Automatic evaluation of task-focused parallel jaw gripper design

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Abstract. In this paper, we suggest *gripper quality metrics* that indicate the performance of a gripper given an object CAD model and a task description. Those, we argue, can be used in the design and selection of an appropriate gripper when the task is known. We present three different gripper metrics that to some degree build on existing grasp quality metrics and demonstrate these on a selection of parallel jaw grippers. We furthermore demonstrate the performance of the metrics in three different industrial task contexts.

1 Introduction

The successful execution of grasping in a robotics system is essential in industrial applications where grasp failure can result in anything from an expensive reduction in throughput to destruction of parts or invaluable fabrication hardware. With the gripper being the only workpiece that physically interacts with the environment, it is obvious that its design characteristics are of influence to successful grasping.

Moreover, robot systems that rely on sensors for object detection and pose estimation introduce increased uncertainties in the system, that will influence grasp success and thereby add additional demands to the robustness of the gripper design.

The design of a gripper includes the selection of the proper gripper kinematics and dynamics. Several of the relevant parameters are depicted in Fig. 1, where a parallel jaw kinematic structure is used. Designing a gripper from scratch is a time-consuming mechanical task and everything but the gripper jaw design are in practice determined by the selection of an off-the-shelf gripper product from one of many companies.

The gripper jaw design is important, since the jaws are the parts of the gripper that are in contact with graspable objects. Several gripper design guidelines [4,3] and papers on gripper design optimization [16,2] have been written to ease, or to better understand how to design a good gripper for a given object and task. However, gripper jaw design remains a cumbersome experts task, that requires special engineering knowledge and often several iterations between designer and floor operator are required to reach a good design.

Hence, a tool for automatically computing optimal gripper designs will be of a huge value to the industrial world of automation, essentially saving weeks of experts

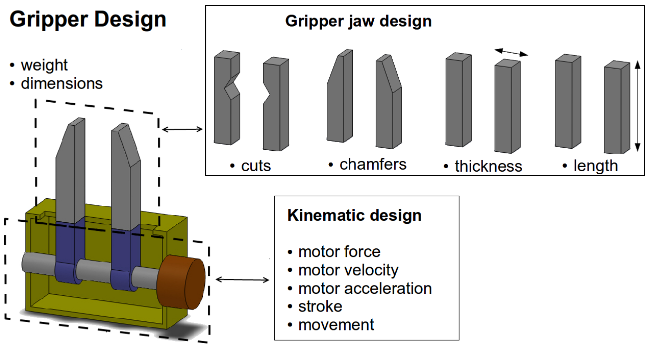


Fig. 1. A limited parameterization of a gripper design. The kinematic design (to the left) is typically determined from off-the-shelf products whereas the gripper jaw design (to the right) is custom designed to allow better grasping of one or multiple specific objects.

work whenever a new part needs to be automatically handled. Such a technology may ideally increase flexibility in automation and change the hesitation that todays small and medium sized enterprises have toward automation.

In this paper, we take a step toward automatic gripper design by introducing three statistical gripper metrics for evaluating gripper performance. These metrics express different properties of a gripper such as how often it succeeds in grasping (success probability), from how many directions a gripper may successfully grasp an object (coverage) and how firmly the gripper holds the object (wrench). These properties have different relevance in different contexts and the relative weighting of these three metrics therefore needs to be chosen context specific. For example, when grasping objects placed unstructured in a box, it is important to be able to grasp from many different direction due to collisions with environment. Or when moving with high accelerations the object should be firmly grasped by the gripper.

Our method evaluates gripper designs by using a combination of existing design guidelines and advances within grasp quality metrics [14,10]. We present gripper metrics that can be automatically computed in a dynamic simulator and used during the selection of a specific gripper design. Most gripper designs from simple parallel jaw grippers to advanced dexterous hands can be evaluated in a dynamic grasp simulator. However, in this work we have focused on parallel jaw grippers since they are widely applied in industrial applications.

In this paper, our contributions are:

– a gripper metric which is based on success probability and dynamic grasp simulation.
– a method for including environmental context into the gripper evaluation.
– a method to include existing grasp quality metrics into the gripper evaluation.

In the next section, Sect. 2 we present related work in the areas of automated gripper design computation, gripper design evaluation and grasp quality metrics. Sect. 3 presents an overview of our method based on gripper quality metrics and our experimental evaluation of it. The gripper quality metrics are then described in more detail in

Sect. 4 and our method is then evaluated and discussed on a selection of gripper designs in Sect. 5. Finally we conclude the paper in Sect. 6.

2 Related work

The difficulty of designing robot grippers has motivated the formulation of several gripper design guidelines [4,3,11]. One of the difficulties implied in these works is that design objectives may conflict, e.g., having a design which is both light and rigid. The design objectives include amongst others: *small gripper footprint, exterior and interior chamfering, small weight, secure grasping, small finger length, avoiding tool changes and aligning grasped objects*.

Furthermore, reviews on the gripper design problem are presented in [2,1]. In [2] a general overview of early gripper designs and control are presented, whereas grippers designed specifically for handling fruits where presented in [1].

In this work, we present a method for evaluation of a specific gripper parameterization which compared to previous approaches is not as fast to compute but instead much more generic, accurate and enables inclusion of context. This is mainly achieved by relying on evaluating grasps using a dynamics based grasp simulator. Such a tool can easily include large parts of the task context in the evaluation of the gripper, which more accurately captures the actual task in which the gripper is to be used. Furthermore, the accuracy over kinematic simulations are also gained due to increased modeling parameters such as friction and motor control.

Early work on the evaluation of gripper mechanism was based on Merit Indexes that described the mechanical effectiveness (Grasp Index G.I.) of a gripper [6] and the Capability Index (C.I.), the latter describing the capability of a gripper in relation to the object dimensions. In [12] these Merit indexes are used in the optimization of the kinematic design of a gripper. The Merit indexes are fast to compute but they are limited to kinematic evaluation and cannot distinguish between changes in the gripper jaw surface.

Changing the surface of gripper jaws can improve how well a gripper aligns objects during grasping. Aligning objects enables more secure grasps but also enables more accurate placement. Gripper jaw design for object alignment was investigated in [16,17,15,7]. In [15] they define a modular gripper surface based on trapezoidal segments for which they present an algorithm that can optimize the gripper design such that a specific alignment of the object is obtained when it is grasped from the top. The work in [7] presents a semi-automatic design of gripper jaws for aligning objects and additionally demonstrates that the jaws can be accurately tested in a dynamic simulation.

Another use of dynamic simulation was presented in [5], where the kinematic design of an under–actuated 2 finger gripper was optimized by first generating a database of grasps using simulation with a fully actuated gripper, which secondly was used to optimize the under–actuated gripper such that it would be able to execute the same grasps as defined in the grasp database. Our use of simulation is a bit similar, however, we define statistical gripper metrics that are computed based on generated grasp databases which then can be used to compare the performance between grippers.

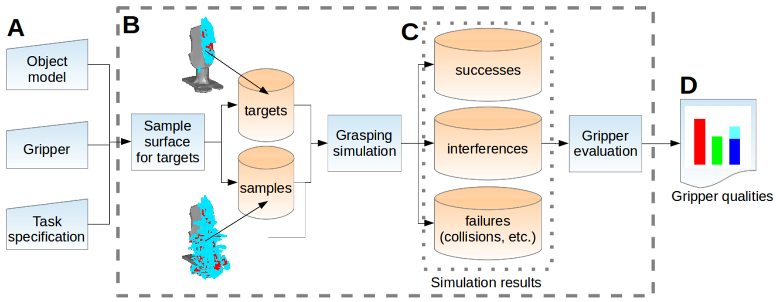


Fig. 2. Computation of gripper quality metrics.

To summarize, our work defines suitable gripper qualities based on evaluating grasp qualities over a set of feasible grasps. Compared to previous work, we pursue a statistical approach relying heavily on dynamic simulation, grasp quality metrics and we include contextual information in the evaluation of the gripper. The inclusion of context was demonstrated to be of importance in [13] when evaluating grasp quality. For computing optimal gripper designs, we believe that context is equally important and therefore our method also relies on a description of the context – namely the task specification.

3 System overview

In this section, we present an overview of our method that is used to compute the quality of a robotic gripper. The method relies on dynamic grasp simulation to evaluate grasps using a specific gripper design.

The method is depicted in Fig. 2, where the inputs to our method (encapsulated in Fig. 2B) are an object model, a gripper design and a task specification.

- The object model consists of a CAD model with associated dynamic properties such as friction, center of mass and inertia.
- The gripper design consists of a collection of CAD models of the gripper, together with the gripper kinematics and dynamics: max gripping force, max gripper velocity, surface friction, inertia and center of mass.
- The task specification defines the actual grasping scenario. This includes the local environment model and an approach direction (see Fig. 3).

The first step in our method (see Fig. 2B) is to compute a database of grasp targets that to a reasonable resolution covers all possible grasps of the object within the task specification. This computation is essentially a sample based grasp planner that, in our case of parallel jaw grippers, base the sampling on nearly parallel surfaces. However, we want to stress that the metrics we propose are generic and can also be applied to other grippers, only the initial sampling strategy would need to be adapted to a novel gripper. The grasp planner used in this work is based on finding near parallel surface

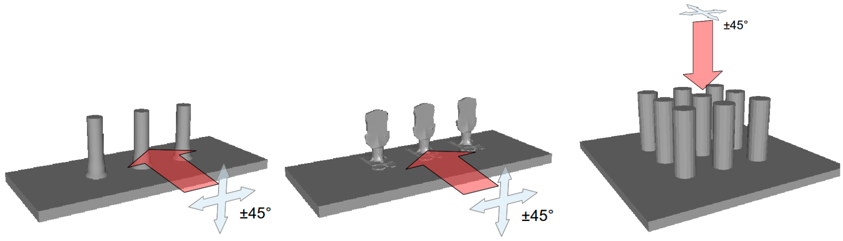


Fig. 3. Scenes used for gripper evaluation. These are in order: a) the belt picking scene with a rotor cap object, b) the belt picking scene with a Dolt object, c) the table picking scene with a cylindrical object. The arrows present the gripper approach direction defined in the task description.

patches, please see [10] for further details. The grasp target sampling generates two databases: *targets* and *samples*. The grasps in the samples-database are the ideal parallel gripper grasps which only need two nearly parallel surfaces to make a grasp. The targets-database is a subset of the samples-database, such that any grasp pose from the samples database are added to the target database only if the gripper can be placed in the grasping pose without being in collision with the object.

The databases are filtered which serves both as downsampling and as rough unbiasing in $SE3$[1].

The next step is to further validate all filtered grasp targets and quantify their grasp quality. The validation is performed in simulation using RobWork [9], where the object is grasped from each grasp target in the filtered database. The simulation includes the static environment described in the task specification. A grasp is deemed successful, if the following conditions are met after the simulated grasp has been executed:

1. the object remains in the gripper with wrench quality exceeding a specified lower limit w_{min},
2. no collisions with fixed obstacles in the scene occurred,
3. the interference (i.e. a measure of negative interaction of gripper with the environment, explained below) at the end of the experiment does not exceed a specified interference limit i_{max}.

The wrench quality represents the robustness of specific grasp, and it is introduced in more detail in Sect. 4.3.

The interference is introduced as a measure of unwanted gripper interaction with movable objects in the scene (e.g. neighbours of the target objects). Interference is calculated as a total sum of differences between the poses of all movable objects from before (P_{start}) and after (P_{end})grasping:

$$I = \sum_{i=0}^{nobjects} |P_{end} - P_{start}| \qquad (1)$$

[1] 3-dimensional Special Euclidean group representing translation and rotation

Successful grasps are added to the *successes* database. If a grasp failed due to interference limit violation (the third condition), then it is added to the *interferences* database. Otherwise, the grasp become part of the *failures* database.

A small fraction of simulations becomes unstable due to limitations of the physical engine. The results of these simulations are discarded. Typically, failures happen in no more than 10% of simulations.

The gripper quality metrics are computed after performing all grasp simulations, based on the numerical results of the simulations and the populations of the databases: *successes*, *interferences* and *failures*. The sizes of the results databases are denoted as $N_{successes}$, $N_{interferences}$ and $N_{failures}$, respectively.

The output (see Fig. 2D) are three continuous values that each describe a gripper quality: *success probability, coverage* and *average wrench space*. *Success probability* is a measure that captures the average probability of successfully grasping the object from the grasping space, constrained by the task specification. The *coverage metric* evaluates how large the success space is compared to using a conceptual idea of an *ideal* gripper. The *ideal* gripper is an infinitely thin (and thus not generating collisions) gripper that is able to grasp successfully at every nearly parallel surface patch pairs on the object surface. The ideal gripper therefore acts as a hypothesis for defining the possible grasping space which can then be compared to the actual success grasp space to define coverage.

A large coverage is especially interesting for tasks where possible collisions with the surroundings may reduce the number of executable grasps, e.g., in bin picking – in which objects are placed in an extremely unstructured environment, randomly oriented and blocking and obstructing each other, thus requiring a large versatility in possible approaches. Finally, the wrench space metric captures the average force closure of the successful grasp space. For each of the grippers, we are interested in obtaining a selection of few good grasps (in terms of robustness) from multitude of those that were generated. Thus, additionally the average wrench quality is computed for the top 20% best grasps (best in terms of wrench space measurement).

4 Gripper quality metrics

In this section, we describe how the three gripper quality metrics are defined and how we calculate these based on the output of the grasp target sampling and the dynamic simulation. It should be noted that these three measures evaluate different characteristics of the gripper performance which we later will demonstrate in Sect. 5.1. As said already above, the relative importance of these characteristics is context– and task–dependent.

4.1 Success ratio

This metric should capture the overall success ratio of grasps in the *targets* database for the specified task context. The actual success ratio naturally depends on which grasps are selected for execution in the real world scenario. However, as an approximation, the overall success rate of all the simulated grasps is sufficient.

The success rate S is evaluated directly in a dynamic grasp simulation, where the static environment and the interference objects are included. The success ratio is then calculated as $S = \frac{N_{successes}}{N_{filteredtargets}}$, where $N_{successes}$ is the number of successfully executed grasps from the filtered targets database and $N_{filteredtargets}$ is the number of grasps in the filtered grasp database.

4.2 Coverage index

The coverage metric should measure from how many different directions an object can be grasped. The need for this metric originates from identifying the possibility that a few very high quality grasps might not be sufficient to compute grasps in highly cluttered scenes, simply because objects in the environment may collide with the gripper and thereby strongly limit the successful grasp space. In general, a gripper with a high coverage is very maneuverable within the task constraints which may enable a higher real success rate and faster execution.

The coverage evaluation is based on comparing the grasp success space of the actual gripper with the grasp success space of an abstract, infinitely thin and unbreakable gripper. Such an *ideal* gripper only requires two nearly parallel surfaces on opposite sides of the object to perform a successful grasp.

The coverage is computed as the ratio between the number of possible grasps of the specific gripper and the number of possible grasps of the *ideal* gripper. Since we assume linear correlation between number of grasps and grasp volume due to the un-biasing of the filtering approach, we may infer that the coverage ratio defines the size of the grasp success space relative to the ideally possible success space. The complete success space is only dependent on the object and not the gripper, thereby enabling comparison across grippers.

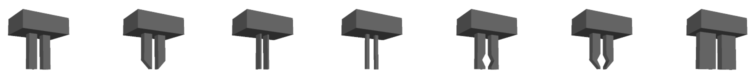
Thus, coverage is calculated as $C = \frac{N_{gripper}}{N_{ideal}} = \frac{N_{successes}+N_{interferences}}{N_{filteredsamples}}$. Notice that $N_{filteredsamples}$ represents the un-biased (filtered) grasp space of the ideal gripper. The $N_{gripper}$ define all successful grasp targets when not considering failures due to inference.

4.3 Wrench index

The wrench index should capture the overall quality of all successfully executed grasps. Where the quality reflects the size of the minimum wrench that can make a specific grasp fail.

We use the Grasp Wrench Space (GWS) measure which was originally introduced in [8]. The GWS measure calculate the minimum wrench w_i that is able to disturb a grasp. Hence, larger w_i makes a better grasp. Please see [10] for more details on the implementation.

The wrench index is, in the context of the gripper quality, given as the average wrench of all successful grasps performed by the gripper. It is common for a gripper to have a small number of exceptionally high quality grasps at specific parts of the object, while the remaining grasps have much lower quality. Hence, an average quality over all sucessful grasps might not be sufficient to distinguish between grippers. To better



	a)	b)	c)	d)	e)	f)	g)
	standard	chamfered	flat	square	std. w/ cut.	chf. w/ cut.	clumsy
dimensions	100x20x25	100x20x25	100x25x5	100x10x10	100x20x25	100x20x25	100x20x50
chamfering	–	25x45°	–	–	–	25x45°	–
cutout	–	–	–	–	10x120°	10x120°	–
force	50 N	50 N	50 N	50 N	50 N	50 N	50 N

Fig. 4. Selected gripper designs used for evaluation. These are in order: a) standard gripper, b) chamfered gripper, c) flat gripper, d) square gripper, e) standard gripper with cutout, f) chamfered gripper with cutout, g) clumsy gripper. Dimensions are presented in millimeters.

evaluate a selection of few good grasps generated for the gripper, the average wrench of the top 20% (by wrench measure) of successful grasps is also calculated and provided as an additional result.

The obtained wrench metric values are denoted as W for the average wrench of the successful grasps, and W_{20} for the average wrench of top 20% grasps. The wrench metrics is calculated as the sum of the wrench of all successfully executed grasps divided by the number of successful grasps.

5 Experiments

In this section, we present our experimental results that demonstrate our quality metric on 8 different grippers in 3 different scene contexts. All experiments have been computed in the dynamic simulator RobWork [9].

We first introduce the experimental setup in Sect. 5.1, namely the grippers, the scenes used and their properties. Then we present the computed gripper qualities for each gripper-scene pair in Sect. 5.2 and finally, in Sect. 5.3, we demonstrate how repetitive computations of the metrics behave.

5.1 Experimental setup

The experimental setup consists of three scenes with a predefined direction of grasp approach (see Fig. 3), and a set of parallel jaw grippers with several hand-designed jaw shapes (see Fig. 4).

For each of the $\{$scene, gripper$\}$ combinations, 10 experiments were performed, each with $N = 10000$ grasp targets to sample. The number of actually simulated grasp targets is reduced to around 1000 due to the grasp filtering in the sampling process.

Scenes The scenes used in the experimental setup are presented in Fig. 3. Three different objects were chosen for the picking task, two objects from industrial applications, i.e. the rotor cap and the DoIt object (top and middle row in Fig. 3). The cylindrical object (bottom row in Fig. 3) was picked to include a simple primitive shape. All of the objects are defined to weigh 1 kg, and the surfaces were assigned the friction properties of plastic.

In both the rotor cap and the Dolt object picking scenarios, three objects are placed in a line on a flat belt surface, 75 mm from one another. The target is the object in the middle, and grasps are performed from one of the sides of the belt, with 45 degrees allowed deviation from that direction.

In the table picking scene, nine cylinders are placed on a 3x3 square grid with 75 mm cell size. The target is the cylinder in the middle, and grasps are performed from the top, with 45 degrees allowed deviation from vertical (see Fig. 3). For all the scenes, the gravitational acceleration was defined to $9.81 m/s^2$.

Grippers Seven different grippers are used in the experimental evaluation, see Fig. 4. The grippers have been selected such that they include commonly encountered features eg. chamfering and presence of cutout.

Each of the grippers has a parallel-jaw kinematic structure with both fingers coupled to a single Degree of Freedom (DoF). Hence, fingers cannot move independently. For all the grippers, the maximum opening distance between the jaws was set to 10 cm. The grippers are presumed to use the same gripper actuation mechanism, thus for all the designs the maximum closing force was defined to be 50 N. The fingers were defined to be made of plastic for the purposes of friction in the simulation.

5.2 Gripper evaluations

The gripper evaluations were performed for all scenes and grippers introduced in Sect. 5.1. The results of the experiments for each of the $\{$scene, gripper$\}$ combinations were averaged and are presented in Fig. 5 for Rotor cap scene, Dolt object scene, and cylindrical object scene.

Bars in the upper part of the figure present the different gripper metrics: success ratio S, coverage C, average wrench W and top wrench W_{20}. All quality visualizations (the bars) have been scaled relative to the best quality in the same particular experiment e.g. all experiments on a single scene but with varying grippers. Top wrench W_{20} is presented as a light-blue bar overlaying the average wrench W bar in deep blue. Numerical data is presented in the tables in the bottom part of each figure.

As expected the best gripper design vary strongly depending on both the scene and the task context.

For the **rotor cap** picking scene (see Fig. 5A), the *flat* gripper (Fig. 5A-c), performs best in success ratio and coverage. It is surpassed however by a *chamfered cut* (Fig. 5A-f) gripper in terms of average and top wrench index, which is expected due to the cut. The *flat* gripper provides the smallest footprint which makes it possible to easily avoid collisions and interference, and yet the contact surface is still big enough to retain the object robustly.

In the **Dolt** object picking scene (see Fig. 5B), the best results were achieved with the *square* gripper (Fig. 5B-d), which offers the highest coverage and success ratios. The small gripper frame provides high maneuverability and allows to exploit the existence

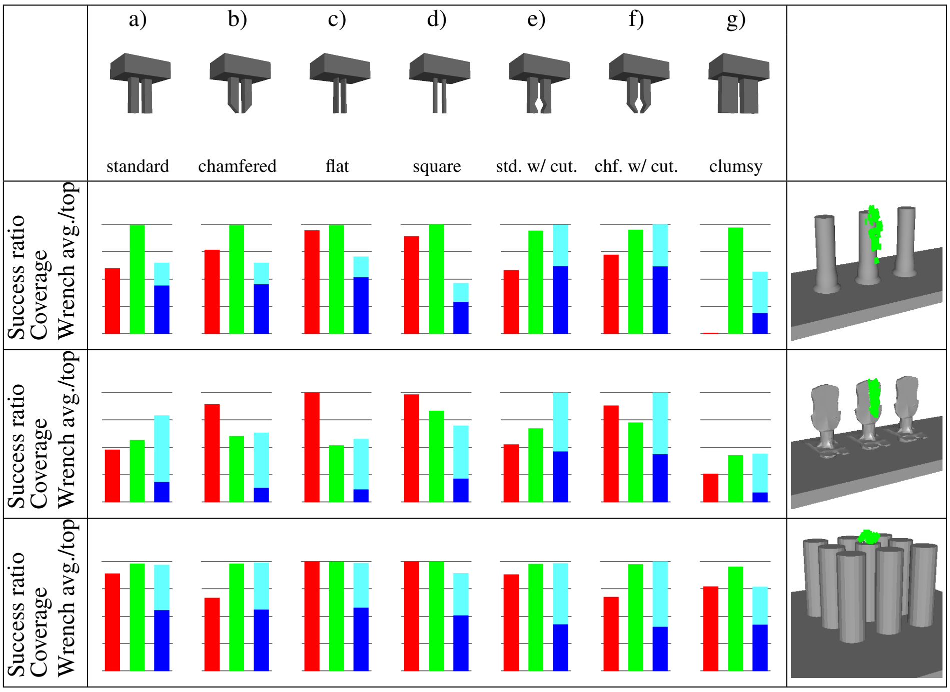


Fig. 5. The results of evaluation for gripper designs a-g for the scenes A-C.

of the DoIt object features, i.e. cuts on the side, for better grasping. The second best gripper design was the *chamfered cut* gripper (Fig. 5B-f), with slightly lower success and coverage, but providing much higher top wrench, due to presence of cutout which improves secure grasps on the object.

The **cylinder** picking scene (see Fig. 5C) provides an unique challenge by putting the target object in a confined space between neighboring objects. Grasping from the top only exposes a small percent of the surface of the object. This also voids the benefit of having a prismatic cutout in the gripper, as for the vertical direction of approach, the cutouts are not aligned with the cylindrical object. The contact area for grippers with cutouts is thus effectively smaller, which becomes apparent in the average wrench score for those grippers. The best gripper designs for the cylinder scene were the *flat* (Fig. 5C-c) and *square* (Fig. 5C-d) designs, both with a small foot-print, and for this specific task they both provide a virtually identical contact surface area.

In general it can be noted that the presence of chamfers is reflected effectively in the success level for the gripper. Moreover, as expected, the coverage score of the gripper is greatly influenced by the gripper footprint and the overall gripper dimensions. Wrench index reflects both the contact surface area, and the force closure ability of the gripper's shape.

5.3 Metric separability

It is crucial that the quality metrics are independent and that they are not influenced by the sampling and filtering approaches. We performed five repetitive evaluations of the quality measures and found that the metrics are clustered in the 3 dimensional quality space with largest variations in coverage. It was also apparent that the clusters where individually separable.

We observed the same behavior of the repetitive quality evaluations on the dolt and cylinder scenes.

6 Conclusion

In this paper, we have presented three statistical metrics covering different aspects important for the evaluation of a gripper. This metric heavily relies on dynamic grasp simulation for computing grasp quality and for dynamically evaluating grasp performance in terms of interference and grasp success.

We demonstrated the use of these metrics, by applying eight different parallel jaw gripper designs to three different scenes. The results were discussed in Sect. 5.2 and the metrics tend to agree with expert design choices eg. gripper designs with cuts will provide more stable grasps and chamfering increase success ratio due to lower interference with surrounding obstacles.

We also demonstrated that the three metrics are independent and we performed repetitive calculations to show that the random and biased sampling does not significantly influence the outcome of the quality measures.

In future work, we will investigate how to use our gripper quality metrics to automatically compute the best possible gripper design for a given task – utilizing, for example, a gradient descent method in the gripper quality space obtained by combining proposed metrics into an objective function. We will also apply our method to a larger variety of kinematic designs and finally we will extend on the concept of the task specification.

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