Dex-Net 3.0: Computing Robust Robot Suction Grasp Targets using a New Analytic Model and Deep Learning

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Keywork	
URL	https://arxiv.org/pdf/1709.06670.pdf
備註	
論文性質	Dex-net

he notion ofwrench resistance, a basic property which helps to ensure grasp security.

參考資料

I. INTRODUCTION

These heuristics work well for prismatic objects such as boxes and cylinders but may fail on objects with non-planar surfaces near the object centroid, which is common for industrial parts and household objects such as staplers or children's toys

過去啟發性的工作可吸菱柱或圓柱體，但如果是不接近重心的平面，例如工業零件或家具，會失敗。

In practice a robot may need to form seals on non-planar surfaces while being robust to **external wrenches** (e.g. gravity and disturbances), sensor noise, control imprecision, and calibration errors, which are significant factors when planning grasps from point clouds

external wrenches：外部干擾

sensor、control imprecision、校正誤差，都是影響點雲規劃的重要因素。

兩個重要元素

(1) a test for whether a seal can be formed between a suction cup and a target object surface and (2) an analysis of the ability of the suction contact to resist external wrenches.

1. 在吸嘴與目標中間達到一個密封空間
2. 分析任意吸取點對於外部干擾的抵抗能力

We use the model to evaluate grasp robustness by analyzing seal formation and wrench resistance under perturbations in **object pose, suction tip pose, material properties,** and disturbing wrenches using Monte-Carlo sampling similar to that in the Dexterity Network (Dex-Net)

1) A compliant suction contact model that quantifies seal formation using a **quasi-static spring system** and the ability to resist external wrenches (e.g. gravity) using a contact wrench basis derived from the ring of contact between the cup and object surface.

準靜態彈簧星，及能力去抵抗外部擾力，使用一個基本的接觸擾力，來自於吸嘴與物品的接觸環。

2) Robust wrench resistance: a robust version of the above model under random disturbing wrenches and perturbations in object pose, gripper pose, and friction.

看不懂

3) Dex-Net 3.0, a dataset of 2.8 million synthetic point clouds annotated with suction grasps and grasp ro-bustness labels generated by analyzing robust

wrench resistance for approximately 375k grasps across 1,500 object models.

總共280萬個合成點雲，混雜抓取點

1500個物件共有375個抓取點，產生穩健的label

4) Physical robot experiments measuring the precision of robust wrench resistance both with and without knowledge of the target object’s shape and pose.

物理機器人在對物體沒有形狀與姿態的知識下，實驗性量測對擾力的穩健度

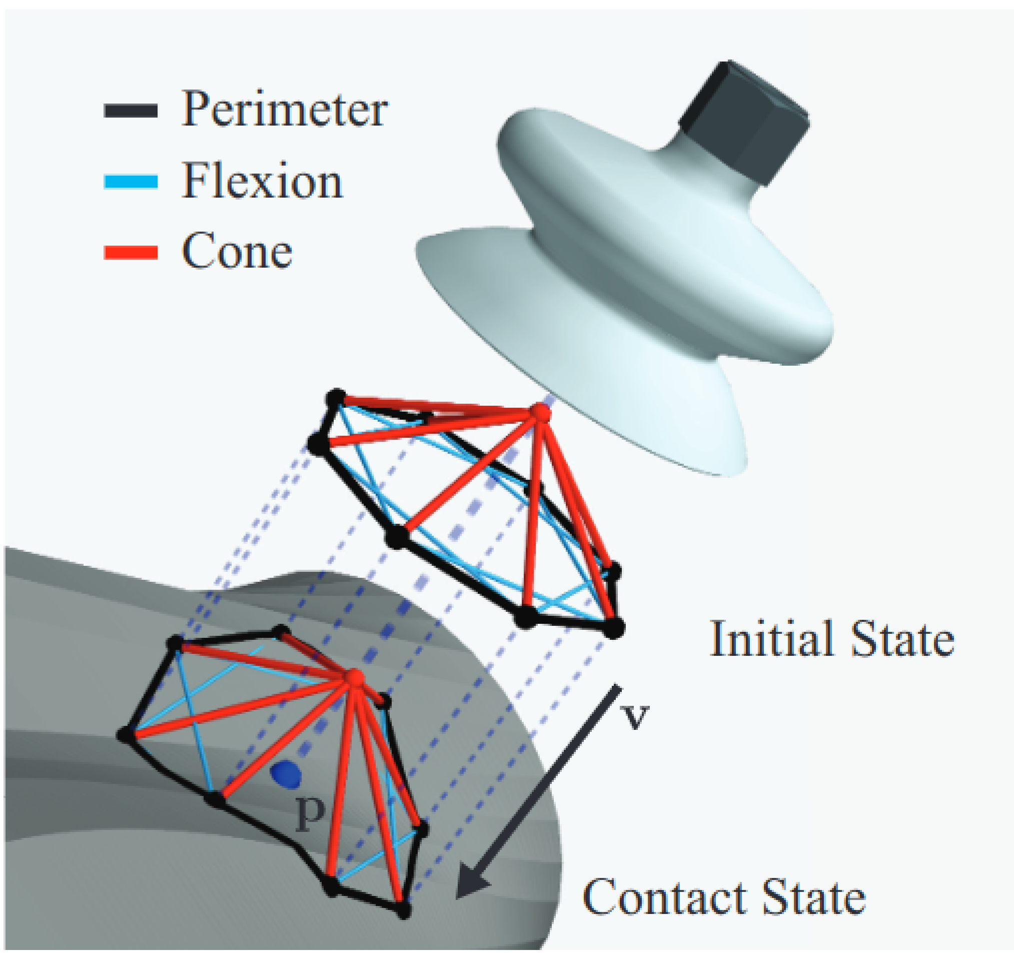


Fig. 1: The quasi-static spring model,C, used for determining when seal formation is feasible. The model contains three types of springs – perimeter, flexion, and cone springs. An initial state for C is chosen given a target point p and an

approach direction v. Then, at contact state for C is computed so that C’s perimeter springs form a complete seal against object mesh M. Seal formation is deemed feasible if the energy required to maintain this contact state is sufficiently low in every spring.

model確定密封的可行性。

model C 遺共有三個元件，圓周長、靈活圈跟錐形彈簧(spring)。初始化的C的決定來自於target p跟距離v。接著在contact state觀察是否對網格M密封。 密封決定是否藉由少量的能源便維持吸力。

We perform physical experiments using an ABB YuMi robot with a silicone suction cup tip to compare the precision of a GQ-CNN-based grasping policy trained on Dex-Net 3.0 with several heuristics such as targeting planar surfaces near object centroids. We find that the method achieves success rates of 98%, 82%, and 58%on datasets of Basic (prismatic or cylindrical), Typical (more complex geometry), and Adversarial (with few available suction-grasp points), respectively.

在ABB YiMi上與矽樹脂吸嘴上測試，多個質心附近的表面。三種規格成功率：98%、82%、58%

II. RELATEDWORK

End-effectors based on suction are widely used in industrial applications such as warehouse order fulfillment, handling limp materials such as fabric [17], and robotics applications suchas the Amazon Picking Challenge [4], underwater manipulation [29], or wall climbing [2]. Our method builds on models of deformable materials, analyses of the wrenches that suction cups can exert, and data-driven grasp planning.

具有皺摺的織布也是可行範圍。可變形材質

A. Suction Models

Several models for the deformation of stiff rubber-like materials exist in the literature. Provot et al. [26] modeled sheets of stiff cloth and rubber using a spring-mass system with several types of springs. Hosseini et al. [1] provided a survey of more modern constitutive models of rubber that are often used in Finite

Element Analysis (FEA) packages for more realisticphysics simulations. In order to rapidly evaluate whether a suction cup can form a seal against an object's surface, **we model the cup as a quasi-static spring system with a topology similar to the one in [26] and estimate the deformation energy required to maintain a seal.**

Provot et al的研究mass-spring system 有著著不同類型。 一項調查對於構成橡膠模型的Finite Element Analysis分析，對於更多物理性質的模擬。

我們模擬一個拓普的靜態彈簧系統，類似於[26]，以及評估保留一個密封的變形需要多少能量

In addition, several models have been developed to check for static equilibrium assuming a seal between the suction cup and the object's surface. Most models consider the suction cup to be a rigid object and model forces into the object along the surface normal, tangential forces due to surface friction, and pulling forces due to suction [17], [29], [31].

多種方法被開發用來確保假設在吸嘴與物體表面中，維持靜態平衡。

多個模型考慮在硬物體上，沿著法向量，由於表現摩擦而產生的切向力，與表面產生的拉力

Bahr et al. [2] augmented this model with the ability to resist moments about the center of suction to determine the amount of vacuum pressure necessary to keep a climbing robot attached to a vertical wall. Mantriota [23] modeled torsional friction due to a contact area between the cup and object similar to the soft finger contact model used in grasping[14]. **Our model extends these methods by combining models of torsional friction [23] and contact moments [2] in a compliant model of the ring of contact between the cup and object.**

[2]討論要多少的真空力才能成功使得爬行機器人能黏在垂直的牆壁。

我們的模型從來自爬行機器人的扭轉摩擦力去拓展，在吸嘴與物品間藉由適應模型產生接觸力矩

B. Grasp Planning

The goal of grasp planning is to select a configuration for an end-effector that enables a robot to perform a task via contact with an object while resisting external perturbations [3], which can be arbitrary [7] or task-specific [18]. A common approach is to select a configuration that maximizes a quality metric (or reward) based on wrench space analysis [24], robustness to perturbations [32], or a model learned from human labels [15] or self-supervision [25].

最通用的方法是選一組在WSA分析上值最好的配置，對於噪聲的魯棒性，由人類或半監督去學習

Several similar metrics exist for evaluating suction grasps. One common approach is to evaluate whether or not a set of suction cups can lift an object by applying an upwards force [17], [29], [30], [31]. Domae et al. [5] developed a geometric model to evaluate suction success by convolving target locations in images with a desired suction contact template to assess planarity.

數種相似方法評估吸取，一個普遍性方法是評估向上拉取力。

Domae et al. 開發一種幾何模型，藉由卷積來評估接觸平面是否成功

Heuristics for planning suction grasps from point clouds have also been used extensively in the Amazon Robotics Challenge. In 2015, Team RBO [6] won by pushing objects from the top or side until suction was achieved, and Team MIT [35] came in second place by suctioning on the centroid of objects with flat surfaces. In 2016, Team Delft [10] won the challenge by approaching the estimated object centroid along the inward surface normal.

使用點雲做啟發式規劃吸取，已經在比賽中獲得廣泛應用

In 2017, Cartman [?] won the challenge and ranked suction grasps according to heuristics such as maximizing distance to the segmented object boundary and MIT [?] performed well using a neural network trained to predict grasp affordance maps from human labeled RGB-D point clouds.

In this work, we present a novel metric that evaluates whether a single suction cup can resist external wrenches under perturbations in object / gripper poses, friction coefficient, and disturbing wrenches. This paper also extends empirical, data-driven approaches to grasp planning based on images and point clouds [3]. A popular approach is to use human labels of graspable regions in RGB-D images [19] or point clouds [15] to learn a grasp detector with computer vision techniques.

我們發展出一個新穎的指標，來評估吸嘴是可抵抗額外的擾力，在受擾動的物件姿態下，摩擦係數以及額外擾力。我們對於照片與點雲用數據驅動的方法去規劃，一個最受歡迎的方法是人工標示可抓取區域。

As labeling may be tedious for humans, an alternative is to automatically collect training data from a physical robot [20], [25]. To reduce the time-cost of data collection, recent research has proposed to generate labels in simulation using physical models of contact [12], [15]. Mahler et al. [21] demonstrated that a GQ-CNN trained on Dex-Net 2.0, a dataset of 6.7 million point clouds, grasps, and quality labels computed with robust quasi-static analysis, could be used to successfully plan parallel-jaw grasps across a wide variety of objects with 99%precision. In this paper, we use a similar approach to generate a dataset of point clouds, grasps, and robustness labels for a suction-based end-effector.

GQCNN在DexNet2.0訓練，有670萬的點雲、抓取以及質量label，計算靜態分析的穩健度。可以在夾取上達到99%的精準度，在這論文上我們使用同樣的方法。

III. PROBLEMSTATEMENT

Given a point cloud from a depth camera, our goal is to find a robust suction grasp (target point and approach direction) for a robot to lift an object in isolation on a planar worksurface and transport it to a receptacle. We compute the suction grasp that maximizes the probability that the robot can hold the object under gravity and perturbations sampled from a distribution over sensor noise, control imprecision, and random disturbing wrenches.

計算吸嘴最大化的機率，對於來自sensor的噪聲擾動下的採樣，以及抵抗重力的影響，以及控制精準度與隨機干擾的擾力。

A. Assumptions

Our stochastic model makes the following assumptions:

1. Quasi-static physics (e.g. inertial terms are negligible) with Coulomb friction.
2. Objects are rigid and made of non-porous material.
3. Each object is singulated on a planar worksurface in a stable resting pose [8].

4. A single overhead depth sensor with known intrinsics, position, and orientation relative to the robot.
5. A vacuum-based end-effector with known geometry and a single disc-shaped suction cup made of linear-elastic material.

已知的真空末端執行氣與單獨的盤狀吸盤，吸盤由彈性力學材質所組成

B. Definitions

A robot observes a single-viewpoint cloudor depth image,y, containing a singulated object. The goal is to find the most robust suction grasp u that enables the robot to lift an object and transport it to a receptacle, where grasps are parametrized by a target point p∈R3 and an approach direction v ∈ S 2 .Success is measured with a binary grasp reward function R, where R= 1 if the grasp u successfully transports the object, and R = 0 otherwise.

點雲 p ∈ R

向量 v ∈ S

function R = 1 成功， 0 失敗

The robot may not be able to predict the success of suction grasps exactly from point clouds for several reasons. First, the success metric depends on a state x describing the object's geometric, inertial, and material properties O and the pose of the object relative to the camera,T, but the robot does not know the true state due to: (a) noise in the depth image and (b) occlusions due to the single viewpoint. Second, the robot may not have perfect knowledge of external wrenches (forces and torques) on the object due to gravity or external disturbances.

如果沒法很好抓取，有幾個原因

1. 成功的指標仰賴state，state來自於物體的幾何型態、慣性、材質屬性(O)，以及相機相對於物體的姿勢(T)，不知道真實state的可能原因來自受噪聲的干擾或遮蔽
2. 機器的先備知識不足，對於在物體擾力(力或扭力)不夠了解，可能因為重力或外部干擾。

This probabilistic relationship is described by an environment consisting of a grasp success distribution modeling P(R | x;u), the ability of a grasp to resist random disturbing wrenches, and an observation model p(yjx). This model induces a probability of success for each grasp conditioned on the robot's observation:

機率關係來自於對環境的描述，組成對於成功率的分佈模型P

對於抓取的能力去承受干擾的擾力，以及一個觀察模型p，

Definition 1:Therobustnessof a graspugiven a point cloudyis the probability of grasp success under uncertainty insensing, control, and disturbing wrenches:Q(y;u) = P(Rjy;u).

Our environment model is described in Section V and further details are given in the supplemental file.

y為觀測的深度圖，u為抓取動作。 Q、R值判定分數

更多環境描述參考第五節

C. Objective

Our ultimate goal is to find a grasp that maximizes robustness given apoint cloud, π(y) =argmax u2C Q(y;u), where C specifies constraints on the set of available grasps, such as collisions or kinematic feasibility. We approximate π by optimizing the weights of a deep Grasp Quality Convolutional Neural Network (GQ-CNN) Q(y;u)on a training dataset D=f(y;u;R) consisting of reward values, point clouds, and suction grasps sampled from our stochastic model of grasp success. Our optimization objective is to find weightsthat minimize the cross-entropy lossL overD:

我們目標是找到一個最大穩健度抓取(函點雲)。π 輸入點雲，得到最好的u。

C指在碰撞與運動學的約束可行下，可活動的抓取動作。

我們近似了π，優化GQCNN的權重。D包含圖像、抓取跟獎勵。

最小化cross-entropy loss

$$\theta^* = \underset{\theta \in \Theta}{\operatorname{argmin}} \sum_{i=1}^{N} \mathcal{L}(R_i, Q_\theta(\mathbf{y}_i, \mathbf{u}_i)). \qquad \text{(III.1)}$$

IV. COMPLIANT SUCTION CONTACT MODEL

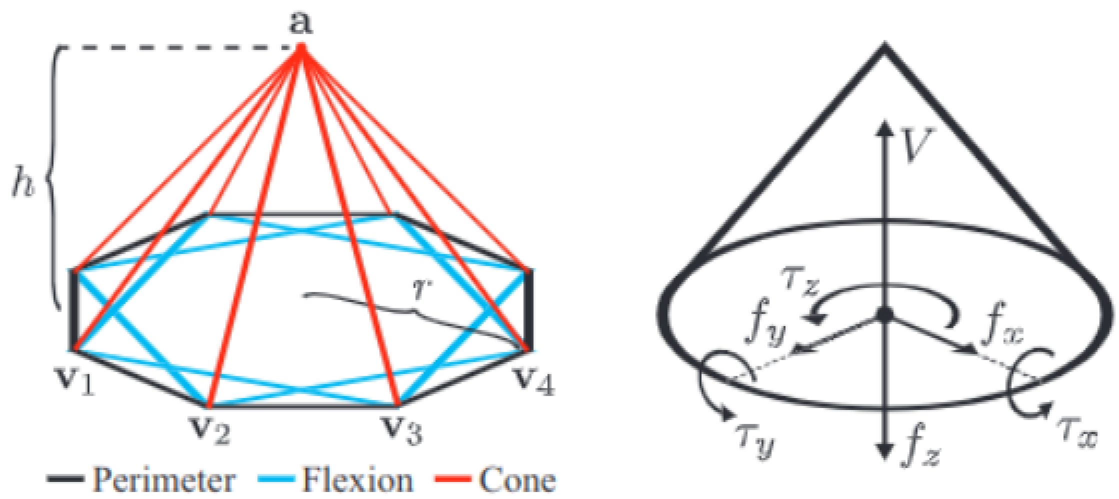


Fig. 2: Our compliant suction contact model.(Left)The quasi-static spring model used in seal formation computations. This suction cup is approximated by n= 8 components. Here,r is equal to the radius of the cup and his equal to the height of the cup. {v1 ... vn} are the base vertices and a is the apex.

結構為8個角度，r為半徑等同於高h。v跟a為頂點

(Right)Wrench basis for the suction ring contact model. The contact exerts a constant pulling force on the object of magnitude V and additionally can push or pull the object along the contact z axis with force fz. **The suction cup material exerts a normal force fN=fz+V on the object through a linear pressure distribution on the ring**. This pressure distribution induces a friction limit surface bounding the set of possible frictional forces in the tangent plane ft= (fx;fy) and the torsional moment γz, and also induces torques γx and γy about the contact x and y axes due to **elastic restoring forces in the suction cup material.**

V產生了在z軸產生一個恆等力V

f(N)=f(z)+V，經過一個環狀線性壓力分佈，V的力是分佈在環平面上

該分佈力在切面平面上，引起一個表面模差限制， f(t) = (fx, fy)

因為吸嘴材質的彈性恢復力，在x跟y軸產生扭力x跟扭力y

扭轉力τ跟正向力f

To quantify grasp robustness, we develop a quasi-static spring model of the suction cup material and a model of contact wrenches that the suction cup can apply to the object through a ring of contact on the suction cup perimeter. Under our model, the reward R= 1 if:

1. A seal is formed between the perimeter of the suction cup and the object surface.
2. Given a seal, the suction cup is able to resist an external wrench on the object due to gravity and disturbances.

靜態環境吸嘴模型跟接觸扭力模型

1.在吸嘴與物體表面產生一個環狀密封

2.藉由密封，吸嘴可以承受來自重量與干擾的擾力

A. Seal Formation

A suction cup can lift objects due to an air pressure differential induced across the membrane of the cup by a vacuum generator that forces the object into the cup. If a gap exists between the perimeter of the cup and the object, then air flowing into the gap may reduce the differential and cause the grasp to fail. Therefore, a tight seal between the cup and the target object is important for achieving a successful grasp.

吸嘴藉由真空產生壓差，讓物體維持力量在吸嘴上

To determine when seal formation is possible, we model circular suction cups as a conical spring system C parame-terized by real numbers(n;r;h), where n is the numer of vertices along the contact ring,r is the radius of the cup, and his the height of the cup. See see Fig. 10 for an illustration.

為了確保密封是可行的，我們建立一個圓形吸嘴環類似一個錐形環狀系統，C的參數有 n r h，n是接觸面環上的頂點，r是吸嘴的半徑，h是吸嘴的高。

Rather than performing a computationally expensive dynamic simulation with a spring-mass model to determine when seal formation is feasible, we make simplifying assumptions to evaluate seal formation geometrically. Specifically, we compute a configuration of C that achieves a seal by projecting C onto the surface of the target object's triangular mesh M and evaluate the feasibility of that configuration under quasi-static conditions as a proxy for the dynamic feasibility of seal formation.

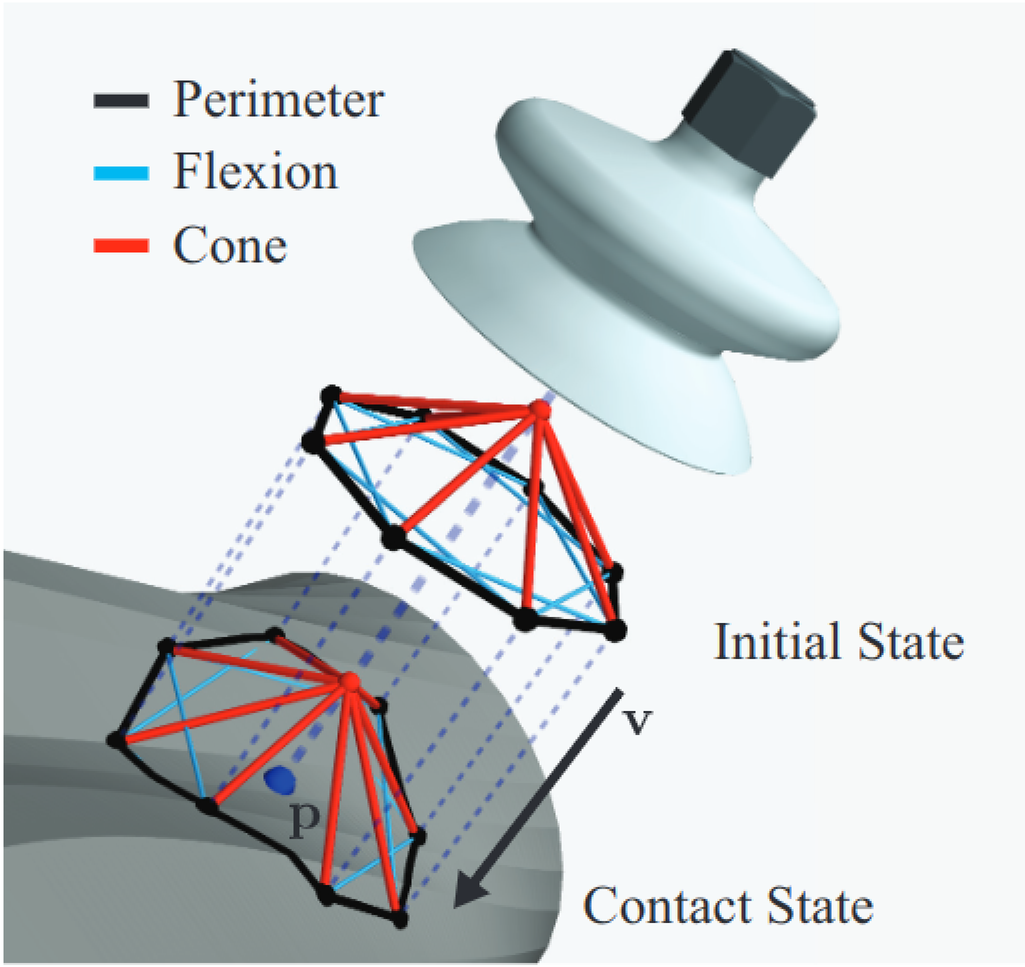
計算configuration C，讓C映射在物體表面的三角網格，並評估在C下靜態條件的動態可行性

In our model,C has two types of springs –structural springs that represent the physical structure of the suction cup and flexion springs that do not correspond to physical structures but instead are used to resist bending along the cup's surface. Dynamic spring-mass systems with similar structures have been used in prior work to model stiff sheets of rubber [26]. The undeformed structural springs of C form a right pyramid with height h and with a base that is a regular n-gon with circumradius r. Let V= {v1;v2;...;v;a} be the set of vertices of the undeformed right pyramid, where each v is a base vertex and a is the pyramid's apex. We define the model's set of springs as follows:

model C有兩種類型的彈簧，結構性彈簧代表著吸嘴的物理結構。彎曲性彈簧不能對印物理結構，但能替代抵抗彎曲性的吸嘴表面。

C不變形的環狀結構，形成一個金字塔狀，h為高以及基本的角n與半徑r。

V為錐形的所有頂點的集合，a為頂點



- **Perimeter (Structural) Springs** – Springs linking vertex $\mathbf{v}_i$ to vertex $\mathbf{v}_{i+1}$, $\forall i \in \{1, \ldots, n\}$.
- **Cone (Structural) Springs** – Springs linking vertex $\mathbf{v}_i$ to vertex $\mathbf{a}$, $\forall i \in \{1, \ldots, n\}$.
- **Flexion Springs** – Springs linking vertex $\mathbf{v}_i$ to vertex $\mathbf{v}_{i+2}$, $\forall i \in \{1, \ldots, n\}$.

In the model, a complete seal is formed between C and M if and only if each of the perimeter springs of C lies entirely on the surface of M. Given a target mesh M with a target grasp u= (p;v)for the gripper, we choose an initial configuration of C such that C is undeformed and the approach line(p;v) passes through a and is orthogonal to the base of C. Then, we make the following assumptions to determine a final static contact configuration of C that forms a complete seal against M(see Fig. 1):

一個完全的密封由C跟M產生，需要C的周長都靠在M表面上。給一個目標網格M加上吸取u，給吸取者，我們選擇一個初始的尚未變形的組態C，線條line(p,v)需要通過a以及與C的底正交。我們假設最終確定靜態接觸組態的C，可完全密封對抗M

- The perimeter springs of C must not deviate from the original undeformed regular n-gon when projected onto a plane orthogonal to v. This means that their locations can be computed by projecting them along v from their original locations onto the surface of M.
- The apex,a, of C must lie on the approach line(p;v) and, given the locations of C's base vertices, must also lie at a location that keeps the average distance along v between a and the perimeter vertices equal to h.

1.C的週邊彈簧不可能可導，來自於原不變形的正規多邊型，當映射到與v正交的平面上，這個位置上的平均可以被映射在沿著的v計算，來自它原本的位置在表面M上。

2.頂點a，必須靠在line上(p,v) 必須維持在C的基本角，以及與v維持平均距離，並且週邊頂點需要等於h。

See the supplemental file for additional details. Given this configuration, a seal is feasible if:

- The cone faces of C do not collide with M during approach or in the contact configuration.
- The surface of M has no holes within the contact ring traced out by C's perimeter springs.
- The energy required in each spring to maintain the contact configuration of C is below a real-valued threshold E modeling the maximum deformation of the suction cup material against the object surface.

被要求的能量在各彈簧，用來維持C的接觸組態，在真實的閥值E模型下，最大化變形的吸嘴承受物體表面

We threshold the energy in individual springs rather than the total energy for C because air gaps are usually caused by local geometry.

我們將單個彈簧的能量而不是總能量作為閾值，因為氣隙通常是由局部幾何形狀引起的。

Details of quasi-static spring seal formation model

B. Wrench Space Analysis

To determine the degree to which the suction cup can resist external wrenches such as gravity, we analyze the set of wrenches that the suction cup can apply.

1.**Wrench Resistance**:The object wrench set for a grasp using a contact model with m basis wrenches is A = {w ∈ R | w=Ga for some a ∈ F}, where G ∈ R is a set of basis wrenches in the object coordinate frame, and F R m is a set of constraints on contact wrench magnitudes [24].

物體的wrench set是給一個抓取，使用一個有m個基礎擾力的接觸模型 → A

2.**Definition** 2:A grasp u achieves wrench resistance with respect to w if -w ∈ A [18], [24]. We encode wrench resistance as a binary variable W such that W= 0 if u resists w and W = 0 otherwise.

w屬於R, w=Ga a屬於F

G是基本的wrenches 在座標系上

參考：https://www.robotic.de/fileadmin/robotic/borst/Borst-ICRA2004-TaskWrenchSpace.pdf

3.**Suction Contact Model** : Many suction contact mod-els acknowledge normal forces, vacuum forces, tangential friction, and torsional friction [2], [17], [23], [29] similar to a point contact with **friction or soft finger model** [24]. However, under this model, a single suction cup cannot resist torques about axes in the contact tangent plane, implying that any torque about such axes would cause the suction cup to drop an object (see the supplementary material for a detailed proof). This defies our intuition since empirical evidence suggests that a single point of suction can robustly transport objects [6], [10].

正向力、真空力、切線摩擦、扭轉摩擦

吸嘴無法抵抗在切面上軸的扭力

We hypothesize that these torques are resisted through an asymmetric pressure distribution on the ring of contact between the suction cup and object, which occurs due to passive elastic restoring forces in the material. Fig. 10 illustrates the suction ring contact model. The grasp map G is defined by the following basis wrenches:

1)**Actuated Normal Force** (f):The force that the suction cup material applies by pressing into the object along the contact z axis.

2)**Vacuum Force** (V):The magnitude of the constant force pulling the object into the suction cup coming from the air pressure differential.

3)**Frictional Force** (ff= (fx;fy)):The force in the contact tangent plane due to the normal force between the suction cup and object,fN=fz+V.

4)**Torsional Friction** (z):The torque resulting from frictional forces in the ring of contact.

5)**Elastic Restoring Torque** (e= (x;y)):The torque about axes in the contact tangent plane resulting from elastic restoring forces in the suction cup pushing on the object along the boundary of the contact ring.

1. 執行器正向力：透命吸嘴材質的壓力壓到物體表現的z軸
2. 真空力：利用氣壓差
3. 切線的摩擦力
4. 扭轉力，環狀接觸所產生的扭轉力
5. 彈性恢復扭力：西嘴在接觸切面上軸上的扭轉，吸嘴橡膠材質物理上的扭力：

The magnitudes of the contact wrenches are constrained due to (a) the friction limit surface [14], (b) limits on the elastic behavior of the suction cup material, and (c) limits on the vacuum force. In the suction ring contact model,F is approximated by a set of linear constraints for efficient computation of wrench resistance:

這些接觸wrenches的大小受到約束

a:表面有限摩擦力

b:吸嘴材質，產生的有限彈性行為

c.有限的真空力

吸嘴環狀接觸模型： F是一組近似線性約束的函式，有效計算承受的擾力

$$
\begin{array}{rlll}
\textbf{Friction:} & \sqrt{3}|f_x| \leqslant \mu f_N & \sqrt{3}|f_y| \leqslant \mu f_N & \sqrt{3}|\tau_z| \leqslant r\mu f_N \\
\textbf{Material:} & \sqrt{2}|\tau_x| \leqslant \pi r \kappa & \sqrt{2}|\tau_y| \leqslant \pi r \kappa & \\
\textbf{Suction:} & f_z \geqslant -V & &
\end{array}
$$

Here u is the friction coefficient,r is the radius of the contact ring, and k is a material-dependent constant modeling the maximum stress for which the suction cup has linear-elastic behavior. These constraints define a subset of the friction limit ellipsoid and cone of admissible elastic torques under a linear pressure distribution about the ring of the cup. Furthermore,we can compute wrench resistance using quadratic programming due to the linearity of the constraints. See the supplemental file for a detailed derivation and proof.

u 是摩擦係數

r 是接觸環的半徑

k 是一個材料的常數，模擬吸嘴吸盤彈性的最大壓力

我們可以用線性約束的二次編程來及算wrench resistance

C. Robust Wrench Resistance

We evaluate the robustness of candidate suction grasps by evaluating seal formation and wrench resistance over distributions on object pose, grasp pose, and disturbing wrenches:

Definition 3:The robust wrench resistance metric for u and x is λ(u;x) =P(W | u;x), the probability of success under perturbations in object pose, gripper pose, friction, and disturbing wrenches.

In practice, we evaluate robust wrench resistance by taking J samples, evaluating binary wrench resistance for each, and computing the sample mean:

$$\frac{1}{J} \sum_{j=1}^{J} W_j .$$

從物體、抓取跟干擾中，評估穩健的候選吸取點，藉由密封形成的模型以及吸取評估的分佈

λ(u;x) =P(W | u;x)

指標u跟x作為評估成功率？ λ(u;x) =P(W | u;x)

V. DEX-NET3.0 DATASET

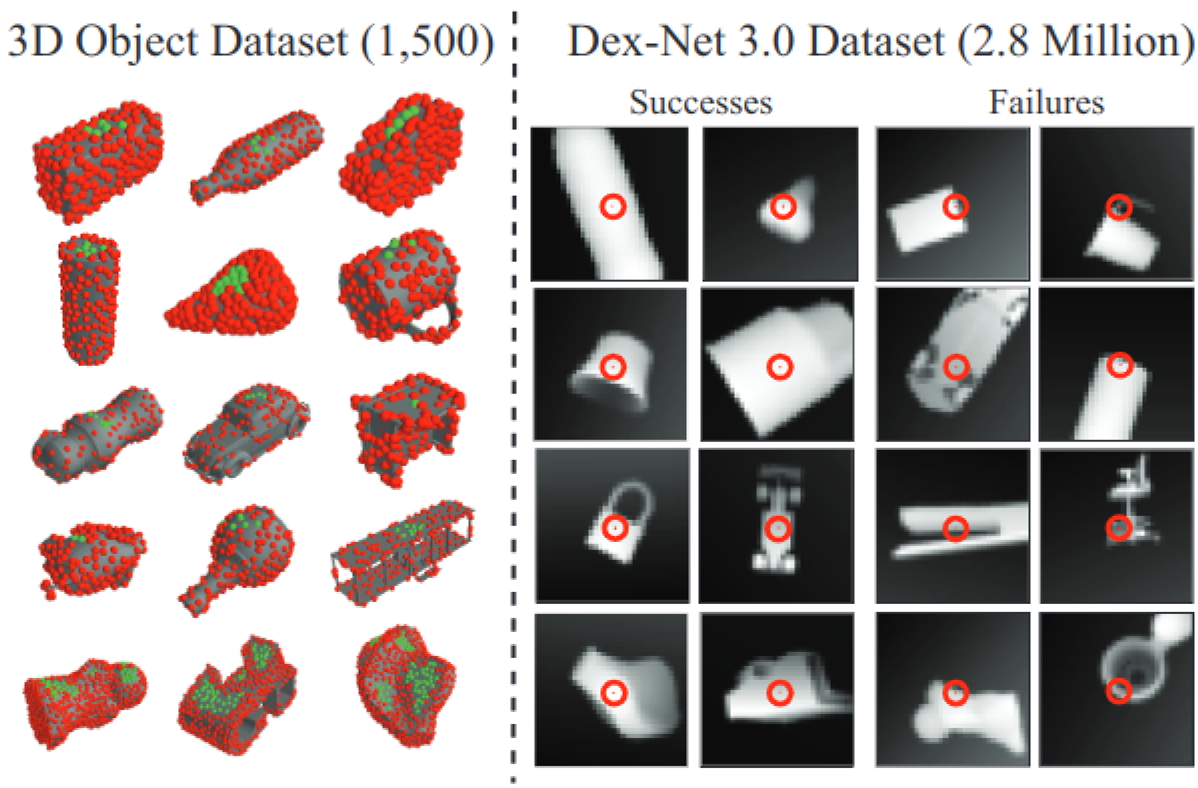


Fig. 3: The Dex-Net 3.0 dataset. (Left) The Dex-Net 3.0 object dataset contains approximately 350k unique suction target points across the surfaces of 1,500 3D models from the KIT object database [16] and 3DNet [33]. Each suction grasp is classified as robust (green) or non-robust (red). Robust grasps are often above the object center-of-mass on flat surfaces of the object. (Right) The Dex-Net 3.0 point cloud dataset contains 2.8 million tuples of point clouds and suction grasps with robustness labels, with approximately 11.8%positive examples.

1. 35萬個抓取點，1500個3D物件

2. 好的抓取點通常都在物件表面的質量中心的上方
3. 280萬個點雲抓取樣本，11.8%為正面樣本
4. 兩個database KIT object database 與 3DNet

To learn to predict grasp robustness based on noisy point clouds, we generate the Dex-Net 3.0 training dataset of point clouds, grasps, and grasp reward labels by sampling tuples (R;u;y) from a joint distribution p(R;x;y;u) modeled as the product of distributions on:

- States:p(x):A uniform distribution over a discrete dataset of objects and their stable poses and uniform continuous distributions over the object planar pose and camera poses in a bounded region of the workspace.
- Grasp Candidates:p(u|x):A uniform random distribution over contact points on the object surface.
- Grasp Rewardsp(R|u;x):A stochastic model of wrench resistance for the gravity wrench that is sampled by perturbing the gripper pose according to a Gaussian distribution and evaluating the contact model described in Section IV.
- Observations p(y|x):A depth sensor noise model with multiplicative and Gaussian process pixel noise.

從資料庫均勻的採取物體與它們的姿態，從均勻連續的分佈選取物體表面姿勢與相機姿勢在一個範圍的工作台內 **取物體 x**

在物體表面均勻的採樣隨機點 **均勻隨機點灑在表面 u**

一個吸取評估的隨機模型，根據高斯模型建立的干擾抓取採樣 **評估 R**

一個可乘的噪聲深度感測，經過高斯像素噪聲 **image y**

Fig. 3 illustrates a subset of the Dex-Net 3.0 object and grasp dataset. The parameters of the sampling distributions and compliant suction contact model(n, r, h, E, V, u, k, ϵ)(see Section IV) were set by maximizing average precision of the Q values using grid search for a set of grasps attempted on an ABB YuMi robot on a set of known 3D printed objects (see Section VII-A).

吻合的吸嘴接觸模型 model(n, r, h, E, V, u, k, ϵ)

對一組3D列印物品，通過網格搜索找夾取點，使用ABB YuMi，嘗試讓平均Q最大化

Our pipeline for generating training tuples is illustrated in Fig. 4. We first sample state by selecting an object at random from a database of 3D CAD models and sampling a friction coefficient, planar object pose, and camera pose relative to the worksurface. We generate a set of grasp candidates for the object by sampling points and normals uniformly at random from the surface of the object mesh.

用Fig4的方法，流水線產生資料

首先選取物品，從dabase 3D CAD，採樣摩擦係數，平面物體的姿勢跟相機，藉由點雲採樣產生集合的候選抓取點，法線在網格表面隨機的均勻分佈

We then set the binary reward label R= 1 if a seal is formed and robust wrench resistance (described in Section IV-C) **is above a threshold value**. Finally, we sample a point cloud of the scene using rendering and a model of image noise [22]. The grasp success labels are associated with pixel locations in images through perspective projection [9]. A graphical model for the sampling process and additional details on the distributions can be found in the supplemental file.

設置獎勵值R=1，只要密封形成，穩健的抓取指標高於在一個閥值

我們使用渲染對影像的點雲進行採樣，使用透視投影在圖像上成功的定位夾取標籤(像素)

VI. LEARNING A DEEP ROBUST GRASPING POLICY

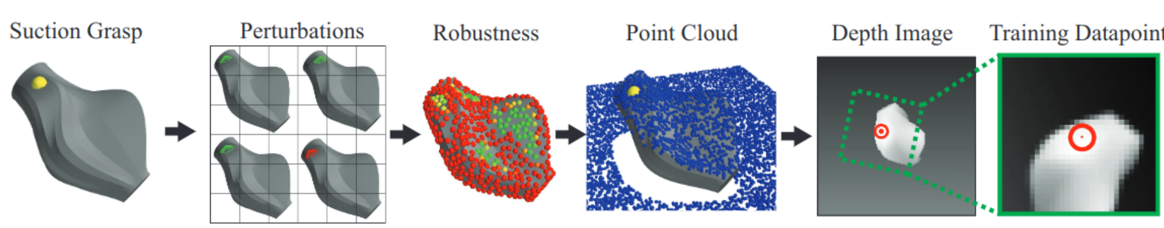


Fig. 4: Pipeline for generating the Dex-Net 3.0 dataset (left to right). We first sample a candidate suction grasp from the object surface and evaluate the ability to form a seal and resist gravity over perturbations in object pose, gripper pose, and friction. The samples are used to estimate the probability of success, or robustness, for candidate grasps on the object surface. We render a point cloud for each object and associate the candidate grasp with a pixel and orientation in

the depth image through perspective projection. Training data points are centered on the suction target pixel and rotated to align with the approach axis to encode the invariance of the robustness to image locations.

表面評估抓取點，藉由密封跟抵抗重力與干擾性評估可能性，並被物體、抓取姿勢與摩擦力影響。

1. 選取抓取點
2. 擾動(有必要?)
3. 評估表面的抓取點(用定義好的函式？)
4. 轉換為點雲
5. 轉換成深度圖
6. 抓取點居中，旋轉

We use the Dex-Net 3.0 dataset to train a GQ-CNN that takes as input a single-view point cloud of an object resting on the table and a candidate suction grasp defined by a target 3D point and approach direction, and outputs the robustness, or estimated probability of success, for the grasp on the visible object.

對一個靜態放置於桌面的單獨視野點雲，以及一個被3D點雲定義的候選抓取點，加上方向，output出穩健度，或評估成功機率。

Our GQ-CNN architecture is identical to Dex-Net 2.0 [21] except that we modify the pose input stream to include the angle between the approach direction and the table normal. The point cloud stream takes a depth image centered on the target point and rotated to align the middle column of pixels with the approach orientation similar to a spatial transforming layer [11].

The end-effector depth from the camera and orientation are input to a fully connected layer in a separate pose stream and concatenated with conv features in a fully connected layer. We train the GQ-CNN with using stochastic gradient descent with momentum using an 80-20 training-to-validation image-wise split of the Dex-Net 3.0 dataset. Training took approximately 12 hours on three NVIDIA Titan X GPUs. The learned GQ-CNN achieves 93.5%classification accuracy on the held-out validation set.

1.隨機梯度下降-動量

2.80 train 2- validation

3.12小時 3個 Titan X，準確率93.5

We use the GQ-CNN in a deep robust grasping policy to plan suction target grasps from point clouds on a physical robot. The policy uses the Cross Entropy Method (CEM) [20], [21], [27]. CEM samples a set of initial candidate grasps uniformly at random from the set of surface points and inward-facing normals on a point cloud of the object, then iteratively resamples grasps from a Gaussian Mixture Model fit to the grasps with the highest predicted probability of success. See the supplemental file for example grasps planned by the policy.

policy用cross entropy method採樣，一開始初始化隨機選取，在從GMM找更好的點

VII. EXPERIMENTS

We ran experiments to characterize the precision of robust wrench resistance when object shape and pose are known and the precision of our deep robust grasping policy for planning grasps from point clouds for three object classes.

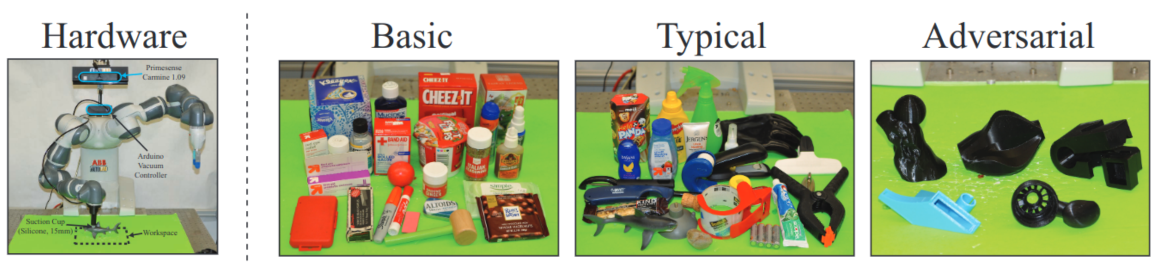


Fig. 5: **(Left)** The experimental setup with an ABB YuMi equipped with a suction gripper. **(Right)** The 55 objects used to evaluate suction grasping performance. The objects are divided into three categories to characterize performance: Basic (e.g. prismatic objects), Typical, and Adversarial.

A. Object Classes

We created a dataset of 55 rigid and non-porous objects including tools, groceries, office supplies, toys, and 3D printed industrial parts. We separated objects into three categories, illustrated in Fig. 5:

1. Basic:Prismatic solids (e.g. rectangular prisms, cylinders). Includes 25 objects.

2. Typical:Common objects with varied geometry and many accessible, approximately planar surfaces. Includes 25 objects.
3. Adversarial:3D-printed objects with complex geometry (e.g. curved or narrow surfaces) that are difficult to access. Includes 5 objects.

直角凌柱體、圓柱體 共25件　幾何物體、有大塊表面物體 25件

進階 3D打印物體、負責的幾何，彎曲或狹窄的表面 5件

For object details, see http://bit.ly/2xMcx3x.

B. Experimental Protocol

We ran experiments with an ABB YuMi with a Primesense Carmine 1.09 and a suction system with a 15mm diameter silicone single-bellow suction cup and a VM5-NC VacMo-tion vacuum generator with a payload of approximately 0.9kg. The experimental workspace is illustrated in the left panel of Fig. 5. In each experiment, the operator iteratively presented a target object to the robot and the robot planned and executed a suction grasp on the object. The operator labeled successes based on whether or not the robot was able to lift and transport the object to the side of the workspace. For each method, we measured:

Primesense Carmine相機 1.09

ABB YuMi

15直徑 矽膠單波紋管 吸嘴

VM5-NC VacMotion 真空機 可吸取0.9

物體標記為成功基於是否能成功讓手臂把東西運送到工作台旁邊

1. Average Precision (AP).The area under the precision-recall curve, which measures precision over possible thresholds on the probability of success predicted by the policy. This is useful for industrial applications where a robot may take an alternative action (e.g. asking for help) if the planned grasp is predicted to fail.
2. Success Rate.The fraction of all grasps that were successful.

All experiments ran on a Desktop running Ubuntu 14.04 with a 2.7 GHz Intel Core i5-6400 Quad-Core CPU and an NVIDIA GeForce 980 GPU.

C. Performance on Known Objects

To assess performance of our robustness metric independently from the perception system, we evaluated whether or not the metric was predictive of suction grasp success when object shape and pose were known using the 3D printed Adversarial objects (right panel of Fig. 5). The robot was presented one of the five Adversarial objects in a known stable pose, selected from the top three most probable stable poses. We hand-aligned the object to a template image generated by rendering the object in a known pose on the table. Then, we indexed a database of grasps precomputed on 3D models of the objects and executed the grasp with the highest metric value for five trials. In total, there were 75 trials per experiment.

D. Performance on Novel Objects

We also evaluated the performance of GQ-CNNs trained on Dex-Net 3.0 for planning suction target points from a single-view point cloud. In each experiment, the robot was presented one object from either the Basic,Typical, or Adversarial classes in a pose randomized by shaking the object in a box and placing it on the table. The object was imaged with a depth sensor and segmented using 3D bounds on the workspace. Then, the grasping policy executed the most robustgrasp according to a successmetric. In this experiment the human operators were blinded from the method they were evaluating to remove bias in human labels.

We compared policies that optimized the following met-rics:

1. Planarity.The inverse sum of squared errors from an approach planeforpoints within a discwith radius equal to that of the suction cup.
2. Centroid.The inverse distance to the object centroid.
3. Planarity-Centroid (PC).The inverse distance to the centroid for planar patches on the 3D object surface.
4. GQ-CNN (ADV).Our GQ-CNN trained on synthetic data from the Adversarial objects (to assessthe ability of the model to fit complex objects).
5. GQ-CNN (DN3).Our GQ-CNN trained on synthetic data from 3DNet [33], KIT [16], and the Adversarial objects.

Table III details performance on the Basic, Typical, and Adversarial objects. On the Basic and Typical objects, we see that the Dex-Net 3.0 policy is comparableto PC in terms of success rate and has near-perfect AP, suggesting that failed grasps often have low robustness and can therefore be detected. On the adversarial objects, GQ-CNN (ADV) sig-nificantly outperforms GQ-CNN (DN3) and PC,suggesting that this method can be used to successfully grasp objects with complex surface geometry as long as the training dataset closely matches the objects seen at runtime. The DN3 policy took an average of 3.0 seconds per grasp.

E. Failure Modes

The most common failure mode was attempting to form a seal on surfaces with surface geometry that prevent seal formation. This is partially due to the limited resolution of the depth sensor, as our seal formation model is able to detect the inability to form a seal on such surfaces when the geometry is known precisely. In contrast, the planarity-centroid metric performs poorly on objects with non-planar surfaces near the object centroid.

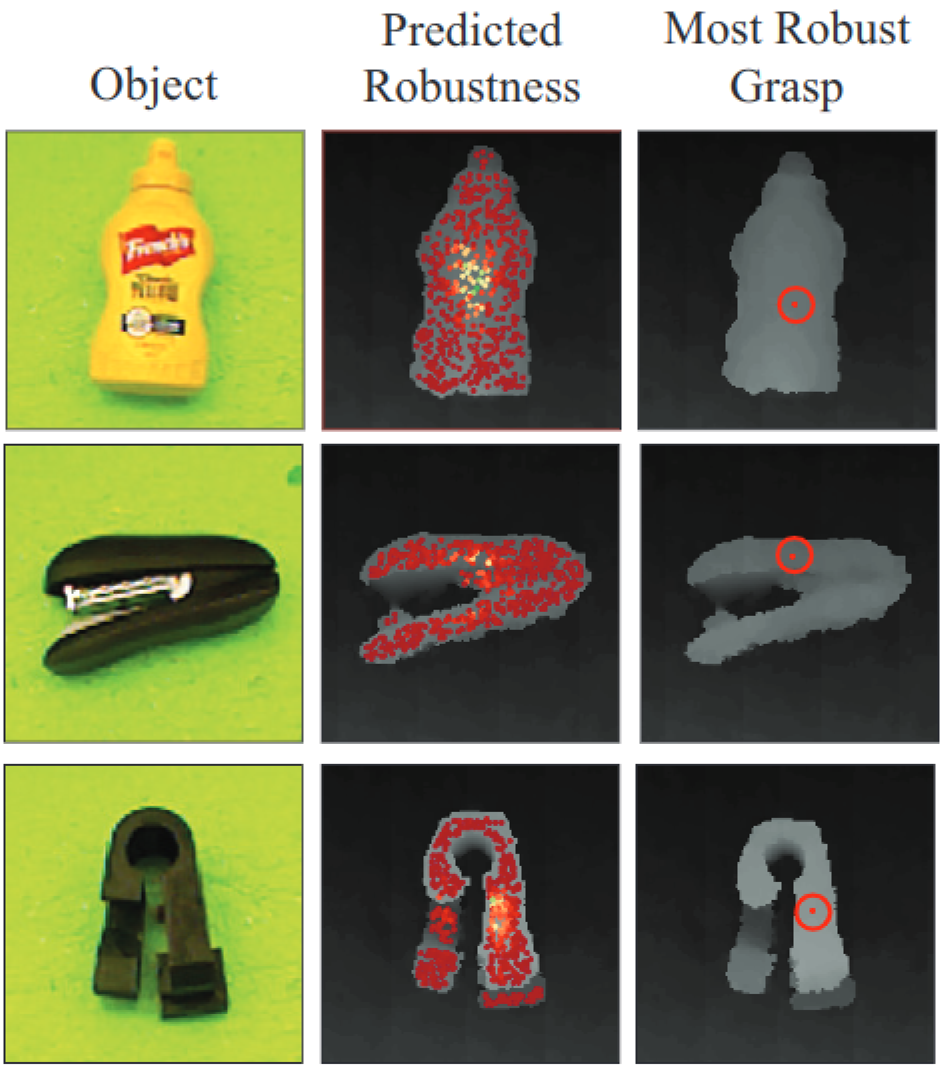
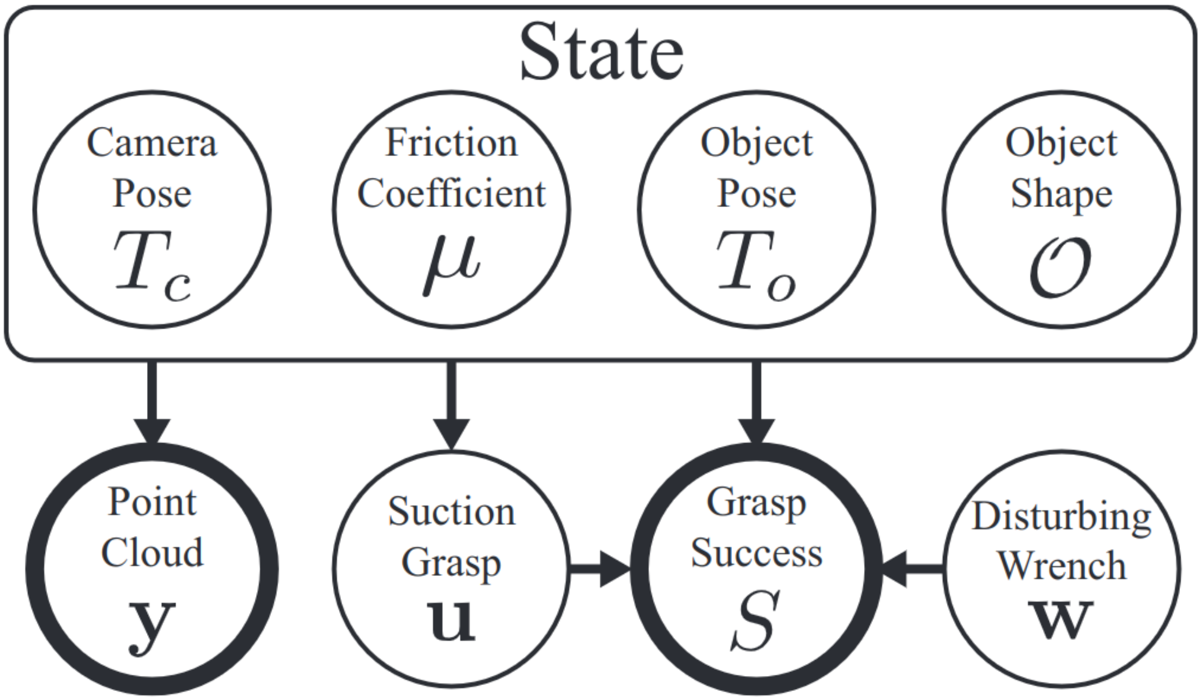


Fig. 12: Robust grasps planned with the Dex-Net 3.0 GQ-CNN-based policy on example RGB-D point clouds.(Left)The robot is presented an object in isolation.(Middle)Initial candidate suction target points colored by the predicted probability of success from zero (red) to one (green). Robust grasps tend to concentrate around the object centroid.(Right)The policy optimizes for the grasp with the highest probability of success using the Cross Entropy Method.

採集的點透過CEM，集中在物件的重心


State
Camera
Pose
T_c
Friction
Coefficient
μ
Object
Pose
T_o
Object
Shape
$\mathcal{O}$
Point
Cloud
$\mathbf{y}$
Suction
Grasp
$\mathbf{u}$
Grasp
Success
S
Disturbing
Wrench
$\mathbf{w}$