Discovering stable robot grasps for unknown objects in presence of uncertainty using Bayesian models*

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Abstract. Autonomous grasping of unknown objects is challenging due to the uncertainty in robotic sensing and action generation. This paper presents a pipeline for predicting a safe grasp in unknown objects using depth and tactile sensing. The main objective of the work is to explore haptically to maximise a given grasp metric, such that the probability of dropping the object after lifting from the surface is minimal. The performance of the uniform grid search method is compared with probabilistic methods (i.e. standard and unscented Bayesian Optimisation) to discover safe points. The results show that unscented Bayesian Optimisation provides better confidence in finding a safe grasp. This is demonstrated by observing optimum points being far from the edges and the exploration converging sooner than other methods in a limited number of exploratory observations.

Keywords: grasp metric · dexterous hand · haptics · manipulation.

1 Introduction

Design solutions for grasping unknown objects often use RGB-D, tactile and proprioceptive sensing modalities. In literature, these modalities are often used separately in different phases of the grasping; however, approaches using multimodal data are increasing in popularity [1]. Indeed, exploiting the multimodality of data to extract knowledge from different data sources can improve robot intelligence performance. The capability to deal with visual-tactile multimodal information enables robots to acquire more human-like capabilities in several tasks like grasping, object manipulation, and slip detection. While vision plays an essential role in grasp planning, which relies on the global visual features of the scene, it is ineffective to detect the safety of the performed grasp. This ineffectiveness occurs because grasping is dependant on physical contact, forces

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exerted by hand, tactile attributes of the object and hand configurations. Vision sensors cannot provide an estimation of these attributes. Thus, incorporating tactile sensing allows enriching the grasping information with features representing the physical contact modalities accessing a safer grasp at the execution stage.

This article describes a model that combines visual and tactile sensory inputs to predict stable grasping points of unknown objects using a grasp metric. The proposed approach can be used to measure the safety of the grasp before lifting the object from the surface. The approach is independent of building an extensive database of 3D objects. Moreover, it does not require the object symmetry assumption or object segmentation for computation. Castanheira et al. [2] proposed the concept of using probabilistic modelling to find a safe grasp in a simulated environment. However, many additional uncertainties are present in a real-world environment (e.g. insensitivity of sensors, disturbance in the position of the object while exploring) that are not present in a controlled simulated environment. This work also validates the practical application of probabilistic modelling in acquiring safer grasp points.

A series of experiments are conducted to compare the performance of probabilistic models with the uniformly distributed model. The experimental results validate the superiority of probabilistic models in finding safer grasp points. Probabilistic models also have a higher probability of convergence during exploration, hence providing confidence in predicting a safe grasp point. The contributions of the paper are threefold:

1. an approach to predict safer grasp of an unknown object from a combination of visual and tactile perception.
2. a model that considers uncertainties of the real world to predict a safer grasp of the object.
3. a series of experiments that demonstrates the proposed system for object grasp prediction.

2 Related Work

Grasping objects of unknown shape is an essential skill for automation in manufacturing industries. Many existing grasping techniques require a 2D or 3D geometrical model, limiting its application in different working environments [3]. On the other hand, acquiring 3D images is an expensive process and mostly simulation-based [4]. Kolycheva et al. [5] introduces a task-specific grasping system for a tridactyl manipulator. The system uses RGB-D vision to estimate for shape and pose of the object. The models for grasp stability are learnt over a set of known objects using Gaussian process regression. The grasp model has iteratively improved through re-planning the grasp around the object and collecting tactile data.

Merzic et al. [6] makes use of deep reinforcement learning technique to grasp partially visible/occluded objects. It does not rely on the dataset of the object models but instead uses tactile sensors to achieve grasp stability on unknown objects in a simulation. Zhao et al. [7] implements probabilistic modelling with a neural network to select a group of grasp points for an unknown object. There is also work on learning object grasping based on visual cues, and the selection of features are often based on human intuitions [8]. However, vision-based accuracy is limited due to its standardization and occlusions. Some details can be overlooked even for known objects, which may cause failure in grasping objects [9].

Tactile sensing is capable of compensating for some of the problems of the vision-only approach. Indeed being able to perceive touch allows the robot to understand when the contact with the object has been made and have a better perception of the occluded areas of the object by making contact with those surfaces of the target object. Techniques are proposed to control slippage and grasp stabilization of the objects using tactile sensors only ([10], [11]). It is independent of the data of object mass, object centre of mass and forces acting on the object to prevent the object from slipping.

There are seven different kinds of grasp quality metrics to predict how well it performs on the robotic platform and in simulations [12]. Different classifiers are trained on the extensive database, and results are evaluated for each grasp. The human labelled database is used in this work, which requires more accuracy in collecting data using different protocols. To accomplish the autonomous grasping of an unknown object, we aim to predict the grasping stability of the object before lifting the object from the surface. In this paper, we used tactile feedback to predict the safety of the robotic grasp of an unknown object. We present real-time grasp safety prediction by haptic probabilistic modelling exploration with a dexterous robotic hand.

3 Methodology

3.1 Object extraction from point cloud

We define a specific area in an environment as a workspace in which the robot operates safely. The object placed on the workspace is perceived by the robot while the remaining point cloud data is filtered out, as shown in Figure 1 part A. We are using a non-deterministic iterative algorithm, random sample consensus (RANSAC) [13], for detection of the object. It tries to fit the points from the point cloud into a mathematical model of a dominant plane. RANSAC then identifies the points which do not constitute the dominant plane model. These points that do not fit into the plane model (called outliers) are clustered together to form one object. Dimensions of the object are used to create a 3D bounding box around the object. The midpoint of the object is computed as the difference between the maximum and minimum boundary points in an axis parallel to the plane. This point is then used to reference the robot to move close to the object and initiate tactile exploration. Figure 1 part B shows the robot's planned trajectory, avoiding collision with the environment. Moveit! framework [14] is utilised for the implementation of motion planning.

3.2 Grasp metric calculation

The volume of the force wrench space (FWS) [15] is used as a force metric to gauge the stability of the grasp during tactile exploration. FWS is defined as the set of all forces applied to the object with all grasp contacts. It is a three-dimensional grasp matrix consisting of force components from all the four tactile sensors positioned on the tip of the fingers of the robotic hand. This metric is also independent of the coordinates of reference system . Function Q_v for this set of FWS ($\wp$) can be described as:

$$Q_v = Volume(\wp) \tag{1}$$

During the closing state, the robotic hand wraps its fingers around the object. The grasp metric is calculated when a connection is established between the hand and the object. Figure 1 part C displays the Allegro hand position, as observed in one experiment. The size and coordinates of the objects are assumed fixed to limit the size of the exploration space.

3.3 Probabilistic Modelling

Bayesian Optimisation (BO) is a probabilistic model to accomplish the task of exploring global optima [16]. For n number of iterations, the input dataset of query point is x=$\{x_{1:n}\}$ and the resulted outcome is z=$\{z_{1:n}\}$. In general, the algorithm depends on tuning parameters where input x ϵ $\mathbb{X}$ in some specified domain, where $\mathbb{X} \subseteq \mathbb{R}^{\mathbb{D}}$ The main goal is to find the global optimisation method, which focuses on finding the minimum optimum value for the objective function $f : \mathbb{X} \to \mathbb{R}$, where $\mathbb{X}$ is a compact space. It works on selecting the best grasp points for every iteration geared towards the minimum Consider this process in two basic steps: First, for each grasp point input, a probabilistic model (in our case, the Gaussian process) is built. Second, using an acquisition function α to decide the model to select the next point for exploration. As the method depends on the trial-and-error approach, BO helps optimise the number of steps required for a safe grasp. Grasp metric score is computed as described in Section 3. The performance of BO is then compared with the uniform distribution exploration model for different kinds of objects.

Unscented Bayesian Optimisation (UBO) is a method to propagate mean and covariance through nonlinear transformation. The basis of the algorithm is better manageability of an approximate probability distribution than approximate arbitrary nonlinear function [17]. To calculate mean and covariance, a set of sigma points are chosen. These sigma points are deterministically chosen points that depict certain information about mean and covariance. The weighted combination of sigma points is then passed through linear function to compute transformed distribution. The advantage of UBO over classical BO is the ability to consider uncertainty in the input space to find an optimal grasp. For dimension d, it requires 2d+1 sigma points that show its computational cost are negligible

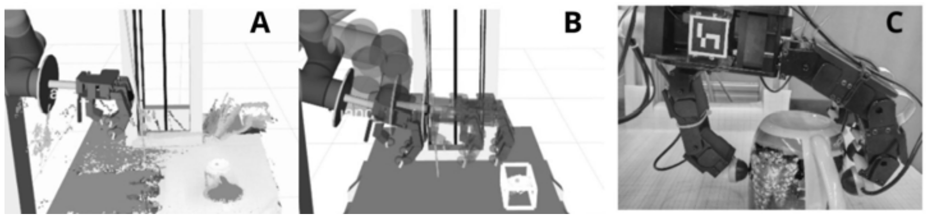

Fig. 1: Methodology for the calculation of force metric. **(A)** Point cloud data of the workspace. **(B)** Path planning towards the bounding box of the object. **(C)** Robotic hand position during metric calculation.

compared to others such as Monte Carlo, which requires more samples or Gaussian function. In UBO, the query is selected based on probability distribution. We choose the best query point considering it as deterministic but also check its surrounding neighbours. Thus, while considering input noise, we will analyze the resulting posterior distribution through the acquisition function. Assuming that our prior distribution is Gaussian distribution where $x \sim \mathcal{N}(\bar{x}, \sum x)$, then the set of 2d + 1 sigma points of the unscented transform is computed as:

$$x^0 = \bar{x}, x^i_{\pm} = \bar{x} \pm \left(\sqrt{(d+\kappa)\sum x}\right)_i, \forall i = 1...d \tag{2}$$

where d is dimensional input space, κ parameter tunes magnitude of sigma points and $\left(\sqrt{(.)}\right)_i$ is the $_ith$ row or column of the corresponding matrix square root. Detailed information of UBO is provided in [2]. UBO reduces the chance that the next query point is in an unsafe region where a small change in input results in a bad outcome.

4 Implementation

4.1 Configuration

To achieve our objective of successfully grasping an unknown object, we set up a UR5 robot in the lab. Allegro hand is mounted at the end of the UR5 arm as an end effector. Kinect is fixed at the top of the robot's base, facing perpendicular to the workspace. Optoforce OMD 20-SE-40N is a 3-axis force sensor that measures the forces experienced by the fingers of the Allegro Hand (at a rate of 1kHz). The workplace is 72 centimetres from the kinect frame. Any object within the workplace area (a rectangular area of 31 cm by 40 cm) is processed, and the extra points are filtered out. The orientation of the Allegro hand is fixed parallel to the axis of the workspace plane. The setup is shown in Figure 2.

4.2 Protocol

To perform the experiments, we apply the following experimental protocol:

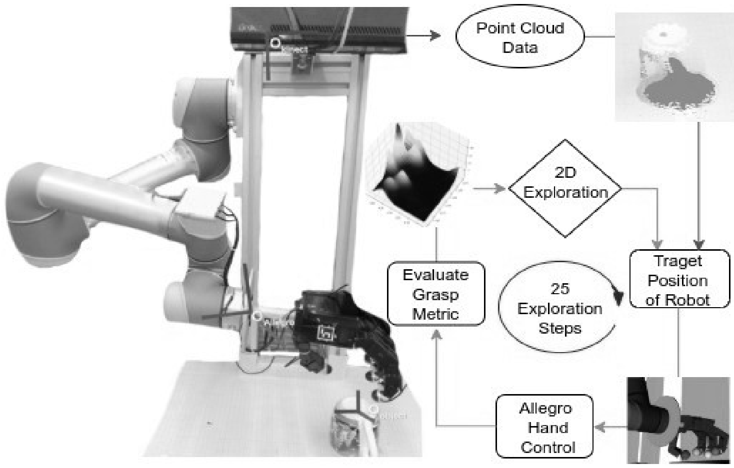

Fig. 2: Overview of the approach to evaluate safe grasps in unknown objects. UR5 robot equipped with an Allegro robotic hand.

1. object detection: unknown object detection using PCL.
2. motion planning: once we have detected the object's pose, the Moveit plans the collision-free movement of the robot to the top of the object.
3. plan execution: after successful planning, the robot navigates itself to the target pose. This is also the starting pose for haptic exploration.
4. gradually gripping the object: when the robotic arm reaches the search point, it starts closing its fingers until contact is detected.
5. applying grasping force: to ensure the gripper applies enough pressure over the object and not just touches it.
6. calculation of grasp metric: evaluate grasp score of the candidate grasp.
7. haptic exploration: open the grip of the robotic hand and move to the next pose directed by the probabilistic model. This process is repeated 25 times.

5 Results

The proposed model is validated by exploring grasp points in the 3D space, but the contact points are searched on two dimensions. Experiments are conducted five times with probabilistic modelling exploration and then compared with the uniformly distributed exploration. BO and UBO models are used for probabilistic modelling exploration. We used the objects from the dataset [1] developed by EU RoMaNs to observe exploration performance. The objects in the dataset are commonly found in nuclear waste and are categorised in different categories such as bottles, cans, pipe joints. We conducted the experiments with different kinds of objects and materials: rectangular-shaped foam (*4.6cm x 15cm x 6cm*

[1] https://sites.google.com/site/romansbirmingham

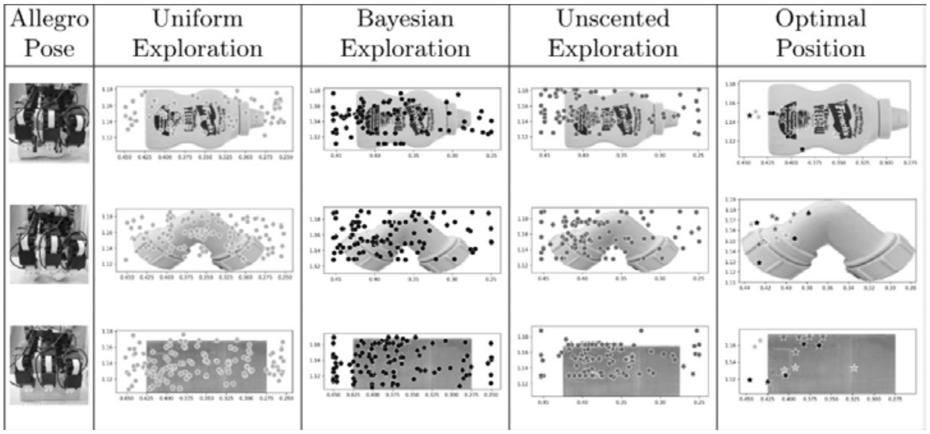

Fig. 3: Scatter plots of all points explored in uniform, BO and UBO for different objects. Pose of Allegro hand at start of experiments is also shown in first column. Final column represents optimum position in 2D from each experiment.

), a complex-shaped c-shaped pipe joint and a complex-shaped mustard plastic bottle. Image of the objects can be seen in the 'objects' column of the Table 1. Objects were slightly fixed to the surface due to the insensitivity of the tactile sensors. Tactile sensors disturb the position of the object during the calculation of the grasp metric.

Scatter plots: Figure 3 represents the points observed by each exploration method in all the experiments. The point represents the location of the middle finger of the robotic arm. A total of 125 search points (5 experiments with 25 iterations each) are plotted for each exploration method. It can be observed that for probabilistic methods, more observations are recorded at the boundaries of the object. This is due to the concavity of the tactile sensor and its contact with the edges in the objects. The figure also represents the optimal position with the highest metric score for all experiments for each exploration model. There are a total of 15 points represented, five for each approach. The points are the location of the middle finger of the robotic arm.

Optimal position: the position with optimal grasp score is the distance from the world frame along the horizontal plane of the object. The frames are shown in Figure 2. Table 1 tabulates the optimal position of the object as observed in each experiment. It also shows the value of grasp metric value in the optimal position. The points are skewed towards one side of the object because of the constraint in the encoders of the thumb, which restricts the movement of the thumb to align with the middle finger. The results indicate that probabilistic models have an optimum position similar to uniform distributed exploration with less standard deviation in position and metric score.

Convergence: convergence of each exploration to its maximum grasp metric value reflects confidence in a safer grasp. The mean of grasp metric value and

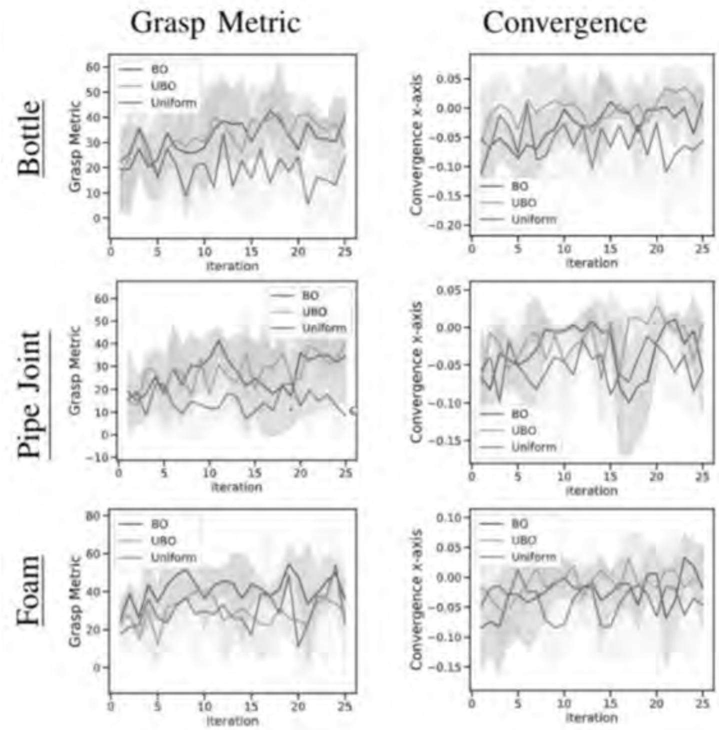

Fig. 4: Mean of grasp metric and convergence of explorations at each observation for all five experiments.

convergence to the final optimum position in each iteration for all experiments is shown in Figure 4. uniform, BO and UBO are represented by green, blue and orange lines, respectively. A total of five experiments are conducted with twenty-five observations for three different shaped objects. Plots present convergence in the x-axis only because of the confined range of exploration in the y-axis ($< \pm 4cm$). It can be seen that the probabilistic models have a higher probability of convergence than the uniform-grid search model. The results validate that probabilistic models have a better ability to converge to the optimum position with a higher grasp metric score in fewer iterations than uniformly distributed exploration. The experimental results collected demonstrates:

- the ability of probabilistic methods to provide confidence in predicting a safe grasp in a very limited number of iterations.
- BO and UBO have the advantage of converging sooner than the uniform exploration even with the low amount of observations.
- the potential of UBO to find grasps that are safer. This is evident in the case of the bottle, as the optimum points lie far from the edges.

Table 1: Mean optimal position for respective objects of all experiments from the world frame. Standard deviation of the mean position in x and y axes

Object		Uniform Exploration	Bayesian Exploration	Unscented Exploration
	Optimal Position(cm)	(40.4,114.2)	(41.6,113.7)	(39.4,114.5)
	Standard Deviation[x,y]	3.1,1.1	1.9,1.6	2.1,0.5
	Mean Metric	47.9	51	48.6
	Metric Deviation	6.3	7.4	7.7
	Optimal Position(cm)	(41.2,115.8)	(40.9,115.5)	(41.1,116.6)
	Standard Deviation[x,y]	1.4,0.8	2,1.6	1.1.1.1
	Mean Metric	46.0	52.8	48.6
	Metric Deviation	05.2	9.5	9
	Optimal Position(cm)	(39.9,114.4)	(40.4,113.7)	(38.5,116.6)
	Standard Deviation[x,y]	4.2,1.5	2.9,2	1.6,0.7
	Mean Metric	52.7	56.1	46.2
	Metric Deviation	10.8	10.7	4.2

6 Conclusion

This work validates our approach of using probabilistic modelling for finding safe grasp points for unknown objects in real-time. The approach outperforms the uniform distributed exploration in acquiring a safe grasp configuration with a limited set of exploratory iterations. The approach has application in handling materials in a nuclear environment where the robot can afford the time to find a safe grasp. For future developments, using tactile sensors that are more sensitive ([18], [19]) and distributed over a larger surface ([20], [21]), could allow to: rely on a more delicate haptic exploration; obtain a more reliable estimation of the grasp metric; consider object properties other than geometric, e.g. elasticity, friction coefficient.

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