Floating Visual Grasp of Unknown Objects

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Abstract— **A new method for fast visual grasp of unknown objects using a camera mounted on a robot in an eye-in-hand configuration is presented. The method is composed of a fast iterative object surface reconstruction algorithm and of a local grasp planner, evolving in a synchronized parallel way. The reconstruction algorithm makes use of images taken by a camera carried by the robot. A reconstruction sphere, virtually placed around the object, is iteratively compressed towards the object visual hull, dragging out the fingers attached to it. Between two steps of the reconstruction process, the planner moves the fingers, floating on the current reconstructed surface, according to suitable quality measures. The fingers keep moving until a local minimum is achieved, then a new object surface estimation provided by the reconstruction process is considered. Quality measures considering both hand and grasp proprieties are adopted. Simulations are presented to show the performance of the proposed algorithm.**

I. INTRODUCTION

Grasping and manipulation tasks generally require a priori knowledge about the object geometry. Autonomous operation in unstructured environments is a challenging research field and, especially the problem of grasping unknown objects, has not been widely investigated yet.

One of the first approaches to grasping in unknown environments can be found in [19], where visual control of grasping is performed employing visual information to track both object and fingers positions. A method to grasp an unknown object using information provided by a deformable contour model algorithm is proposed in [11]. Recently, in [18], an omnidirectional camera is used to object shape recognition while grasping is achieved on the basis of a grasping quality measure, using a soft-fingered hand.

It is easy to recognize that two main tasks have to be performed to achieve unknown objects grasping, namely, object recognition/reconstruction and grasp planning.

Different methods have been proposed in the literature to cope with 3D model reconstruction of objects. The main differences rely on how the available images are processed and, of course, on the algorithms used for object reconstruction. A number of algorithms can be classified under the so called *volumetric scene reconstruction* approach [3]. This category can be further divided into two main groups: the *shape from silhouettes* and the *shape from photo-consistency* algorithms. Another method, proposed in [17], considers a surface that moves towards the object under the influence of internal forces, produced by the surface itself, and external forces, given by the image data.

A technique for computing a polyhedral representation of the *visual hull* [7] –the set of points in the space that are projected inside each image silhouette– is studied in [5]. Other approaches rely on the use of *apparent contours* [2], [12]; in these cases, the reconstruction is based on the spatio-temporal analysis of deformable silhouettes.

On the other hand, grasp planning techniques rely upon the choice of grasp quality measures used to select suitable grasp points. Several quality measures proposed in the literature depend on the grasp geometry and on the positions of the contact points. Some of them are based on the properties of the grasp matrix; others are based on the area of the polygon created by the contact points or on the external resistent wrench. Simple geometric conditions to reach an optimal force closure grasp both in 2-D and in 3-D are found in [10]. The geometric properties of the grasp are used also in [8] to define quality measures; moreover, suitable task ellipsoids in the object wrench space are proposed to evaluate grasp quality also with respect to the particular manipulation task.

A geometrical approach to obtain at least one force closure grasp in 3D discretized objects is studied in [13], where two algorithms are investigated: the first finds at least one force closure grasp, while the second optimizes it to get a locally optimum grasp.

Another class of quality measures is based on the evaluation of the capability of the hand to realize the optimal grasp. Therefore, these measures depend on the hand configurations [14]. To plan a grasp for a particular robotic hand, quality measures depending both on grasp geometry and hand configuration should be taken in account. In the literature, only few papers address the whole problem of grasping an object using a given robotic hand, able to reach the desired contact points in a dexterous configuration. Some examples can be found in [1], [4], [6] and a rich survey of grasp quality measures can be found in [16].

In this paper, a new method for fast visual grasping of unknown objects using a camera mounted on a robot in an eye-in-hand configuration is presented. This method is composed of an iterative object surface reconstruction algorithm and of a local grasp planner, which evolve in a synchronized parallel

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way. The reconstruction algorithm makes use of images taken by a camera carried by the robot. First, a rough estimation of the object position and dimensions is performed, a reconstruction spherical surface is virtually placed around the object, and the fingers of the robotic hand are suitably placed on it. Then, the reconstruction sphere, sampled by points, is iteratively compressed towards the visual hull of the object projections, dragging out the fingers attached on it. Between two steps of the reconstruction process, the planner moves the fingers, floating on the current reconstructed surface at an imposed (security) distance, according to some quality measures. For this reason, we call this new method *Floating Visual Grasp*. The fingers keep moving until a local minimum is achieved, then a new object surface estimation provided by the reconstruction process is considered. Quality measures considering both hand and grasp proprieties are adopted: the directions of the finger motion leading toward grasp configurations that are not physically reachable, or causing collisions or loss of hand manipulability, are discarded. Moreover, a discretized method of the Mirtich and Canny quality measure is applied to the remaining possible motion directions to select those leading toward an optimal (in a local sense) grasp configuration. Notice that many other quality measures may be chosen in substitution of those proposed in [10], without affecting the the proposed framework.

Simulations results are presented to show the performance of the proposed algorithm.

II. FLOATING VISUAL GRASP ALGORITHM

The block diagram of the proposed visual grasp algorithm is shown in Fig. 1. It can be observed that the algorithm may be divided into three main parts: some *preliminary steps*, the *object surface reconstruction algorithm*, and the *local grasp planner*.

Initially, using a detection algorithm based on a classical blob analysis, the presence of an object in the field of view of the camera is detected. Therefore, by holding the optical axis perpendicular to the plane where the object has been detected, the camera is moved until the optical axis intercepts the centroid of the object. At the end of this step, the camera is exactly over the unknown object and ready to start the image acquisition process. Moreover, during this step, a rough estimation of the object center is evaluated using the centroid of the object shape extracted from some images.

The image acquisition stations are chosen as illustrated in Fig. 2. The image acquisition step is carried out as follows: 1) an image is acquired from the top of the object; 2) a subset of n_1 images are taken from camera stations equally distributed over a circular path of radius r_1, with the optical axis of the camera pointing to the estimated center of the object and forming an angle α_1 with respect to the revolution axis $\mathbf{z}$; 3) a subset of n_2 images are acquired as in 2), but using a radius r_2 and an angle α_2. In the following, the total number of acquired images will be denoted as $n = n_1 + n_2 + 1$.

After the acquisition of n images, a blob analysis technique is employed to determine the silhouette of the object

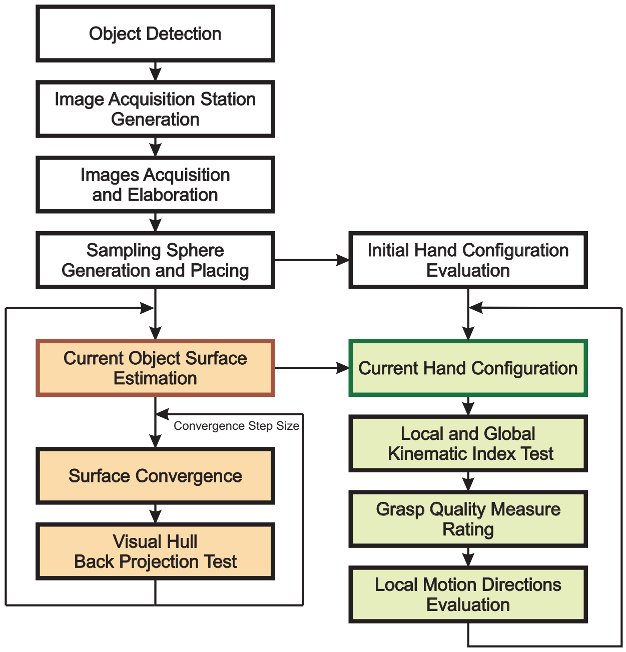

Fig. 1. Block diagram of the visual grasp algorithm.

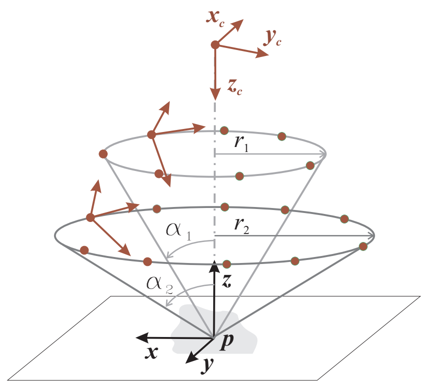

Fig. 2. Camera stations (bullets) and trajectories of the camera during image acquisition.

for each image. Each silhouette is improved using suitable filtering technique (e.g. dilatation and erosion iterative process) to reduce the effects of the image noise, and the centroid of the corresponding blob is evaluated. Then, the center of mass of the object (assuming homogeneous mass distribution) is estimated using a least-squares triangulation method.

On the basis of the dimension of each silhouette, the radius r_s of a 3D spherical surface that surely contains the object (with a safety margin ϵ) is estimated. Finally, the *reconstruction sphere* with radius r_s, centered at the estimated center of mass of the object, and sampled with a number of points n_s is built, as shown in Fig. 3.

The initial grasp configuration of the hand can be set on the basis of the initial reconstruction sphere. In this paper, a three-fingered hand and point contact type at the tip of each finger are considered. Hence, a direct correspondence between the position of a point on the sphere and the position of each finger of the hand can be assumed.

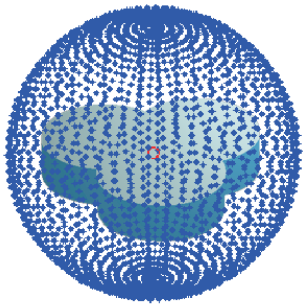

Fig. 3. Sampled reconstruction sphere surrounding the object.

Due to the symmetry of the sphere, infinite grasp configurations could be selected on the sphere, ensuring force-closure grasp. To this purpose, it is well known that a three contact grasp of a sphere is force-closure if the contact points are $120°$ apart on the same plane. Therefore, the plane parallel to the floor halving the sphere is chosen, and three points $120°$ apart are selected on the circumference intercepted by the plane. These points have to be reachable on the basis of the kinematics of the selected hand.

At this point, both the object model reconstruction process and the local planner start in parallel and cooperate to the final goal. In particular, as shown in Fig. 1, the reconstruction algorithm updates in real-time the estimation of the object surface, while the local planner, on the basis of the current estimation, computes the fingers trajectories to reach the current local optimal configuration for the grasp.

These two parallel processes are independent and can be allocated under two different threads or, in a multi-processor system, on different CPUs. In other words, the proposed method exhibits an intrinsic capability to be run in parallel. More details of these two crucial steps are provided in the next two sections.

III. FAST OBJECT SURFACE RECONSTRUCTION

The object surface reconstruction method employed in this paper is an evolution of the method proposed in [9].

Starting from the set of n silhouettes evaluated as described in the previous section, the reconstruction sphere radius is progressively reduced, using a variable step size depending on the distance from the object surface (the step size is set larger at the start, to reduce the overall computational time). When a sample point of the sphere intersects the visual hull, it is brought back of one step and, in the next iteration, a smaller step size is used for that point. At the occurrence of the second intersection, the point is fixed to the reached position. The iterative process is stopped when all the points are fixed or are lost (points are lost when the center of mass is outside the object volume).

It can be easily understood that the precision of the reconstruction depends on the number of views, on the observation angles and distances, and on the density of the points of the reconstruction sphere. On the other hand, the computational time of the algorithm increases if n and/or n_s are increased. Considering that the reconstruction process is the most computationally expensive step of the whole algorithm, a suitable trade-off must be found between time and precision. However, the final goal of the algorithm is object grasping and not model reconstruction; this latter can be considered as a secondary outcome of the proposed method. Therefore, the accuracy of the reconstruction process needs only to be adequate for the requirements of the grasp planner algorithm.

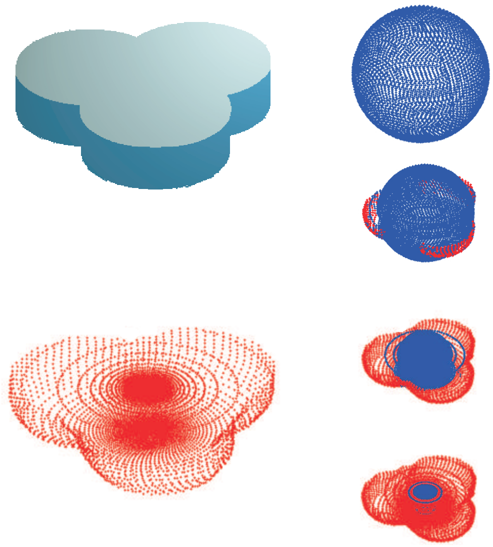

Fig. 4. Steps of the object surface reconstruction process.

In Fig. 4 some images showing intermediate steps of the reconstruction algorithm of an object are shown, with parameters: $\alpha_1 = 45°$, $\alpha_2 = 80°$, $n_1 = 4$, $n_2 = 8$, and $n_s = 6500$ sampling points for the reconstruction sphere. The corresponding computational time, using a Pentium IV 3.4GHz processor, for 1500 reconstruction points is of 49 ms, for 3300 points is 52 ms, and for 6000 points is 61 ms.

IV. LOCAL GRASP PLANNER

The local grasp planner proposed here makes use of the current estimation of the discretized object surface to update the trajectories of the finger tips which move floating on the surface, keeping a fixed *floating distance* δ_f between the fingers and the surface along the outgoing normals, on the basis of suitable quality indices (see Fig. 5).

Namely, starting from the initial grasp configuration on the reconstruction sphere (chosen as described in the previous sections), at the end of each step of the reconstruction algorithm, the planner generates the motion of the fingers from the current position to a point of the updated surface.

The contact points of the grasp are first "virtually" moved to the updated surface, achieving an initial "target" grasp configuration. Then, for each contact point of the current target grasp configuration, the contour made by the eight neighboring points of the surface is selected. Considering the contours of all the contact points, the set of all the combinations of possible reachable grasp configurations is evaluated on the basis of suitable quality measures. If the

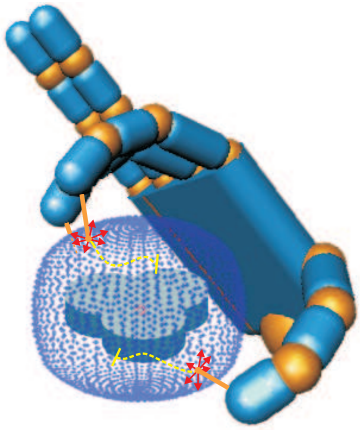

Fig. 5. Floating visual grasp.

current grasp configuration of the set has a value better than the value of the target configuration, this is chosen as the new target grasp configuration, establishing "de facto" the motion direction of each finger, as shown in Fig. 6. The process is repeated in a recursive manner until there are no more improvements of the quality measures and restarts anytime the object surface is updated. The whole process ends when the object reconstruction algorithm stops and the planner computes the final grasp configuration. Hence, the security floating distance δ_f is progressively reduced to achieve the desired grasp action.

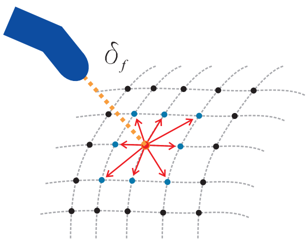

Fig. 6. Contour of neighbor points of the current target grasp point.

The floating distance is used to avoid collisions of the fingers with the object during the object reconstruction and approaching, and before that the final grasp configuration is reached. Moreover, the final progressive reduction of the floating distance allows a perpendicular grasp for each finger.

Notice that only a limited number of points are considered as candidates for the next grasp configuration, so that the number of combinations to be inspected is limited, resulting in a computationally fast algorithm. Moreover, a certain number of grasp configurations are discarded during the evaluation process. In detail, a *local kinematic index* is used to discard all the candidate grasp configurations that cannot be reached. Then, a *global kinematic index* is adopted to discard all the configurations causing finger collisions or lack of manipulability for the hand. Finally, a *grasp quality measure* is applied to the remaining configurations to evaluate possible improvements of the grasp quality.

In the following subsections, the quality indices and the finger trajectory planner are presented.

A. *Local kinematic index*

The local kinematic index allows to discard all the candidate contact points that cannot be reached, on the basis of the finger kinematics. With reference to a single contact point and finger, the kinematic test is carried out for all the contour points (see Fig.6). Namely, for each point, finger joints are computed using an inverse kinematics algorithm. Hence, those points for which joint limits are exceeded, or that are too close to kinematics singularity, are discarded. This latter condition is evaluated on the basis of the condition number of the finger Jacobian.

A standard CLIK algorithm [15] is adopted to compute the inverse kinematics; in particular, the scheme based on the transpose of the Jacobian has been used to achieve a faster computation, together with a Singular Value Decomposition technique for the evaluation of the Jacobian condition number.

B. *Global kinematic index*

For the remaining points of the contour, the global kinematic index computes the distance between the fingers corresponding to all the possible grasp configurations. Hence, all the configurations for which the distances are under a given security threshold, are discarded.

Moreover, the condition number of the hand Jacobian is evaluated to discard the configurations close to hand singularities.

C. *Grasp quality measure*

The grasp quality is evaluated only for the configurations that are left after the kinematic tests. The method proposed in [10] is adopted, suitably modified to cope with the discretization of the grasp configurations. Assuming the neglecting of the moments and transversal forces, the method proposed in [11] can be easily integrated in this method.

Let us denote with $\mathbf{w} = \begin{bmatrix} \mathbf{f}^{\mathrm{T}} & \mathbf{m}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$ the wrench vector collecting force $\mathbf{f}$ and moment $\mathbf{m}$. Assuming that the finger forces are applied along the direction normal to the object surface, the force direction is specified only by the contact point.

Let $\mathcal{W}$ denote the space of wrenches, $\mathcal{W}_f \subset \mathcal{W}$ the space of unit forces acting in the grip plane (the plane containing the three contact points) through the center of grip, $\mathcal{W}_{\perp m} \subset \mathcal{W}$ the space of pure moments acting along the direction perpendicular to the grip plane. Moreover, let $\mathbf{g}^{-1}(-\mathbf{w})$ denote the set of finger forces which can resist the external wrench $\mathbf{w}$.

Finally, consider the quantity

$$Q_1 = \min_{\mathbf{w} \in \mathcal{W}_f} \left(\max_{\mathbf{f} \in \mathbf{g}^{-1}(-\mathbf{w})} \frac{1}{\| \mathbf{f} \|_f} \right),$$

which is a measure of the grasp ability to resist unit forces in the grip plane, and the quantity

$$Q_2 = \min_{\mathbf{w} \in \mathcal{W}_{\perp m}} \left(\max_{\mathbf{f} \in \mathbf{g}^{-1}(-\mathbf{w})} \frac{1}{\| \mathbf{f} \|_f} \right),$$

which is a measure of the grasp ability to resist unit moments normal to the grip plane.

The optimal grasp proposed in [10] is defined as the grasp that maximizes Q_2 among all grasps which maximize Q_1.

It can be proven (see [10]) that the optimum grasp with three fingers in a 2-D case under the above optimal criterion is reached when the normal forces are symmetric, with directions spaced 120° apart. Moreover, this grasp maximizes also the size of the outer triangle, defined as the triangle formed by the three lines perpendicular to the normal finger forces passing through the respective contact points. Under the same criterion, the optimum grasp with three fingers in a 3-D case is achieved when the maximum circumscribing prism-shaped grasp, that has the largest outer triangle, is selected among the grasps where the normal finger forces lie within the same grip plane and are in equilateral configuration.

Therefore, to reach the optimum in the 3-D case with three fingers, the planner has to seek three points in equilateral configuration on the object surface, so that the normal forces lie in the same (grip) plane, and for which the circumscribing prism grasp is maximum.

In our case, since the reconstructed object surface is discretized, the above method cannot be directly applied. Differently from the continuous case, due to the presence of a finite set of sampled points, the existence of a "grip plane" containing all the normal forces is not guaranteed. This is mainly due to the fact that, because of the discretization, the surface normals are an approximation of the real ones. Considering that the optimal criterion requires that the desired normals have to be spaced 120° apart, a discretized implementation of the method of [10] is proposed here.

For each candidate configuration of three grasp points, the normal directions are estimated on the basis of the available point-wise approximation of the surface. Then, the unit vector normal to the grip plane containing the three points is evaluated. Denoting with α_j the angle between the direction of the normal force applied to point j and the direction normal to the grip plane, a Coplanarity Error Index (CEI) can be defined as follow:

$$CEI = \frac{\sum_{j=1}^{3} \mid \alpha_j - 90^\circ \mid}{3}.$$

Obviously, the closer the CEI to zero, the more the normal forces lie in the same plane. The definition of a threshold Φ_{CEI} allows discarding of all those configurations having a value of the CEI higher than Φ_{CEI}; hence, all the remaining grasp configurations are assumed to have forces lying in the same grip plane and can be further processed.

The next step consists in looking for an equilateral grasp configuration. To this purpose, for each grasp configuration, the unit vector normal to the object surface at each contact point is projected on the grip plane. Denoting with β_j the angle between these projections for each of the 3 couple of points of the considered configuration, an Equilateral Error Grasp Index ($EEGI$) can be defined as:

$$EEGI = \frac{\sum_{j=1}^{3} \mid \beta_j - 120^\circ \mid}{3}.$$

Clearly, the closer the $EEGI$ to zero, the nearer the configuration to an equilateral grasp. The definition of a threshold Φ_{EEGI} allows discarding of all those configurations with value of the $EEGI$ higher than Φ_{EEGI}; hence, all the remaining grasp configurations are assumed to be equilateral.

Among all the equilateral configurations, the maximum circumscribing prism has to be found; if the grasp configuration associated with the largest prism is different from the current target configuration, this is taken as new grasp configuration.

Notice that, in the case that the grasp configuration changes, the whole process starts again with the new contact points, by considering the new contours and applying the complete sequence of index-based tests starting from the kinematic ones. The algorithm stops if the best grasp configuration remains unchanged at the end of the optimization process, or in the case that all the candidate grasp configurations are discarded during the process.

D. Finger trajectory planner

At each iteration of the object reconstruction algorithm, the local grasp planner produces a sequence of intermediate target grasp configurations which ends with the optimal grasp configuration (in local sense), as illustrated in Fig. 5. These configurations are used to generate the finger paths.

Namely, the sequence of intermediate configurations is suitably filtered by a spatial low-pass filter in order to achieve a smooth path for the fingers on the object surface. To this purpose, notice that only the final configuration needs to be reached exactly, while the intermediate configurations can be considered as via points.

With respect to the smooth paths through the points of the filtered configurations, the actual finger paths generated by the finger trajectory planner keep a floating distance δ_f along the normal to the surface (as explained in Section IV). This feature produces a floating effect of the fingers over the reconstructing object surface during the reconstruction process while they move according to the deformation of the reconstruction sphere. When the final configuration is reached, this safety distance is progressively reduced to zero, producing the desired grasp action.

V. SIMULATIONS

The proposed method has been first tested in simulations on the synthesized object shown in Fig. 4. The first three fingers of the virtual hand of Fig. 5 have been used. Setting $\Phi_{CEI} = 15^\circ$, and $\Phi_{EEGI} = 10^\circ$, the grasp configuration and the finger trajectories are those of Fig. 7. The final grasp configuration (which can be proven to be the global optimal grasp configuration) is characterized by the values $CEI = 8.15^\circ$ and $EEGI = 1.79^\circ$.

A prism with smooth lateral corners has also been considered. The grasp configuration and the corresponding trajectories are shown in Fig. 8. The values $CEI = 9.20^\circ$ and $EEGI = 2.89^\circ$ are obtained in the final configuration. Remarkably, an equilateral symmetry is achieved in the final grasp configuration: two fingers are placed on the smooth

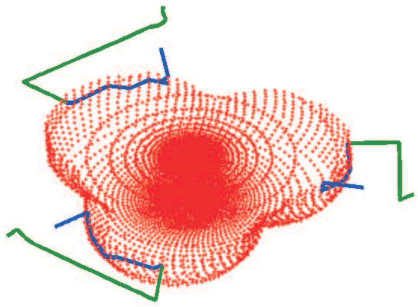

Fig. 7. Finger trajectories evaluated by the local grasp planner (green) and the corresponding sequence of grasp points on the reconstructed object surface (blue).

corners, and the other finger is placed in the middle of the opposite surface. This configuration corresponds to an opposite grasp ensuring force closure; as before, it can be proven that this grasp configuration is optimal also in a global sense, although the proposed approach can only guarantee that a local minimum is achieved.

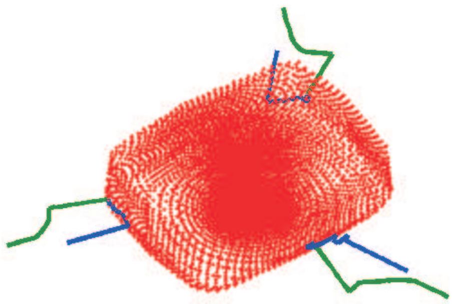

Fig. 8. Finger trajectories evaluated by the local grasp planner (green) and the corresponding sequence of grasp points on the reconstructed surface for the smooth prism (blue).

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

A new method for fast visual grasp of unknown objects has been presented. The proposed method is composed of a fast iterative object surface reconstruction algorithm and of a local optimal grasp planner, which evolve in a synchronized parallel way. An eye-in-hand camera is adopted to acquire the images used by the reconstruction algorithm. A reconstruction sampled sphere, virtually placed around the object, is iteratively compressed towards the visual hull, dragging out the fingers attached on it. During the reconstruction process, the planner moves the fingers, floating on the current reconstructed surface at a safety distance, according to local and global kinematic indices and grasp quality measures. In particular, a discretized version of the Mirtich and Canny quality measure has been developed to guide the hand toward an optimal grasp configuration. The effectiveness of the proposed method has been shown in simulation.

B. Future Work

Future developments of the algorithm will be devoted to the improvement of the object reconstruction algorithm, e.g., for the case of objects with holes. Moreover, quality indices connected to the tasks to be performed by the hand with the object could be considered. A further improvement may be the adoption of suitable pre-shaping techniques, based on visual information, for the choice of the initial grasp configuration. Finally, the extension of the proposed approach to the case of more than three fingers or to bi-manual manipulation, with the adoption of suitable quality measures, is an interesting issue of research.

VII. ACKNOWLEDGMENTS

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