad \dots \quad \boldsymbol{f_{n_c}}^T\right]^T \in \Re^{mn_c}$, where $\boldsymbol{f_i} \in \Re^m$ is the vector of the i-th contact force, defined relative to a local contact frame $\{C_i\}$. The dimension m depends on the adopted contact model. In our analysis we adopt the *Hard Finger* (*HF*) model [22], which assumes that only the three *force* components of the contact wrench can be transmitted from each finger to the object. Thus, $m = 3$ in our case.

A successful grasp may be guaranteed by the satisfaction of two conditions: *i*) the object's equilibrium and *ii*) the friction constraints. The balance equation for the generalized forces applied to the object, can be written as follows:

$$\boldsymbol{f_{ext}} = -\boldsymbol{G}\boldsymbol{f} \tag{1}$$

where $\boldsymbol{G} \in \Re^{6\times mn_c}$ is the grasp matrix and $\boldsymbol{f_{ext}} \in \Re^6$ is the external wrench applied at the object's center of mass and defined relative to $\{N\}$ by the vector $\mathbf{c_m} \in \Re^3$. Regarding the friction constraints, the *HF* model imposes the following nonlinear inequalities:

$$\sqrt{{f_{t_i}}^2 + {f_{o_i}}^2} \leqslant \mu f_{n_i}, \qquad i = 1 \dots n_c \tag{2}$$

where f_{n_i} represents the contact force component which is normal to the object's surface and f_{t_i}, f_{o_i} lie in the contact tangent plane. By μ we denote the friction coefficient between the contact surfaces of the fingers and the object. These inequalities, which are commonly referred to as "friction cone constraints" owing to their geometrical representation, constrain the normal components of the contact forces to be non-negative, which indicates that the fingers tend to squeeze the object. When both constraints (1) and (2) are satisfied, a grasp is said to be stable or force closure. Force closure is a preliminary requirement for almost every task to be executed by a robot hand. However, as it was mentioned above, it is quite a generic criterion. When a robot has to grasp an object to perform a certain task, we also need to take into consideration several aspects associated with the task and the hand's mechanical structure.

In particular, robot hands are mechanical artifacts requiring power to execute the task they have been programmed for. Hence, a fundamental requirement for a grasp concerns its implementation using the lowest possible amount of power. This implies that the required contact forces exerted by the hand's fingers will be produced by low joint torques, demanding low amounts of energy. Towards this goal, many algorithms have been proposed that minimize a cost function associated with the contact forces and respect simultaneously the force closure requirements [11]. In our analysis we adopted the following function:

$$F(\boldsymbol{f}) = \sqrt{\sum_{i=1}^{n_c} {f_{n_i}}^2} \tag{3}$$

Another important aspect when a robot hand grasps an object is its ability to reach the desired contact locations with its fingertips and also exert the required forces in order to perform the desired task. This can be ensured by the maximization of the following manipulability measure:

$$M(\boldsymbol{q}) = \sqrt{det(\boldsymbol{J}(\boldsymbol{q})\boldsymbol{J}(\boldsymbol{q})^T)} \tag{4}$$

where $\boldsymbol{J} \in \Re^{mn_c\times n_q}$ is the hand Jacobian and $\boldsymbol{q} \in \Re^{n_q}$ is the vector containing the angular displacements of the fingers' joints. According to [23], by maximizing manipulability measure, redundancy is exploited to move away from singularities.

Furthermore, the motors in the fingers' joints usually have mechanical limits. This implies that the hand's configurations are constrained by the kinematic abilities of the joints. In order to ensure that a grasp is implemented in a feasible way wrt the robot hand's kinematic abilities we can use the following metric, defined in [6]:

$$Q(\boldsymbol{q}) = \sum_{i=1}^{n_q} \left(\frac{q_i - q_{0i}}{q_{max_i} - q_{min_i}}\right)^2 \tag{5}$$

where q_i is the i-th joint angle, q_{0i} is the middle range position of the i-th joint and q_{max_i}, q_{min_i} are the corresponding upper and lower bounds respectively. By minimizing Q, the joint angles tend to be positioned in the middle of their mechanical limits. Hence, this quality metric forces the configuration inside the feasible region.

The grasp synthesis strategy we propose in this work improves grasp quality relatively to the aforementioned criteria. Given n_c feasible contact points and a locally optimal force distribution $\boldsymbol{f^*}$ wrt (3), our algorithm adjusts appropriately the contact points, the wrist's position/orientation and the force distribution such that the grasp quality is improved. It should also be noticed that contrary to a common assumption in the relative literature, the proposed scheme utilizes only local knowledge of the object's surface at the contact points, thus facilitating its hardware implementation.

III. Sequential Grasp Improvement

Towards addressing the grasp improvement problem, we employed a mathematical programming technique to obtain the efficient as well as feasible directions of the contact points and wrist's transitions that improve force distribution. Specifically, we adopted the first order sensitivity analysis presented in [20]. This methodology considers a general mathematical programming problem in its optimal state wrt the decision variables, studies how infinitesimal perturbations of the problem's parameters affect the optimal state and provides the partial derivatives, called sensitivities, of the primal (decision variables) and dual (Lagrange multipliers) variables as well as of the objective function wrt the perturbed parameters. Fig. 2 shows how small parameter perturbations lead in sequential changes of the optimal state, that can be calculated by the aforementioned sensitivities.

In our problem, we consider the contact forces $\boldsymbol{f} \in \Re^{3n_c}$ as decision variables and the contact points as well as the hand's wrist position and orientation as parameters $\boldsymbol{p} \in \Re^{2n_c+6}$. Our goal is to employ the aforementioned sensitivities to propose parameter changes to the directions of grasp improvement. Given any feasible contact points, we assume that the robot hand stably grasps the object with locally optimal forces:

$$\boldsymbol{f}^* = \underset{\boldsymbol{f}}{\operatorname{argmin}}\ F(\boldsymbol{f}) \tag{6}$$

wrt to the cost function (3), satisfying:

$$\boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p}) = \boldsymbol{0} \tag{7}$$

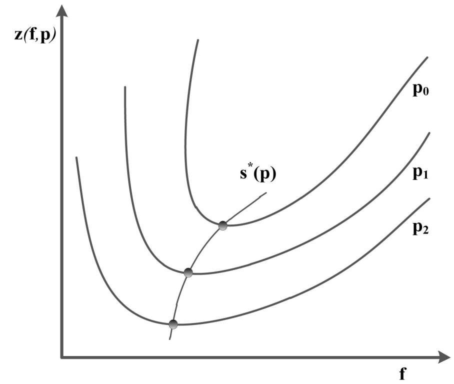

Fig. 2. The optimal states s^* wrt the function $z(\mathbf{f},\mathbf{p})$ are affected by small perturbations of the parameters $\mathbf{p}$.

$$\boldsymbol{g}(\boldsymbol{f}^*) \leqslant \boldsymbol{0} \tag{8}$$

where $\boldsymbol{h} : \Re^{3n_c} \times \Re^{2n_c+6} \rightarrow \Re^6$ represents the balance linear equalities (1) and $\boldsymbol{g} : \Re^{3n_c} \rightarrow \Re^{n_c}$ represents the friction cone nonlinear inequalities (2). As a result, the Karush-Kuhn-Tucker first order necessary conditions hold (see for example [24]):

$$\nabla_{\boldsymbol{f}} F(\boldsymbol{f}^*) + \boldsymbol{\lambda}^{*T} \nabla_{\boldsymbol{f}} \boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p}) + \boldsymbol{\mu}^{*T} \nabla_{\boldsymbol{f}} \boldsymbol{g}(\boldsymbol{f}^*) = 0 \tag{9}$$

$$\boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p}) = \boldsymbol{0} \tag{10}$$

$$\boldsymbol{g}(\boldsymbol{f}^*) \leqslant \boldsymbol{0} \tag{11}$$

$$\boldsymbol{\mu}^{*T} \boldsymbol{g}(\boldsymbol{f}^*) = \boldsymbol{0} \tag{12}$$

$$\boldsymbol{\mu}^* \geqslant \boldsymbol{0} \tag{13}$$

where $\boldsymbol{\lambda}^* \in \Re^6$ and $\boldsymbol{\mu}^* \in \Re^{n_c}$ are the Lagrange multipliers associated with the equality and inequality constraints respectively.

In order to incorporate in our analysis the quality measures (4) and (5), mentioned in the previous section, we employ the following objective function:

$$z = w_1 \cdot F(\boldsymbol{f}) + w_2 \cdot \frac{1}{M(\boldsymbol{q})} + w_3 \cdot Q(\boldsymbol{q}) \tag{14}$$

where w_1, w_2, w_3 are suitably chosen weights that normalize the quality measures and favor those we want to emphasize more, depending on the task. Incorporating the hand's inverse kinematics:

$$\boldsymbol{q} = \boldsymbol{T}(\boldsymbol{p}) \tag{15}$$

into (14) we derive the expression of the objective function wrt the system parameters $\boldsymbol{p}$, as follows:

$$\boldsymbol{z}(\boldsymbol{f}, \boldsymbol{p}) = w_1 \cdot \mathbf{F}(\boldsymbol{f}) + w_2 \cdot \frac{1}{\boldsymbol{M}(\boldsymbol{p})} + w_3 \cdot \boldsymbol{Q}(\boldsymbol{p}) \tag{16}$$

Since system parameters were considered constant in the initial optimal grasp and since $\boldsymbol{M}$ and $\boldsymbol{Q}$ are independent of the decision variables $\boldsymbol{f}$, their incorporation does not affect the optimality conditions. Thus, the system is also in a locally optimal state wrt the cost function (16).

The derivation of the sensitivities of the optimal state ($\boldsymbol{f}^*$, $\boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, \boldsymbol{z}^*$) wrt the parameters $\boldsymbol{p}$ is carried out by differentiating the KKT conditions, as follows:

$$(\nabla_{\boldsymbol{f}} \boldsymbol{z}(\boldsymbol{f}^*, \boldsymbol{p}))^T d\boldsymbol{f} + (\nabla_{\boldsymbol{p}} \boldsymbol{z}(\boldsymbol{f}^*, \boldsymbol{p}))^T d\boldsymbol{p} - d\boldsymbol{z} = 0 \quad (17)$$

$$\left(\nabla_{\boldsymbol{ff}} \boldsymbol{z}(\boldsymbol{f}^*, \boldsymbol{p})) + \sum_{j=1}^{n_c} \mu_j^* \nabla_{\boldsymbol{ff}} g_j(\boldsymbol{f}^*, \boldsymbol{p})\right) d\boldsymbol{f} + \sum_{k=1}^{6} \lambda_k^* \nabla_{\boldsymbol{fp}} h_k(\boldsymbol{f}^*, \boldsymbol{p}) d\boldsymbol{p} + \nabla_{\boldsymbol{f}} \boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p}) d\boldsymbol{\lambda} + \nabla_{\boldsymbol{f}} \boldsymbol{g}(\boldsymbol{f}^*, \boldsymbol{p}) d\boldsymbol{\mu} = \boldsymbol{0}_{3n_c} \quad (18)$$

$$(\nabla_{\boldsymbol{f}} \boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p}))^T d\boldsymbol{f} + \nabla_{\boldsymbol{p}} \boldsymbol{h}(\boldsymbol{f}^*, \boldsymbol{p})^T d\boldsymbol{p} = \boldsymbol{0}_6 \quad (19)$$

$$(\nabla_{\boldsymbol{f}} \boldsymbol{g}(\boldsymbol{f}^*))^T d\boldsymbol{f} = \boldsymbol{0}_{n_c} \quad (20)$$

The aforementioned set of equations requires that the KKT conditions are satisfied after an infinitesimal perturbation of system parameters. We also demand that active constraints remain active and inactive constraints keep their value inside the feasible region after each perturbation. In matrix form, the system (17)-(20) can be written as follows:

$$\begin{bmatrix} \boldsymbol{z_f} & \boldsymbol{z_p} & \boldsymbol{0} & \boldsymbol{0} & -1 \\ \boldsymbol{z_{ff}} + \sum_{j=1}^{n_c} \mu_j^* \boldsymbol{g_{ff}} & \sum_{k=1}^{6} \lambda_k^* \boldsymbol{h_{fp}} & \boldsymbol{h_f} & \boldsymbol{g_f} & \boldsymbol{0} \\ \boldsymbol{h_f^T} & \boldsymbol{h_p^T} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{g_f^T} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} d\boldsymbol{f} \\ d\boldsymbol{p} \\ d\boldsymbol{\lambda} \\ d\boldsymbol{\mu} \\ d\boldsymbol{z} \end{bmatrix} = \boldsymbol{0} \quad (21)$$

If we consider the submatrices:

$$U = \begin{bmatrix} \boldsymbol{z_f} & \boldsymbol{0} & \boldsymbol{0} & -1 \\ \boldsymbol{z_{ff}} + \sum_{j=1}^{n_c} \mu_j^* \boldsymbol{g}_{ff} & \boldsymbol{h_f} & \boldsymbol{g_f} & \boldsymbol{0} \\ \boldsymbol{h_f^T} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{g_f^T} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \end{bmatrix} \quad (22)$$

and

$$S = \begin{bmatrix} -\boldsymbol{z_p} \\ -\sum_{k=1}^{6} \lambda_k^* \boldsymbol{h_{fp}} \\ -\boldsymbol{h_p^T} \\ \boldsymbol{0} \end{bmatrix} \quad (23)$$

we obtain all sensitivities through the inversion of the square matrix U. Under the assumption that the optimal solution $\boldsymbol{f}^*$ is a non-degenerate regular point [20], matrix U is invertible. Thus, the sensitivities are calculated as follows:

$$D = \begin{bmatrix} \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{p}} \\ \frac{\partial \boldsymbol{\lambda}}{\partial \boldsymbol{p}} \\ \frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{p}} \\ \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{p}} \end{bmatrix} = U^{-1} S \quad (24)$$

As a result, the expected change of the optimal state ($\boldsymbol{f}^*, \lambda^*, \mu^*, z^*$) after an infinitesimal perturbation $d\mathbf{p}$ of the parameters may be derived to a first order approximation, through the corresponding differentials:

$$\begin{bmatrix} d\boldsymbol{f} \\ d\boldsymbol{\lambda} \\ d\boldsymbol{\mu} \\ d\boldsymbol{z} \end{bmatrix} = D \cdot d\boldsymbol{p} \quad (25)$$

It should be noticed that the aforementioned method has local validity. However, incorporating it in an iterative algorithm can lead to sequential improvements of the cost function (16). Thus, via calculating the sensitivities and adopting a suitable step selection strategy for the system parameters, we can change appropriately the optimal state. Hence, our goal is to apply perturbations of the parameters in such directions that lead to the decrease of the objective function (16). Subsequently, we present an algorithm that incorporates the aforementioned methodology into a general grasp synthesis strategy aiming at post optimal grasp improvement.

A. The Sequential Grasp Improvement Algorithm

The Sequential Grasp Improvement (SGI) Algorithm initializes with an optimal grasp on prespecified feasible contact points and wrist's position/orientation. The initial optimal state is obtained via a grasping force optimization algorithm. At this point, the iterative algorithm begins. At the i-th iteration, the sensitivities are first calculated and subsequently, an appropriate and sufficiently small parameter perturbation $d\boldsymbol{p}$ is determined. A well established method that calculates the magnitude of the parameter perturbations can be found in [25]. The parameters are then updated via:

$$\boldsymbol{p}_{i+1} = \boldsymbol{p}_i + d\boldsymbol{p} \quad (26)$$

and the new optimal state ($\boldsymbol{f}_{i+1}^*, \boldsymbol{\lambda}_{i+1}^*, \boldsymbol{\mu}_{i+1}^*, \boldsymbol{z}_{i+1}^*$) is calculated via the corresponding sensitivities, as described in (25). The iterative process continues until (*i*) an insignificant grasp improvement is determined or (*ii*) a possible collision between the hand's fingers is detected or (*iii*) any of the joint limits is violated. Although an appropriate metric (see eq. 5) was included in the cost function (14), the decrease of (14), which in general leads the configuration inside the feasible region, cannot guarantee by itself that the joint limits are not violated. Finally, it should be noticed that the proposed algorithm avoids any singular configurations owing to metric (4) that was employed in the objective function. Thus, starting from a nonsingular configuration (i.e., $M(\boldsymbol{q_0}) > 0$) and decreasing the objective function (16), it is impossible to approach a singular point (i.e., $M(\boldsymbol{q}) \to 0$), since in such case the objective function would approach to infinity, which is a clear contradiction.

The proposed scheme is presented in Alg. 1 (SGI) in pseudocode. The vector **var** contains the optimal state ($\boldsymbol{f}^*, \boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, z^*$). GFO is an algorithm implementing the initial grasping force optimization, for a given set of feasible contact points (e.g. [11]). *MOVEHAND* is the procedure that implements the determined perturbation of contact points and wrist. Let **dp** be the vector of the parameters perturbations, that is calculated in Alg. 2 and **dvar** denote the change of the optimal state. The vector $\boldsymbol{\varepsilon}$ contains the step size for each of the system's parameters, while δ contains a desired improvement of the objective function. *Imp* is a logical variable, whose value is *TRUE* while the grasp improvement is considered as satisfactory wrt a prechosen desired decrease of the cost function z and turns *FALSE* when

Algorithm 1 Sequential Grasp Improvement

```
procedure SGI(p, q, cm, Weight, frcoef, ε, δ, w1, w2, w3)
    var ← GFO(p, cm, Weight, frcoef)
    Imp ← TRUE
    col ← FALSE
    while (q ∈ Q) and (Imp = TRUE) and (col = FALSE) do
        MOVEHAND(q,var)
        D ← SENSITIVITY(var, p, q, cm, Weight, frcoef)
        dp ← STEP(D, ε)
        dvar ← D ∗ dp
        var ← var + dvar
        p ← p + dp
        q ← INVKINE(p, cm)
        if dvar(4n_c + 7) < −δ) then
            Imp ← TRUE
        else
            Imp ← FALSE
        end if
        for i=1 to 10 do
            j ← 2 ∗ i + 1
            if p[j+2] − p[j] < 0 then
                col ← TRUE
            end if
        end for
    end while
end procedure
```

Algorithm 2 Step Determination

```
function STEP(D, ε)
    for i=1 to 16 do
        if D[4n_c + 7, i] > 0 then
            dp[i] = −ε[i]
        else
            dp[i] = ε[i]
        end if
    end for
end function
```

the improvement is considered as insignificant. Collision is checked using the logical variable *col*. As long as no collision is detected, *col* remains *FALSE* and the algorithm proceeds. When *col* turns *TRUE*, a collision is about to happen and the algorithm stops. Functions *SENSITIVITY* and *INVKINE* implement the calculations of Sensitivities and inverse kinematics respectively, while *STEP* is the function that determines the appropriate parameter perturbation.

IV. Simulation Results

The robotic hand we that we use in the simulated paradigms is the DLR/HIT Hand II, which is a five fingered fifteen DoFs dexterous robotic hand, jointly developed by DLR (German Aerospace Center) and HIT (Harbin Institute of Technology). It has five kinematically identical fingers with three DoFs per finger, two DoFs for flexion and extension and one DoF for abduction-adduction. The last joint of each finger is coupled with the middle one, using a mechanical coupling based on a steel wire with transmition ratio 1:1. More details regarding the kinematics or other specifications of the DLR/HIT II, can be found in [26]. We also considered the position and the orientation of the hand's wrist as parameter values assuming that a dexterous robot arm could implement the small wrist perturbations derived by the SGI Algorithm. Finally, the grasped objects are a cylinder with diameter 6 cm and height 15 cm and a sphere with diameter 4 cm, both weighting 200 gr. The friction coefficient between the surface of the fingers and the object was set to be 0.8.

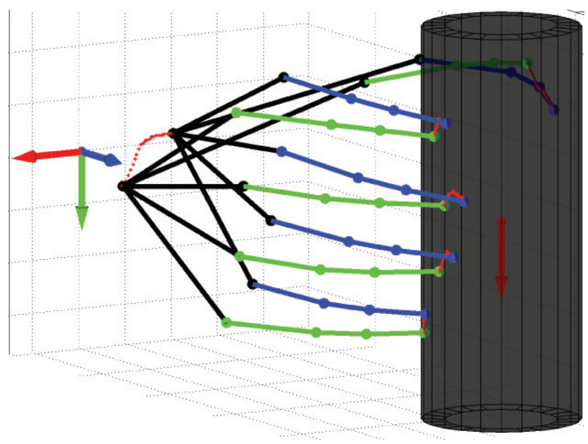

Fig. 3. Cylindrical object: The initial (green color) and the final (blue color) hand configuration as well as the transitions (red color) between the contact points.

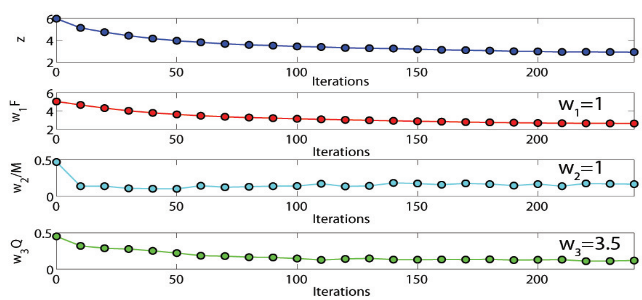

Fig. 4. Cylindrical object: Comparative illustration of the cost function components.

Simulation results for the case of a cylindric object are presented in Fig. 3 and Fig. 4. Fig. 3 illustrates the initial and final configurations/contact points after 240 iterations, after which, no significant progress is observed and the SGI Algorithm terminates without violating joint limits. As it is illustrated in Fig. 4, the force metric (3) decreases, leading in a more energy efficient grasp. The scaled manipulability inverse exhibits a fast decrease at the beginning and then is kept constant around a low value, avoiding thus any singularities. Measure Q is decreasing slowly, practically ensuring that the configuration remains feasible wrt the joint limits. Similar results (see Fig. 5 and 6) were obtained for the case of the spherical object. Finally, the weighting factors of the objective function have been selected as depicted in Figs. 4 and 6 to favor mechanical feasibility.

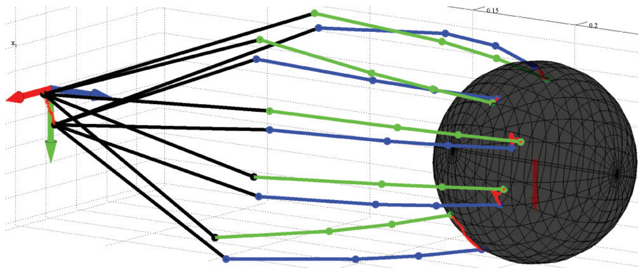

Fig. 5. Spherical object: The initial (green color) and the final (blue color) hand configuration as well as the transitions (red color) between the determined contact points.

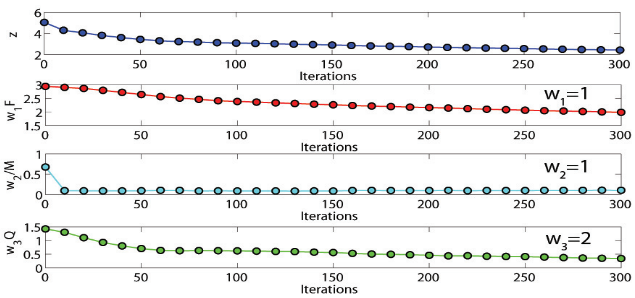

Fig. 6. Spherical object: Comparative illustration of the cost function components.

V. Conclusions and Discussion

A sequential grasp improvement scheme was proposed based on a general post-optimality analysis. It initializes with an optimal grasp on prespecified feasible contact points and wrist's position/orientation. Subsequently, it determines appropriate changes on the contact points and the wrist's position/orientation, that lead gradually to better grasps wrt the force distribution and the manipulability. The proposed methodology takes into account the mechanical constraints of the robot hand, incorporating only local knowledge of the object surface at the contact points. Tactile sensing can provide a robot hand with the required local surface knowledge to execute the algorithm in a real life unstructured and dynamic environment.

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