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Synergy-based affordance learning for robotic grasping

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HIGHLIGHTS

- An affordance learning system is designed.
- The affordance memory is modeled with a modified growing neural gas network.
- The system can explore grasp postures efficiently in the synergy space.

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ABSTRACT

In this paper, we present an affordance learning system for robotic grasping. The system involves three important aspects: the affordance memory, synergy-based exploration, and a grasping control strategy using local sensor feedback. The affordance memory is modeled with a modified growing neural gas network that allows affordances to be learned quickly from a small dataset of human grasping and object features. After being trained offline, the affordance memory is used in the system to generate online motor commands for reaching and grasping control of the robot. When grasping new objects, the system can explore various grasp postures efficiently in the low dimensional synergy space because the synergies automatically avoid abnormal postures that are more likely to lead to failed grasps. Experimental results demonstrated that the affordance memory can generalize to grasp new objects and predict the effect of the grasp (i.e., the tactile patterns).

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1. Introduction

1.1. Affordances in robots

Psychologist James J. Gibson originally defined affordances as all "action possibilities" latent in the environment, objectively measurable and independent of the individual's ability to recognize them, but always in relation to the actor and therefore dependent on their capabilities. However, Gibson's definition of affordances does not provide any clue on how to represent or implement affordances in robotics.

Most of the works on robot affordance learning address one of the several parts/correlations of Gibson's affordance concepts. Paletta et al. [1] demonstrated the learning of causal relations between visual cues and associated anticipated interactions. In [2], a robot builds probabilistic models about the conditions for successful interactions, which they call environmental affordances. Montesano and Lopes [3] proposed an algorithm to learn local visual descriptors of good grasp points. Akgun et al. [4] studied the effect aspect of affordance: they clustered the effect features to generate a set of effect categories using unsupervised learning. Detry et al. [5] defined object affordances as the object-gripper relative configurations that lead to successful grasps. Sun et al. [6] learned the visual object categories, rather than the direct visual features, and used them as an intermediate representation, in order to make the affordance learning problem scalable when learning from limited datasets.

Currently, in robots, an affordance is usually learned in the context of an on-going interaction with the world. In [7], the affordance representation of tools is learned during a behavioral babbling stage in which the robot randomly chooses different exploratory behaviors, applies them to the tool, and observes their effects on environmental objects. As a result of this exploratory procedure, the tool representation is grounded in the behavioral and perceptual repertoire of the robot. Erdemir [8] models affordances in a robot as statistical relations among actions, object properties and the effects of actions on objects. The robot learns the affordance using internal rehearsal. Montesano et al. [9] uses Bayesian networks to encode the dependencies between the actions, object features and the effects of these actions while a humanoid robot interacts with objects.

Another functional module related to affordances is the value system. As reviewed by Lungarella and Metta [10], value systems appear to exist in n to mediate neural plasticity and modulate learning in a self-supervised and self-organized manner. They allow organisms to learn autonomously via self-generated

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activity, and they gate the current behavioral state, or act as internal mediators of value and environmental saliency. Oudeyer and Kaplan [11] proposed a value system for robots called Intelligent Adaptive Curiosity, which involves curiosity and intrinsic motivation; the motivation being to maximize the learning progress. Huang and Weng [12] introduced an inherent hard-wired value system that has three components: punishment, reward, and novelty. This value system guided the development of a robot's sensorimotor skills through online interaction with the environment.

In summary, most of these robotics studies on affordance learning have two characteristics:

(1) Most of them are focused on the perception aspect of the affordance concept. Very few works have demonstrated how the learned affordance could improve the robot's control or performance.
(2) The learning process demands a large number of trials when the robot explores the object/environment or interacts with humans, which may be time-consuming, inefficient and impracticable.

The affordance learning system in this study is designed for real-time grasping control, rather than for perception. It learns the affordances from human grasping data, thus avoiding a long and costly exploration process in the robot. More importantly, by generalizing the learned affordances, our system can facilitate affordance learning and grasping control on new objects. Although it is not new for a robot to learn motor skills by imitating human behavior, one novelty of our system is that we use synergies to reduce dimensionality for the learning. As will be shown in the experiments, when the robot grasps a new object that is not in its training set, synergies make the exploration much more efficient.

1.2. Affordance learning algorithms

One central issue in robot affordance learning is, how to represent the affordances? [9] used Bayesian networks as a general tool to learn the affordance in grasping visa the interaction between the robot and human. By using Bayesian inference, the robot was able to predict the action and effects using the available information. In [1], affordances were learned by reinforcement learning of predictive perceptual states. [6] developed a probabilistic graphical model to describe the relationships between object categories, affordances, and appearance. Another widely used method for affordance learning in robots is the Self-organizing Map. In [4], effect features are clustered using SOM to generalize effects. [13] use SOM to associate the object invariant descriptors to the success or failure of an action.

In this study, we have designed a novel method, called Reverse Neural Gas, for modeling the associative memory and learning the grasping affordances. As will be shown below, the proposed method performs batter than SOM and can learn the affordances quickly with a limited training dataset.

1.3. Robotic grasping

Grasp synthesis, determining an appropriate hand position/orientation and posture to grasp a specific object, is not an easy task for robots (see [14] for a review). Methods for grasp synthesis can be divided into two categories. One category is analytical grasp synthesis that use kinematics or dynamics criteria (e.g., form closure, force closure, and equilibrium) to estimate the quality/stability of grasps, and search for grasps that optimize these measures. These methods usually demands precise models of the objects and accurate sensing of the interaction between the fingers and the objects, which are often infeasible in real-time applications. The other category is empirical methods that avoid the inherent difficulties of analytical methods by attempting to mimic human grasping strategies [15]. The grasping control structure we designed in this paper belongs to this second category. Empirical methods reduce possible hand postures to a limited number of standard grasps. Unlike analytical methods that plan the grasp before executing it, empirical methods use automated local control schemes and immediate sensory feedback at fingers, an example of which is the study of Teichmann and Mishra [16]. They equipped a two-fingered gripper with distance and angle sensors then, using a simple reactive algorithm based on the immediate feedback from these sensors, the gripper could grasp objects of unknown geometry and dynamics [16].

1.4. Synergies in human grasping

While grasp synthesis is still a tough problem for robot hands, humans can grasp and manipulate various objects effortlessly. One challenge in robotic grasping is how to coordinate the several joints of the fingers to generate an appropriate grasp posture for a specific object. Humans and animals have the same problem in the motor control of their huge number of muscles. Selecting the appropriate muscle pattern to achieve a given goal is an extremely complex task due to the high dimensionality of the search space [17]. Recent research in biology suggests that, to deal with this dimensionality problem, animal motor controllers employ a modular organization based on synergies [17,18]. A synergy refers to a subgroup of muscles or joints that are activated together in a stereotyped pattern [17], which is in contrast to the decoupled control of individual joints in many robots. d'Avella and Bizzi [17] recorded electromyographic activity from 13 muscles of the hind limb of intact and freely moving frogs during their movements, and used multidimensional factorization techniques to extract synergies, that is, invariant amplitude and timing relationships among the muscle activations. They have found, in frogs, that combinations of a small number of muscle synergies account for a large fraction of the variation in the muscle patterns observed during jumping, swimming, and walking [17].

Particularly in human hands, synergies refer to the muscular and neurological coupling between the finger joints. The human hand has more than 20 degrees-of-freedom. But, two synergies that co-activate several fingers and joints have been shown to account for 84% of the variance in human hand grasping [19]. The big benefit of synergies is that the computations for motor control can be greatly simplified at the synergy level.

In our previous study [20], we extracted three synergies from human grasping postures and then mapped them to a robot hand. In this study, we map the human hand postures to the robot hand first, and then extract synergies from the robot hand postures, rather than the human hand postures. Thus, the exploration for grasping new objects will be implemented in the synergy space of a greatly reduced dimensionality.

1.5. The aim of this study

The aim of this study is to learn grasping affordances from human data and apply them to robotic grasping. The learning involves three stages. Firstly, we map the human grasps to a robot hand and extract synergies from them. Secondly, the affordance memory is trained offline with these data. Finally, the affordance memory is used for online control of the robot to grasp objects. The main contributions of this study are:

(1) By modifying the neural gas method, we developed a new learning algorithm for affordance learning in robotic grasping, which can learn the affordances quickly with a small dataset and generalize well when grasping new objects.

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