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GPAtlasRRT: A probabilistic next-best tactile action strategy for object shape modelling and exploration

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Abstract Information on object shape is a fundamental parameter for robot grasps to be successful. However, incomplete perception and noisy measurements impede obtaining accurate models of novel objects. Especially when vision and touch simultaneously are envisioned for learning object models, a representation able to incorporate prior shape knowledge and heterogeneous uncertain sensor feedback is paramount to fusing them in a coherent way. Moreover, by embedding a notion of uncertainty in shape representation allows to more effectively bias the active search for new tactile cues. In this paper, we firstly represent the shape of an object as a Gaussian Process (GP). Then, using the concept that the 0-levelset of the GP — the surface of the approximated object — is an implicitly defined manifold, we extend the AtlasRRT algorithm to simultaneously: (i) build an atlas via continuation methods that locally parameterizes the object and that is used to select the next-best touch, and (ii) use an RRT-like strategy to devise directions for the expansion of the atlas to trade completeness in the exploration for efficiency. We integrate this strategy in a framework for iterative learning the object shape and implement a tactile exploration scenario in the bimanual setting of our Vito robot. The experimental results confirm that the devised methodology yields better models and does it with a reduced number of touches.

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1 Introduction

One of the main reasons that makes autonomous grasping tasks very challenging is that object properties required for grasp planning like shape and friction are not known in advance. This requires robots to perceive objects around them based on sensory information. However, sensory systems are prone to errors. As an example, when considering vision, some sources of noise are imperfect scene segmentation, occlusions, and poor lighting conditions.

Although for robotic grasp planning the use of vision has been studied more in depth by Kragic and Christensen (2002), the superior capabilities of humans in interacting with the environment come from rich sensory information where both visual and haptic modalities contribute to the combined percept. Working toward this ability in robots, the goal of our work is to complement visual information with tactile sensing in order to acquire 3D object models.

Even if tactile perception needs have been authoritatively spelled out in Bajcsy (1988) in the 1980's and early perception algorithms date back to the same years Grimson and Lozano-Perez (1984), Faugeras and Hebert (1983), Shekhar et al (1986), Bajcsy et al (1989), touch-based perception has lagged behind vision for two main reasons. The first is technological: standardized touch sensors are not easily available and have to be hand crafted for the specific robot and task. The second is intrinsic to the perception modality which requires the mechanical interaction of the sensor with the object being perceived with its inevitable perturbation and, to minimize this effect, calls for a complex control of the ongoing movement of the sensor: requirement which is completely absent, e.g., in vision.

The scenario we pursue is motivated by tactile exploration when other sensor modalities, like vision, already provided initial and incomplete information on object shape. More in details, we provide a systematic methodology to plan the next-best tactile exploration action. This is intrinsically a contact hypothesis that needs to be accepted or discarded after execution. Despite being the hypothesis verified or falsified, it helps to improve the object shape prediction up to a prespecified variability.

The object shape representation we employ is a probabilistic one and it is based on Gaussian Process (GP), a machine learning formalism for nonlinear function estimation that naturally provides a quantification of the uncertainty about object point estimates, i.e. the variance of the estimate. Being the 0-levelset of the approximating function an implicitly defined surface that represents the outer surface of an object, it comes handy to interpret it as a manifold and build on recent results on sample-based exploration of general manifolds to extend such algorithms to define hypotheses on where to sample next — next-best touch — to reduce uncertainty. More in details, without the need to embed the manifold in its ambient space, we build a set of charts (atlas) that locally parameterizes it, and select among the points on the current atlas the one associated to the maximum variance: this represents the location where the next touch will be directed. Then, the growth of the atlas itself does not follow a predefined sequence of steps, but an RRT-like strategy is employed to devise random direction of expansions for the atlas. The process is then repeated until the maximum variance is below a predefined threshold. This trades completeness in the exploration for efficiency: RRT drives the growth of the atlas toward regions of the object surface that are more uncertain, delaying the refinement of areas that have been already explored.

The structure of the paper is described in the following: in Sec. 2 we first review previous work related to tactile exploration and object shape representations. In Sec. 3.3 we clearly state the problem we aim to solve and in Sec. 4 we present the envisioned approach for its solution. The experimental results and their discussion are presented in Sec. 5. Finally, conclusions and points deserving further attention are given in Sec. 6.

2 Related work

2.1 State of the art

One of the first early attempts to exploit active tactile exploration with passive stereo vision for object recognition was proposed in Allen and Bajcsy (1987). In this paper, a rigid finger-like tactile sensor was used to trace along the surface with predefined movement cycles and provided a limited amount of information on object surface. The work was later extended to develop different exploratory procedures to acquire and interpret 3D touch information Allen and Michelman (1990). The exploratory procedures were, however, commanded by a human experimenter and therefore not linked to a fully autonomous system.

Single finger tactile exploration strategies for recognizing polyhedral objects have also been presented and evaluated in simulation, see Roberts (1990) and Caselli et al (1996). In Moll and Erdmann (2003) a method for reconstructing shape and motion of an unknown convex object using three sensing fingers is presented. In this approach, friction properties must be known in advance and the surface is required to be smooth, i.e., it must have no corners or edges. Moreover, multiple simultaneous sensor contacts points are required resulting in additional geometric constraints for the setup.

In Petrovskaya and Khatib (2011) exploratory procedures have been considered with the aim to globally localize an object of known shape. Since the Bayesian posterior estimation for objects in 6D is known to be computationally expensive, this paper proposes an efficient approach, termed Scaling Series, that approximates the posterior by particles. For fully constraining datasets, this approach performs the estimation in under 1 s with very high reliability.

In Meier et al (2011) the tactile shape reconstruction employs a Kalman filter, while in Bierbaum et al (2008) the tactile exploration is guided by Dynamic Potential Fields for motion guidance of the fingers. Here, the authors show that grasp affordances may be generated from geometric features extracted from the contact point set extracted during tactile exploration.

Interestingly, in Sommer et al (2014) a bimanual compliant tactile exploration is addressed that uses the GP representation to smooth noisy point data, but does not exploit the GP representation to define specific exploratory strategies.

Dragiev et al (2011) is one of the first works that employs Gaussian Process Implicit Surfaces (GPIS) for the concurrent representation of the object shape and to guide grasping actions towards the object. However, this work concentrates only on the mean of the shape distribution, i.e. the maximum a posteriori (MAP) estimate of the shape and practically ignores one of the gains of the GP — the error bars. Later work by the same authors in Dragiev et al (2013) offers also a way to give preference to regions of the model with particular certainty level and introduce the notion of explore-grasp and exploit-grasp primitives.

Bjorkman et al (2013) focus the attention on building object models that can be extracted with a small number of actions (touches) with the ultimate aim of understanding the category objects belong to, rather than exhaustively trying to explore the whole object. In this paper, the implicit function representation of the object surface is modelled by Gaussian Process regression, where the shape of the GP is governed by a thin plate covariance function derived by Williams and Fitzgibbon (2007). A set of predefined tactile glances are performed on the object: however, these are not updated as the object model gets refined as successive touches are performed.

This paper is one of closest work to ours among the references. The main difference being: the space in which the next-best exploratory action is computed, the terminal condition for the overall algorithm, and the descriptor used. Bjorkman et al (2013) use Zernike moments which imply extra computation time, and lack of a probabilistic interpretation, which is one of advantages of using Gaussian Process in first place. Moreover, the exploratory actions are searched in a discrete space in the vertical direction and the approach angle, which seem extrinsic to the shape model. Using the ambient space instead of the intrinsic representation does not guarantee that the new observations will be on the desired shape region to be explored. Finally, the number of actions, or touches in this case, are limited to a certain number, and then ordered according to the closes point on the implicit function with higher variance. In contrast, we set the highest expected variance in the shape prediction, so we explore until, probabilistically speaking, that goal is achieved.

2.2 Background

Regarding the shape representation...

Faria et al (2010) probabilistic representations of shapes

Using Gaussian Process for shape modelling is having an intensive development in recent years (Mahler et al 2015; Rosales et al 2014; Bjorkman et al 2013; Dragiev et al 2011), due to its versatility to accomadate noisy information, provide smooth regression of data, and a natural way to fuse different sources of information (Rasmussen and Williams 2006).

Manifold gaussian process: Calandra et al (2014) "The quality of a Gaussian Process model strongly depends on an appropriate covariance function."

The tree is constructed incrementally from samples drawn randomly from the search space and is inherently biased to grow towards large unsearched areas of the problem Space-filling trees are Rapidly-exploring random trees LaValle (2011)

Continuation method for implicitly defined surfaces Henderson (1993)

More general continuation method used in a more complex scenario combined with rapidly-exploring random trees (LaValle 2011) by Jaillet and Porta (2013), where the idea is to explore the part of the manifold defined by several kinematic loop constraints that solves the motion planning query.

Zhu et al (2009) succesfully recover non-rigid shape, means that gaussian processes can be used

Dragiev et al (2011) uses a squared-exponential-like covariance function. This is selection seems to be in agreement with the use is given to the shape estimation as a gradient field that drives the reach-to-grasp controller in a smooth way.

Rosales et al (2014) exploits the Gaussian Process modelling the object shape to find geodesic trajectories on the surface that are later followed by an exploratory probe to gather frictional properties. However, no further use of that propery is given.

Mahler et al (2015) proposes similar ideas as those given in Dragiev et al (2011), in fact they follow the same covariance function for the shape modelling, but adds a local optimization step to have a more elaborated grasp controller that drives the hand to the most-likely succesful object grasp using a metric that involves the well-known Ferrari-Canny measure.

Williams and Fitzgibbon (2007) derives the thin-plate covariance function for 3D shapes represented by implicit functions. The property of the thin-plate function to keep the tendency outside the training data is ideal for tactile exploration (Williams and Fitzgibbon 2007, Fig. 2)

Still not sure whether it should go in intro, soa, or background. Li et al (2016)

3 Scope

We rely on previous works that have proved useful object shape representations via Gaussian Processs in the derivation of grasp controllers.

3.1 Equipment specification

The vision system should be able to provide an initial guess on the object location and observation points on the surface. This is not an strict requirement, since one might be completely blind and still recognize objects around (Petrovskaya and Khatib 2011, e.g.). However, the use of an initial set of observation can be done quickly using RGBD sensors to speed up the overall process.

It is true that mounting the camera as the end-effector of a robot might allow a full object scanning, but there might be cases where this might not be possible either due to reaching limitations or even sensing capabilities on reduced spaces.

3.2 Assumptions

We assume that a point cloud of a segmented object is provided. However, we provide an optional pre-processing step that shows a reasonably way to do it when the object model is unkown.

Workspace. This is not to be thought as the workspace of a robot, but of the strategy algorithm that works on top of the object shape model. That is, we assume that we are modelling and exploring household objects that can be grasped and manipulated using a human-sized hand. This is specially useful in cases where the predicted shape is not bounded using the given observations, so this workspace will shrink the predicted shape to prevent the robot from going to an empty space, or worst, hitting undesirebly.

We consider contact to appear when the force torque sensor measures a value higher than 1N. The robot motion is set slow such that inertial forces are not reflected on the measurements. This is done for safety reasons, since in the phase when the robot is approaching, there is a stop signal if this threshold is superated.

3.3 Problem statement

Considering the equipment limitations 3.1 and the assumptions 3.2, the problem for which we propose a solution can be stated as:

Given a point cloud of an object, $\mathcal{O}$, find a suitable represention for the shape that can be exploited for tasks such as object identification and grasping, and a coherent strategy to improve the representation independent of external references, i.e. intrinsic or exploiting the representation, and flexible enough to generate different exploratory actions such as poking points and sliding paths.

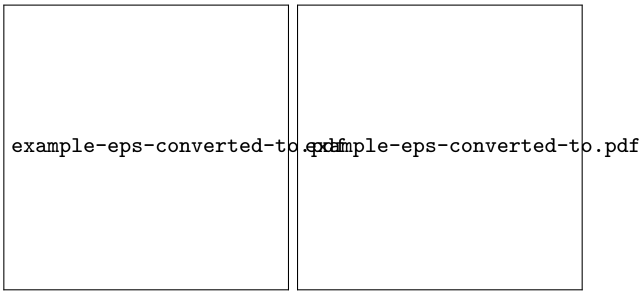

Fig. 1 A picture of the in-hand object segmentation using a soft-adaptive hand on a 7-dof arm in the real scene (left) and the resulting point cloud (right).

4 Solution

First, we provide a pre-processing step with the objective of having a segmented point set of the object **??**. This is then used to create the probabilistic shape representation **??**. This is then exploited in

4.1 Object Segmentation

(Hudson et al 2012, Sec. III.A) provides good candidates for object segmentation that are well oriented to object grasp, manipulation, and for our purposes, exploration. In fact, the combination of their "Table Plane Estimation" with their "Volume-Based Segmentation" yields the ubiquituos tabletop object segmentation (Muja and Ciocarlie 2014). However, to improve the rechability of the exploration, we prefer to hold the object in one hand-arm system and explore with another, as described in Sec. 3. Thus, our selected approach for object segmentation is simpler than those approaches. The difficulties is in measuring the configuration of a soft and adaptable gripper that keeps the object in position to filter out the points belonging to the hand-arm system. For this purpose, one can rely in body-type measurements instead of traditional encoders, as described by Santaera et al (2015). Once the hand-arm system pose is measured, then a trivial passthrough filter with slightly scaled bounding boxes of the robot geometry is used to obtain a point cloud of the object isolated from the scene. Algorithm 1 shows the pseudo-code of this procedure, indicating the actual. Additionally,

It is worth noting, that this module is here just to show how visual and tactile data might be merged into a single shape model. But as a matter of fact, the initial training point set can be empty and start by simply probing naively towards the gripper to initialize the training set.

The LISTENTOROBOTSTATE($\cdot$) method considers the measurement of soft-adaptive mechanism

Algorithm 1: In-hand object segmentation.

segmenInHand($\mathcal{R}, \kappa, \delta$)
input : The point cloud of the scene $\mathcal{P}$, the robot model, $\mathcal{R}$, its visual geometry inflation factor, κ, and the downsampling resolution, δ.
output: The point cloud of the object isolated from the scene, $\mathcal{O}$.

$\mathbf{s} \leftarrow$ LISTENTOROBOTSTATE($\mathcal{R}$)
$\mathcal{B} \leftarrow$ COMPUTEBOUNDINGBOXES($\mathcal{R}$, $\mathbf{s}$, κ)
$\mathcal{O} \leftarrow$ APPLYPASSTROUGHFILTER($\mathcal{P}$, $\mathcal{B}$)
$\mathcal{O} \leftarrow$ APPLYDOWNSAMPLEFILTER($\mathcal{O}$, δ)
return $\mathcal{O}$

4.2 Shape modelling

What makes a good surface representation?

- Accurate (we handle this with probability)
- Concise (we might want this)
- Intuitive specification (we don't need this)
- Local support
- Affine invariant
- Arbitrary topology (we need this)
- Guaranteed continuity (we need this)
- Natural parameterization (we don't need this)
- Efficient display (we shouldn't need this)
- Efficient intersections (we could need this)

Looks like implicitly defined surfaces are the best...
How do we define implicit function?

- Algebraics
- Blobby models
- Skeletons
- Procedural
- Samples
- Variational
- Gaussian Process !

Variational surfaces:

- Advantages:
  - Easy to test if point is on surface
  - Easy to compute intersections/unions/differences
  - Easy to handle topological changes
- Disadvantages:
  - Indirect specification of surface
  - Hard to describe sharp features
  - Hard to enumerate points on surface !
  - Slow rendering !

Except from rendering and surface explicit related things... but we don't actually need that except from debug.

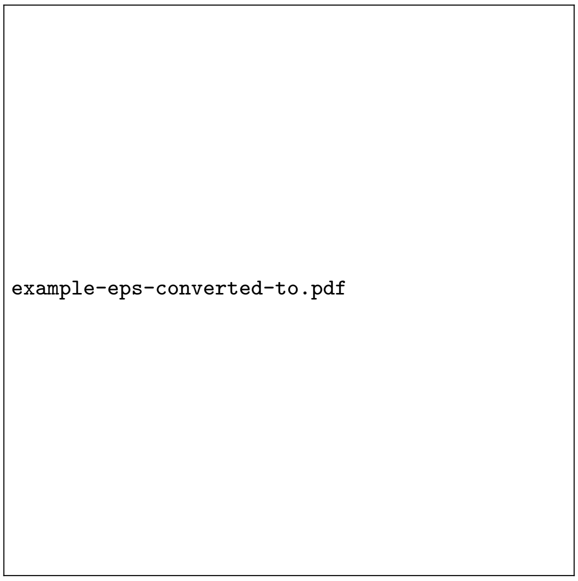

Fig. 2 Different shape representations

Algorithm 2: Gaussian Process regression

createGaussianProcess(X)
input : The training data, $\mathcal{X}$, in the form of a point cloud.
output: The Gaussian Process that models the object shape.

$\mathcal{D} \leftarrow$ DEMEANNORMALIZEANDLABEL($\{\mathcal{X}, \mathbf{0}_{\mathrm{sizeOf}(\mathcal{X})}\}$)
ADDLABELEDPOINT($\{\mathbf{0}_3, -1\}$, $\mathcal{D}$)
ADDLABELEDPOINTS($\{$SPHERE$(\mathbf{0}_3, 1.1, N)$, $+\mathbf{1}_N\}$, $\mathcal{D}$)
$\mathcal{G} \leftarrow$ DOREGRESSION($\mathcal{D}$)
return $\mathcal{G}$

4.3 Exploration strategy

We don't need all the conditions described in Jaillet and Porta (2013, Fig. 8).

The exploration strategy, employs the concept of RRTs and builds an Atlas on the Gaussian Process surface, $\mathcal{S}$. Then it decides which is the best next tactile action to perform in order to improve the current object shape estimation. Algorithm 3 describes the implemented procedure.

Specifically, given an Atlas($\mathcal{A}$), as a collection of Charts $\mathcal{C}_i$, and a RRT explorer ($\mathcal{T}$) the strategy creates a starting chart on a random point $\mathbf{x}_{c,i} \in \mathcal{M}$, belonging to the object training set(χ), which in turn is part of the Gaussian Process Model ($\mathcal{M}$). Then it rapidly builds an exploration tree on the object estimated surface until a solution chart is found or the maximum allowed number of charts has been reached. The solution, if found, is then the path from the chart to the tree root.

In order to do this, the atlas must be able to create new charts on the estimated surface according to a supplied criteria (Ω) and the current Gaussian Pro-

Algorithm 3: Best-next tactile action planner

```
exploreGPAtlasRRT(M, Ω)
input : A Gaussian Process model, M and the set of
        criteria to decide how to search and end the
        exploration, Ω.
output: The best next action, P, in the form of a
        path, if any, or ∅ otherwise.
P ← ∅
A ← initGPAtlas(M)
T ← initRRTs(A)
x_{c,i} ← selectStartPoint(M)
C_i ← createChart(A, x_{c,i}, Ω)
while terminationCriteriaNotMet(C_i, Ω) do
    C_j ← selectChartToExpand(T, Ω)
    x_{c,k} ← findExpansion(A, C_j, Ω)
    C_k ← createChart(A, x_{c,k}, Ω)
    connectCharts(T, C_k, C_j)
    C_i = C_k
if isSolution(C_i) then
    return P ← generatePath(C_i, T)
else
    return ∅
```

cess model ($\mathcal{M}$). Consequently a chart, must also contains a point on the surface, called the center $\mathbf{x}_c$, such that $\mathbb{E}(\mathcal{S}(\mathbf{x}_c)) \approx 0$, a search space defined by a tangent disc at the surface, centered on $\mathbf{x}_c$, with radius $R \propto \frac{1}{\mathbb{V}(\mathcal{S}(\mathbf{x}_c))}$ and finally the gradient information at the center $G \approx \frac{\partial \mathcal{S}}{\partial \mathbf{x}}$.

With such information we first ask the RRT explorer to select a chart to expand, among the chart collection ($\mathcal{A}$). This is done this by selecting one at random with a bias to increase the probability of selecting the last created chart. This criteria is adopted to grow a tree which is likely to expand on a single branch, but at the same time maintain the possibility to create new branches from previous charts. So efficiency and speed is preserved, while we make sure we are exploring as much surface as possible, before reaching to a solution.

After a chart ($\mathcal{C}_j$) is selected, it is expanded by sampling k points on its tangent discs then selecting one at maximum variance and at the same time, not in collision with other charts search spaces. So a sample $\mathbf{s}_i$ is selected if $\mathbb{V}(\mathcal{S}(\mathbf{s}_i))$ is *max* in $\mathbb{V}(\mathcal{S}(\mathbf{s}_k))$ and $\| \mathbf{s}_i - \mathbf{x}_{c,j} \|_2 > \mathcal{C}_j \rightarrow R$, $\forall \mathcal{C}_j \in \mathcal{A}$, with $i \neq j$.

$\mathbf{s}_i$ is then projected back on the surface, using a gradient descend method, creating a center for a new chart, $\mathbf{x}_{c,k}$.

The new chart is created and connected to the one which originated it, progressively growing a tree of charts on the object surface. when one reaches the termination criteria, the procedure terminates and the full path from the converging chart to the root of the tree is reported as a solution.

The area covered by a given chart on the surface is never empty, and it always includes the center of the chart, $\mathbf{x}_i$, but its shape depends on the local shape. However, in this work, we are not interested in computing this area, since we will be traversing trees using compliance control to compensate for the errors between linear interpolation between $\mathbf{x}_i$ and $\mathbf{x}_j$ in 3D and actual arbitrary shape countour joinning them.

4.4 Solution in a nutshell

The methods from the previous sections are independent from each other, being the last one, Algorithm 3, our main contribution. Here, we show an example of how these methods intercommunicate to estimate the shape of an unkonwn object.

Algorithm 4: Probabilistic object shape modelling

```
ObjectShapeExploration(P, V_des)
input : An initial point cloud of the scene, P, if any,
        for instance from visual object segmentation,
        and the desired variance, V_des, for the overall
        shape estimation.
output: The estimated object shape, S
1  S ← ∅
2  if isEmpty(P) then
3      χ ← naiveProbe()
4  else
5      χ ← segmentObject(P)
6  S ← createGaussianProcess(χ)
7  while true do
8      Γ ← exploreGPAtlasRRT(S, V_des)
9      if Γ = ∅ then
10         return S
11     else
12         ApproachTo(Γ)
13         χ̄ ← probeObject(Γ)
14         if wasContactDetected() then
15             υ ← 0_sizeOf(χ̄)
16         else
17             υ ← 1_sizeOf(χ̄)
18         addLabelPoints({χ̄, υ}, χ)
19         S ← createGaussianProcess(χ)
20         MoveAway()
```

During the ApproachTo (line 12) (MoveAway, line 20) phases, the robot uses position control and standard motion planning techniques with collision avoidance. Since we are modelling the shape, we need to ensure that everytime the robot moves close (away) from the object, it does not collide with the object. It is tentative to use the current estimated shape, but since we are not actually computing it explicitly in our approach, we choose the bounding sphere as the collision geometry of the object. Thus the robot moves towards (away from) the surface at the contact location in the normal direction until reaching the bounding sphere. After that, a standard motion planning is used to approach the object (get to the rest position).

The PROBEOBJECT (line 13) phase is engaged once the robot is within the bounding sphere. The robot uses Cartesian impedance control, with the Cartesian force, pose and impedance set properly for the given setup. These implementation details are given in the next section. Since we don't actually know where the surface is, we need to whether the robot actually touched something or not, in order to properly label the acquisition (lines 15 and 17)

The method finishes when EXPLOREGPATLASRRT (line 8) described in Algorithm 2 has explore sufficiently the estimated shape and could not find an exploratory action Γ (line 10), i.e. the object shape is probabilistically estimated within the 95% of the confidence interval computed from $\mathbb{V}_{des}$.

The complete solution of the problem as stated in 3 is depicted in Algorithm 4.

4.5 Parameters and probabilistic completeness

We can safely assume that the surface has only one component when seen as a manifold.

5 Experiments

5.1 Apparatus

We repeat the exploratory probe given in Rosales et al (2014). The probe is composed of a semispherical tip (radius 2cm) on top of an ATI Nano 17 and an in-parallel passive compliant coupler to safely attach it as the end-effector of the 7 degrees of freedom KUKA LWR 4+ robot arm.

The object is grasped by a soft-hand. The assumption that the object is unknown holds to the adaptability of the hand. There is no need to have a precise model of the object, but a rough approximation of the shape. The hand softness will do the rest. This setup complies with the specifications given in Sect. 3.1.

5.2 Results

6 Conclusions and future directions

We have developed...

As an immediate future research is the study of manifold Gaussian Process as presented by Calandra et al (2014), so the application of the AtlasRRT as presented by Jaillet and Porta (2013) can be applied in a more precise manner.

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