Dynamic Potential Fields for Dexterous Tactile Exploration

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Abstract Haptic exploration of unknown objects is of great importance for acquiring multimodal object representations, which enable a humanoid robot to autonomously execute grasping and manipulation tasks. In this paper we present our ongoing work on tactile object exploration with an anthropomorphic five-finger robot hand. In particular we present a method for guiding the hand along the surface of an unknown object to acquire a 3D object representation from tactile contact data. The proposed method is based on the dynamic potential fields which have originally been suggested in the context of mobile robot navigation. In addition we give first results on how to extract grasp affordances of unknown objects and how to perform object recognition based on the acquired 3D point sets.

1 Introduction

Humans make use of different types of haptic exploratory procedures for perceiving physical object properties such as weight, size, rigidity, texture and shape [12]. For executing subsequent tasks on previously unknown objects such as grasping and also for non-ambiguous object identification the shape property is of outmost importance. In robotics this information is usually obtained by means of computer vision where known weaknesses such as changing lightning conditions and reflections seriously limit the scope of application. For robots and especially for humanoid robots, tactile perception is supplemental to the shape information given by visual perception and may directly be exploited to augment and stabilize a spatial representation of real world objects. In the following we will give a short overview on the state of the art in the field of robot tactile exploration and related approaches.

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Different strategies for creating polyhedral object models from single finger tactile exploration have been presented with simulation results in [19] and [5]. Experimental shape recovery results from a surface tracking strategy for a single robot finger have been presented in [6]. A different approach concentrates on the detection of local surface features [15] from tactile sensing. In [13] 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. must have no corners or edges. Further, multiple simultaneous sensor contacts points are required resulting in additional geometric constraints for the setup.

In the works mentioned above the exploration process is based on dynamic interaction between the finger and object, in which a sensing finger tracks the contour of a surface. Other approaches are based on a static exploration scheme in which the object gets enclosed by the fingers and the shape is estimated from the robot finger configuration. In [14], [9] and [20] the finger joint angle values acquired during enclosure are fed to an appropriately trained SOM-type neural network which classifies the objects according to their shape. Although this approach gives good results in terms of shape classification, it is naturally limited in resolution and therefore does not provide sufficient information for general object identification as with dynamic tactile exploration.

In this work we will present the current state and components of our system for acquiring a 3D shape model of an unknown object using multi-fingered tactile exploration based on dynamic potential fields. In addition we give first results on how to extract grasp affordances of unknown objects and how to perform object recognition based on the acquired 3D point sets.

2 Dynamic potential fields for exploration

We have transferred the idea of potential field based exploration to tactile exploration for surface recovery using an anthropomorphic robot hand. Potential field techniques have a long history in robot motion planning [11]. Here, the manipulator follows the streamlines of a field where the target position is modelled by an attractive potential and obstacles are modelled as repulsive potentials. By assigning regions of interest to attractive sources and already known space to repulsive sources this scheme may also be exploited for spatial exploration purposes with mobile robots [18]. The notion of dynamic potential fields evolves as the regions of interest and therefore the field configuration changes over time due to the progress in exploration. Yet, this method has not been reported for application in multifingered tactile exploration. For this purpose we have defined a set of *Robot Control Points* (RCPs) at the robot hand to which we apply velocity vectors calculated from the local field gradient

$$\mathbf{v} = -k_v \nabla \Phi(x) \quad .$$

The potential $\Phi(x)$ is calculated from superposition of all sources. We use harmonic potential functions to avoid the formation of local minima in which the imaginary force exerted on an RCP is zero. Further, we deploy a dedicated escape strategy to resolve structural minima, which naturally evoke from the multiple end-effector problem given by the fingers of the hand. The velocity vectors applied to the RCPs are computed in the cartesian coordinate frame therefore an inverse kinematic scheme is required to calculate joint angles for the robot hand and arm. In our case we have chosen Virtual Model Control (VMC) [17] to solve for the joint angles, as it links the potential field approach to inverse kinematics in an intuitive way.
Initially we have evaluated our approach in a detailed physical simulation using the model of our humanoid robot hand [8]. During exploration the contact location and estimated contact normals are acquired from the robot hands tactile sensor system and stored as a oriented 3D point set. We have modelled tactile sensors in the simulation environment which determine contact location. The contact normals are estimated from the sensor orientation to reflect the fact that current sensor technology can not measure contact normals reliably. The object representation may be used for further applications such as grasping and object recognition as we will describe in the following sections.

3 Tactile Exploration

Fig. 1 gives an overview on our tactile exploration module. An initial version of this method has been presented in [3]. As prerequisite the system requires a rough initial estimate about the objects position, orientation and dimension. In simulation we introduce the information to the system, while this information will be provided by a stereo camera system in the real application. From this information an initial potential field containing only attractive sources is constructed in a uniform grid which covers the exploration space in which the object is situated.

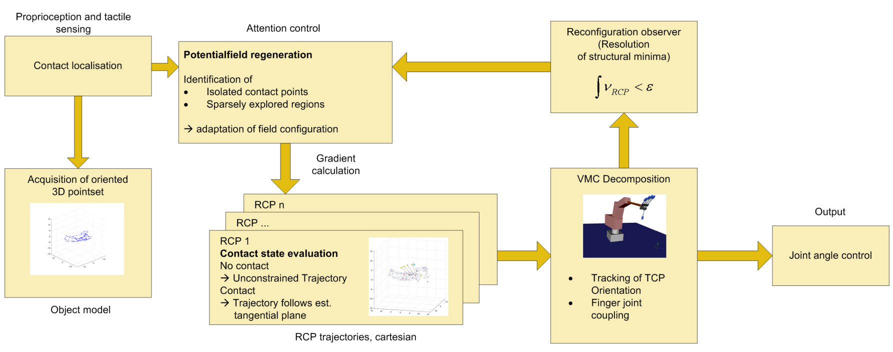

Fig. 1 Tactile exploration scheme based on dynamic potential field.

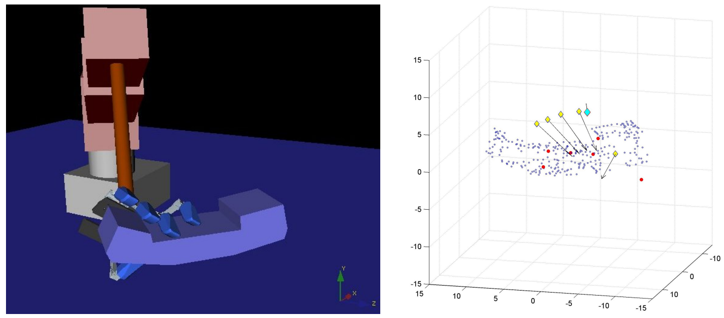

Fig. 2 Tactile exploration of a phone receiver (left) and acquired 3D point set (right).

During exploration it is required to fixate the object as contact points are acquired in world reference frame. The trajectories for the RCPs become continuously calculated from the field gradient, while contact point locations and normals are sensed and stored as oriented 3D point set. The normal vectors are estimated from finger sensor orientations. The RCP trajectories are constrained depending on the contact state of the sensor associated with each RCP, which aims to produce tangential motion during contact.

The potential field is updated from the tactile sensor information as follows. If no contact is found in the circumference of an attractive source it becomes deleted. If a contact is detected a repelling source is inserted at the corresponding location in the grid.

The robot system is likely to reach structural minima during potential field motion. We therefore introduced a reconfiguration observer which detects when the TCP velocity and the mean velocity of all RCPs fall below predefined minimum velocity values. This situation leads to a so called *small reconfiguration* which is performed by temporarily inverting the attractive sources to repulsive sources and thus forcing the robot into a new configuration which allows to explore previously unexplored goal regions. As this method is not guaranteed to be free of limit cycles we further perform a *large reconfiguration* if subsequent small reconfigurations remain ineffective, i.e. the robot does not escape the structural minimum. During a large configuration the robot is moved to its initial configuration.

Our approach to extract grasp affordances relies on identifying suitable opposing and parallel faces for grasping. Therefore, we needed to improve the original tactile exploration process to explore the object surface with preferably homogenous density and prevent sparsely explored regions. The faces become extracted after applying a triangulation algorithm upon the acquired 3D point set. Triangulation naturally generates large polygons in regions with low contact point count. We use this property in our improved exploration scheme to introduce new attractive sources and guide the exploration process to fill contact information gaps. Within fixed time step intervals we execute a full triangulation of the point cloud and rank the calculated faces by their size of area. In our modification we add an attractive source each at the centers of the ten largest faces. This leads to preferred exploration of sparsely explored regions, i.e. regions that need further exploration, and consequently lead to a more reliable estimate for the objects surface. As further improvement we apply a similar scheme to isolated contact points, i.e. contacts which have no further contact points in their immediate neighborhood, by surrounding these points with eight cubically arranged attractive charges. This leads to the effect that once an isolated contact is added, the according RCP now explores its neighborhood instead of being repelled to a more distant unexplored region.

4 Extraction of Grasp Affordances

As an exemplary application for our exploration procedure we have implemented a subset of the automatic robot grasp planner proposed in [16] in order to compute possible grasps based on the acquired oriented 3D point set, we call *grasp affordances*. A grasp affordance contains a pair of object features which refer to grasping points of a promising grasp candidate using a parallel grasp. We prefered to investigate this geometrical planning approach in contrast to grasp planning algorithms using force closure criteria, e.g. [7], due to its robustness when planning with incomplete geometric object models as they arise from the described exploration scheme. In our case we only consider planar face pairings from the given 3D point set as features for grasping, which we extract from the contact normal vector information using a region growing algorithm. Initially every possible face pairing is

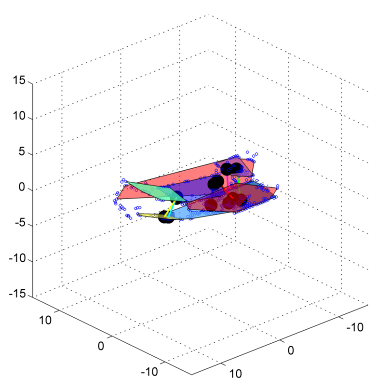

Fig. 3 Extracted grasp affordances for the telephone receiver.

considered as a potential symbolic grasp. All candidates are submitted to a geometric filter pipeline which eliminates impossible grasps from this set. The individual filter j returns a value of $f_o, j = 0$ when disqualifying and a value $f_o, j > 0$ for accepting a pairing. For accepted pairings the individual filter outputs are summed to

a score for each symbolic grasp, where the filter pairing with the highest score is the most promising candidate for execution.
The filter pipeline comprises the following stages in order of their application.

- *Parallelism:* This filter tests the two faces for parallelism and exports a measure indicating the angle between the two faces.
- *Minimum Face Size:* This filter compares the two faces to minimum and maximum thresholds. Selection of these values depends on the dimensions of the robot hand and fingers.
- *Mutual Visibility:* This filter determines the size of overlapping area when the two faces are projected into the so called grasping plane, which resides in parallel in the middle between the faces.
- *Face Distance:* This filter tests the distance of the two faces which must match the spreading capability of the robot hand. Therefore, this filter is also parameterized by the dimensions of the robot hand.

Fig. 3 shows symbolic grasps found for the receiver from Fig. 2. Face pairings are indicated by faces of the same color, the black spots mark the centers of the overlapping region of opposing faces in respect to the grasping plane. These points will later become the finger tip target locations during grasp execution.

5 Future concepts for object recognition

The oriented 3D point set acquired from tactile exploration is inherently sparse and of irregular density which makes shape matching a difficult task. In a first approach we have investigated a superquadric fitting technique which allows to estimate a super quadric function from tactile contacts in a robust manner [2]. Fig. 4 (left) shows a superquadric recovered from tactile exploration data using a hybrid approach where a genetic algorithm is used to identify the global minimum region

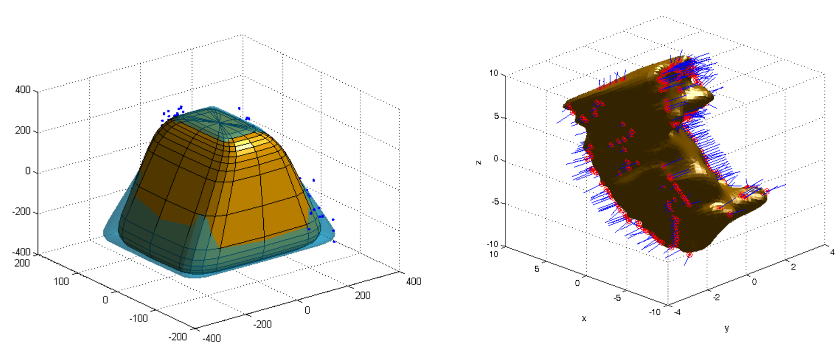

Fig. 4 Superquadric reconstructed from a tactile point set (left). A surface reconstructed using 3D Fourier transform (right).

and a least-squares-method converges to an optimum solution. Yet, this method is limited to representing and recognizing shapes only from a set of major geometric primitives such as spheres, cylinders, boxes or pyramids. For representing more complex shapes, different shape descriptors which may also become applied to partial models have been investigated in the research fields of computer vision and 3D similarity search [4]. The methods reported are mainly designed for large 3d data sets with uniform sampling density. Therefore, we have focused on investigating suitable point set processing methods which may interpolate the tactile contact data in order to compute robust shape descriptors. Fig. 4 (right) shows an oriented point set from tactile exploration which has been interpolated by using an algorithm for reconstruction of solid models [10]. From uniform density point sets stable shape descriptors may be computed using methods developed in the context of computer vision. Promising candidates for distinct shape descriptors here are geometric hash tables and spectra from spherical harmonic transforms. Both provide means for translational and rotational invariance, which is essential in object recognition from exploration data in human environments.

6 Discussion

In this paper we presented an overview on our system for tactile exploration. Our approach is based on dynamic potential fields for motion guidance of the fingers of a humanoid hand along the contours of an unknown object. We added a potential field based reconfiguration strategy to eliminate structural minima which may arise from limitations in configuration space. During the exploration process oriented point sets from tactile contact information are acquired in terms of a 3D object model. Further, we presented concepts and preliminary results for applying the geometric object model to extract grasp affordances from the data. The grasp affordances comprise grasping points of promising configurations which may be executed by a robot using parallel-grasps. For object recognition we have outlined our approach which relies on transforming the sparse and non-uniform pointset from tactile exploration to a model representation appropriate for 3D shape recognition methods known from computer vision.
We believe that the underlying 3D object representation of our concept is a major advantage as it provides a common basis for multimodal sensor fusion with a stereo vision system and other 3D sensors. As finger motion control during exploration is directly influenced from the current model state via the potential field, this approach becomes a promising starting point for developing visuo-haptic exploration strategies.
Currently we extend our work in several ways. In a next step we will transfer the developed tactile exploration scheme to our robot system Armar-III [1] which is equipped with five-finger hands and evaluate the concept in a real world scenario. Further, we are developing and implementing a motion controller which is capable to execute and verify the grasp affordances extracted from exploration. For object

recognition we will continue to investigate suitable shape descriptors and evaluate them with simulated and real world data from tactile exploration.

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