Interactive Perception: Leveraging Action in Perception and Perception in Action

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Abstract—Recent approaches in robot perception follow the insight that perception is facilitated by interaction with the environment. These approaches are subsumed under the term Interactive Perception (IP). This view of perception provides the following benefits. First, interaction with the environment creates a rich sensory signal that would otherwise not be present. Second, knowledge of the regularity in the combined space of sensory data and action parameters facilitates the prediction and interpretation of the sensory signal. In this survey, we postulate this as a principle for robot perception and collect evidence in its support by analyzing and categorizing existing work in this area. We also provide an overview of the most important applications of IP. We close this survey by discussing remaining open questions. With this survey, we hope to help define the field of Interactive Perception and to provide a valuable resource for future research.

I. INTRODUCTION

There is compelling evidence that perception in humans and animals is an active and exploratory process [1][2][3]. Even the most basic categories of biological vision seem to be based on active visual exploration, rather than on the analysis of static image content. For example, Noë [3] argues that the visual category circle or round cannot be based on the direct perception of a circle, as (i) we rarely look at round objects from directly above, and (ii) the projection of a circle onto our retina is not a circle at all. Instead, we perceive circles by the way their projection changes in response to eye movements.

Held and Hein [4] analyzed the development of visually-guided behavior in kittens. They found that this development critically depends on the opportunity to learn the relationship between self-produced movement and concurrent visual feedback. The authors conducted an experiment with kittens that were only exposed to daylight when placed in the carousel depicted in Fig. 1. Through this mechanism, the active kittens (A) transferred their own, deliberate motion to the passive kittens (P) that were sitting in a basket. Although, both types of kittens received the same visual stimuli, only the active kittens showed meaningful visually-guided behavior in test situations.

Gibson [5] showed that physical interaction further augments perceptual processing beyond what can be achieved by deliberate pose changes. In the specific experiment, human subjects had to find a reference object among a set of irregularly-shaped, three-dimensional objects (see Fig. 2). They achieved an average accuracy of 49% if these objects were shown in a single image. This accuracy increased to 72% when subjects viewed rotating versions of the objects. They achieved nearly perfect performance (99%) when touching and rotating the objects in

Fig. 1. A mechanical system where movement of Kitten A is replicated onto Kitten P. Both kittens receive the same visual stimuli. Kitten A controls the motion, i.e. it is active. Kitten P is moved by Kitten A, i.e. it is passive. Only the active kittens developed meaningful visually-guided behavior that was tested in separate tasks. Figure adapted from Held and Hein [4].

Fig. 2. Set of irregularly-shaped objects among which subjects had to find a reference object. Subjects achieved near perfect performance when they could touch and rotate these objects as opposed to just looking at them in a static pose. Figure adapted from Gibson [5] p.124 with permission.
their hands. These three examples illustrate that biological perception and perceptually-guided behavior intrinsically rely on active exploration and knowledge of the relation between action and sensory response. This contradicts our introspection, as we just seem to passively see. In reality, visual perception is similar to haptic exploration. “Vision is touch-like” [3] p.73 in that, perceptual content is not given to the observer all at once but only through skillful, active looking.

This stands in stark contrast to how perception problems are commonly framed in Machine Vision. Often, the aim is to semantically annotate a single image while relying on a minimum set of assumptions or prior knowledge. These requirements render the considered perception problems under-constrained and thereby make them very hard to solve.

The most successful approaches learn models from data sets that contain hundreds of thousands of semantically annotated static images, such as Pascal VOC [6], ImageNet [7] or Microsoft COCO [8]. Recently, Deep Learning based approaches led to substantial progress by being able to leverage these large amounts of training data. In these methods, data points provide the most important source of constraints to find a suitable solution to the considered perception problem. The success of these methods over more traditional approaches suggests that previously considered assumptions and prior knowledge did not correctly or sufficiently constrain the solution space.

Different from disembodied Computer Vision algorithms, robots are embodied agents that can move within the environment and physically interact with it. Similar to biological systems, this creates rich and more informative sensory signals that are concurrent with the actions and would otherwise not be present. There is a regular relationship between actions and their sensory response. This regularity provides the additional constraints that simplify the prediction and interpretation of these high-dimensional signals. Therefore, robots should exploit any knowledge of this regularity. Such an integrated approach to perception and action may reduce the requirement of large amounts of data and thereby provide a viable alternative to the current data-intensive approaches towards machine perception.

II. INTERACTIVE PERCEPTION

Recent approaches in robot perception are subsumed by the term Interactive Perception (IP). They exploit any kind of forceful interaction with the environment to simplify and enhance perception. Thereby, they enable robust perceptually-guided manipulation behaviors. IP has two benefits. First, physical interaction creates a novel sensory signal that would otherwise not be present. Second, by exploiting knowledge of the regularity in the combined space of sensory data and action parameters, the prediction and interpretation of this novel signal becomes simpler and more robust. In this section, we will define what we mean by forceful interaction. Furthermore, we explain the two postulated benefits of IP in more detail.

A. Forceful Interactions

Any action that exerts a potentially time-varying force upon the environment is a forceful interaction. A common way of creating such an interaction is through physical contact that may be established for the purpose of moving the agent (e.g. in legged or wheeled locomotion), for changing the environment (e.g. to open a door or pushing objects on a table out of the way) or for exploring environment properties while leaving it unchanged (e.g. by sliding along a surface to determine its material). It may also be a contact-free interaction that is due to gravitational or magnetic forces or even lift. An interaction may only be locally applied to the scene (e.g. through pushing or pulling a specific object) or it may affect the scene globally (e.g. shaking a tray with objects standing on it). This interaction can be performed either by the agent itself or by any other entity, e.g. a teacher to be imitated or someone who demonstrates an interaction through kinesthetic teaching.

In this survey we are interested in approaches that go beyond the mere observation of the environment towards approaches that enable its Perceptive Manipulation. Therefore, we focus on physical interactions for the purpose of changing the environment or for exploring environment properties while leaving it unchanged. We are not concerned with interactions for locomotion and environment mapping.

B. Benefits of Interactive Perception

Create Novel Signals (CNS): Forceful interactions create novel, rich sensory signals that would otherwise not be present. These signals are beneficial for estimating the quantities that are relevant to manipulation problems such as haptic, audio and visual data correlated over time. Relevant quantities include object weight, surface material or rigidity.

Action Perception Regularity (APR): Forceful interactions reveal regularities in the combined space (S×A×t) of sensor information (S) and action parameters (A) over time (t). This regularity is constituted by the repeatable, multi-modal sensory data that is created when executing the same action in the same environment. Not considering the space of actions amounts to marginalizing over them. The corresponding sensory signals would then possess a significantly higher degree of variation compared to the case where the regularity in S×A×t is taken into account. Therefore despite S×A×t being much higher dimensional, the signal represented in this space has more structure.

Using the Regularity: Knowing this regularity corresponds to understanding the causal relationship between action and sensory response given specific environment properties. Thereby, it allows to (i) predict the sensory signal given knowledge about the action and environment properties, (ii) update the knowledge about some latent properties of the environment by comparing the prediction to the observation and (iii) infer the action that has been applied to generate the observed sensory signal given some environment properties. These capabilities simplify perception but also enable optimal action selection.

Learning the Regularity: Learning these regularities corresponds to identifying the causal relationship between action and sensory response. This requires information about the action that produced an observed sensory effect. If the robot autonomously interacts with the environment, this information is automatically available. Information about the action can also be provided by a human demonstrator.

III. HISTORICAL PERSPECTIVE

In robotics, the research field of Active Perception (AP) pioneered the insight that perception is active and exploratory. In this section, we relate Interactive to Active Perception. Additionally, we discuss the relation of IP to other perception approaches that neglect either the sensory or action space in S×A×t. Figure 3 summarizes the section.

We consider Perceptive Manipulation to be the equivalent term to Interactive Perception. This emphasizes the blurred boundary which is traditionally drawn between manipulation and perception.
Another example considers the problem of image restoration. Xue et al. [13] exploit whole image sequences to separate obstructing foreground like fences or window reflections from the main subject of the images, i.e. the background. This would be a very hard problem if only a single image were given or without the prior knowledge of the relation between optical flow and depth.

Aloimonos et al. [14] show how challenging vision problems, such as shape from shading or structure from motion, are easier to solve with an active than a passive observer. Given known camera motion and associated images, the particular problem can be formulated such that it has a unique solution and is linear. The case of the passive observer usually requires additional assumptions or regularization and sometimes nonlinear optimization.

C. Active Perception

In 1988, Bajcsy [15] introduced AP as the problem of intelligent control strategies applied to the data acquisition process. Ballard [16] and Aloimonos et al. [14] further analyzed this concept for the particular modality of vision. In this context, researchers developed artificial vision systems with many degrees of freedom [17, 18, 19] and models of visual attention [20, 21] that these active vision systems could use for guiding their gaze.

Recently, Bajcsy et al. [22] revisited AP giving an excellent historical perspective on the field and a new, broader definition of an active perceiver based on decades of research:

"An agent is an active perceiver if it knows why it wishes to sense, and then chooses what to perceive, and determines how, when and where to achieve that perception."

The authors identify the why as the central and distinguishing component to a passive observer. It requires the agent to reason about so called Expectation-Action tuples to select the next best action. The expected result of the action can be confirmed by its execution. Expectation-Action tuples capture the predictive power of the regularity in $S \times A \times t$ to enable optimal action selection.

1) Relation to Interactive Perception: The new definition of AP is not only restricted to vision. However, the majority of approaches gathered under the term of active perception consider vision as the sole modality and the manipulation of extrinsic or intrinsic camera parameters as possible actions. This is also reflected by the choice of examples in [22]. The focus on the visual sense has several implications for Active Perception in relation to Interactive Perception. First, an active perceiver with the ability to move creates a richer and more informative visual signal (e.g. from multiple viewpoints or when zooming) that would otherwise not be present. However, this may not provide all relevant information, especially not those required for manipulation problems. Natale et al. [23] emphasize that only through physical interaction, a robot can access object properties that otherwise would not be available (like weight, roughness or softness).

Second, as shown in Aloimonos et al. [14], we have very good understanding of multi-view and perspective geometry that can be leveraged to formulate a vision problem in such a way that its solution is simple and tractable. However, when it comes to predicting the effect of physical interaction that does not only change the viewpoint of the agent on the environment, but the environment itself, we are yet to develop rich, expressive and tractable models.
Lastly, AP mainly focuses on simplifying challenging perception problems. However, a robot should also be able to manipulate the environment in a goal-directed manner. Sandini et al. [23, p.167] formulate this as a difference in how visual information is used: in AP it is mainly devoted to exploration of the environment whereas in IP it is also used to monitor the execution of motor actions.

2) Early Examples of Interactive Perception: There are a number of early approaches within the area of Active Perception that exploit forceful interaction with the environment and are therefore early examples for IP approaches. Tsikos and Bajcsy [25, 26] propose to use a robot arm to make the scene simpler for the vision system through actions like pick, push and shake. The specific scenario is the separation of random heaps of objects into sets of similar shapes. Bajcsy [27], Bajcsy and Sinha [28] propose the *Looker and Feeler* system that allows to perform material recognition of potential footholds for legged locomotion. The authors hand-design specific exploration procedures of which the robot observes the outcome (visually or haptically) to determine material attributes. Salganicoff and Bajcsy [29] show how the mapping between observed attributes, actions and rewards can be learned from training data gathered during real executions of a task. Sandini et al. [24, Section 3] propose to use optical flow analysis of the object motion while it is being pushed. The authors show that through this analysis, they can retrieve both geometrical and physical object properties which can then be used to adapt the action.

D. Active Haptic Perception

Haptic exploration of the environment relies on haptic sensing that requires contact with the environment. Interpretation of a sequence of such observations is part of IP as it requires a forceful and time-varying interaction. The interpretation of an isolated haptic *frame* without temporal information is similar to approaches in Computer Vision such as semantic scene understanding from static images [40].

Early approaches that use touch in an active manner are applied to problems such as reconstructing shape from touch [31], recognizing objects through tracing their surface [32] or exploring texture and material properties [31]. The complementary nature of vision and touch has been explored by Allen and Bajcsy [33] in reconstructing 3D object shape. A more complete review of these early approaches towards active haptic perception is contained in [30, 22].

More recent examples include [23] to learn haptic object representations, [34, 35, 36] for object detection and pose estimation, [37, 38, 39] for reconstructing the shape of objects or the environment as well as [40, 41, 42] for texture classification or description. The most apparent difference of these recent approaches to earlier work lies in the use of machine learning techniques to either automatically find suitable exploration strategies, to learn suitable feature representations or to better estimate different quantities.

In general, active haptic perception requires deliberate contact interaction but the majority of the cases do not aim at changing the environment. Instead, for simplification, objects or the environment are often assumed to be rigid and static during contact.

IV. APPLICATIONS OF INTERACTIVE PERCEPTION

Interactive perception methods may be applied to achieve an estimation or a manipulation goal. Currently, the vast majority of IP approaches estimate some quantity of interest through forceful interaction. Other IP approaches pursue either a grasping or manipulation goal. This means that they aim to manipulate the environment to bring it into a desired state. Usually this includes the estimation of quantities that are relevant to the manipulation task.

Existing IP approaches can be broadly grouped into ten major application areas as visualized in Figure 4. In this section, we briefly describe each of these areas. For the first three applications (Object Segmentation, Articulation Model Estimation and Object Dynamics Learning), we use a couple of simple examples (Figures 5 and 6) to allow the reader to better appreciate the benefits of IP and understand its distinction to Active Perception.

A. Object Segmentation

Object segmentation is a difficult problem and, in the area of Computer Vision, it is often performed on single images [104, 105, 106]. To illustrate the challenges, consider the simple example scenario depicted in Figure 5. Two Lego blocks are firmly attached to the table. The robot is supposed to estimate the number of objects on the table. When the robot is a passive observer of the scene as in Fig. 5 [Left], it would be very challenging to estimate the correct number of Lego blocks on the table without incorporating a lot of prior knowledge. The situation does not improve in this static scenario even with more sensory data from different viewpoints or after zooming in.

When the robot observes another agent interacting with the scene as shown in Fig. 5 [Center], it will be able to segment the Lego blocks and correctly estimate the number of objects in the scene. This is an example of how forceful interactions can create rich sensory signals that would otherwise not be present (CNS). The new evidence in form of motion cues simplifies the problem of object segmentation.

The ability to interact with the scene allows a robot to also autonomously generate more informative sensory information as visualized in Fig. 5 [Right]. Reasoning about the regularity in $S \times A \times t$ may lead to even better segmentation since the robot can select actions that are particularly well suited for reducing the segmentation uncertainty (APR).

For these reasons, object segmentation has become a very popular topic in Interactive Perception. For example, Fitzpatrick and Metta [53], Metta and Fitzpatrick [54] are able to segment the robot’s arm and the objects that were moved in a scene. Gupta and Sukhatme [50], Chang et al. [56] use predefined actions to segment objects in cluttered environments. van Hoof et al. [48] can probabilistically reason about optimal actions to segment a scene.

B. Articulation Model Estimation

Another problem that is simplified through Interactive Perception is the estimation of object articulation mechanisms. The robot has to determine whether the relative movement of two objects is constrained or not. Furthermore, it has to understand whether this potential constraint is due to a prismatic or revolute articulation mechanism and what the pose of the joint axis is. Fig. 5 [Left] visualizes an example situation in which the robot has to estimate the potential articulation mechanism between two Lego blocks given only visual observations of a static scene. This is almost impossible to estimate from single images without including a lot of prior semantic knowledge. It is also worth noting that this situation is not improved if gathering more information from multiple viewpoints of this otherwise static scene.
In Fig. 5 [Center], the robot observes an agent lifting the top-most Lego block. This is another example of how forceful interactions create a novel, informative sensory signal (CNS). In this case it is a straight-line, vertical motion of one Lego block. It provides evidence in favor of a prismatic joint in between these two objects (although in this case, this is still incorrect).

When the robot autonomously interacts with the scene it creates these informative sensory signals not only in the visual but also haptic sensory modality. This data is strongly correlated with a particular articulation mechanism. Fig. 5 [Right] visualizes this scenario. By leveraging knowledge of the regularity in $S \times A \times t$, the robot can also form a correct hypothesis of the articulation model (APR). The Lego blocks are rigidly attached at first, but when the robot applies enough vertical force to the top-most Lego block, there is sensory evidence for a free body articulation model.

In the literature, there are offline estimation approaches towards this problem that either rely on fiducial markers [95] or marker-less tracking [99, 103]. There are also online approaches [96] where the model is estimated during the move-
ment. Most recent methods include reasoning about actions to actively reduce the uncertainty in the articulation model estimates [98] [100] [101].

C. Object Dynamics Learning and Haptic Property Estimation

Interactive Perception has also made major inroads into the challenge of estimating haptic and inertial properties of objects. Fig. 6 shows a simple example scenario that shall serve to illustrate why IP simplifies the problem. Consider a sphere that is lying on a table. The robot is supposed to estimate the weight of the sphere given different sources of information. We assume that the robot knows the relationship between push force, distance the sphere traveled and sphere weight. In the trivial static scenario illustrated in Fig. 3 [Left], the robot is not able to estimate any of the inertial properties. It encounters similar problems as in the previous example (Fig. 3) even if it was able to change the viewpoint.

In Fig. 6 [Center], the robot can observe the motion of the sphere that is pushed by a person. Now, the robot can easily segment the ball from the table due to the additional sensory signal that was not present before (CNS). However, it remains very difficult for the robot to estimate the inertial properties of the sphere because it does not know the strength of the push. Without this information, the known regularity in $S \times A \times t$ cannot be exploited. The robot will only be able to obtain a very uncertain estimate of the sphere weight because it needs to marginalize over all the possible forces the person may have applied.

In Fig. 6 [Right], the robot interacts with the sphere. It can control the push force that is applied and observe the resulting distance at which the sphere comes to rest. Given the knowledge of the strength of the push, it can now exploit the known associations between actions and sensory responses to estimate the spheres inertial properties (APR).

There are several examples that leverage the insight that IP enables the estimation of haptic and inertial properties. For example, [92] [42] show that surface and material properties of objects can be more accurately estimated if the robot’s haptic sensor is moved along the surface of the object.

Atkeson et al. [75] and Zhang and Trinkle [76] move the object to estimate its inertial properties or other parameters of object dynamics which are otherwise unobservable.

D. Object Recognition or Categorization

Approaches to detect object instances or objects of a specific category have to learn the appearance or shape of these objects under various conditions. There are many challenges in object recognition or categorization that make this task very difficult given only a single input image. A method has to cope with occlusions, different lighting conditions, scale of the images, just to name a few. State-of-the-art approaches in Computer Vision as e.g. [107] [108] require enormous amounts of training data to handle these variations.

Interactive Perception approaches allow a robot to move objects and hence reveal previously hidden features. Thereby it can resolve some of the aforementioned challenges autonomously and may alleviate the need for enormous amounts of training data. Example approaches that perform object segmentation and categorization can be found in [46] [57]. The challenge of object recognition/categorization has been tackled by Sinapov et al. [59] and Hausman et al. [61].

E. Multimodal Object Model Learning

Learning models of rigid, articulated and deformable objects is a central problem in the area of Computer Vision. In the majority of the cases, the model is learned or built from multiple images of the same object or category of objects. Once the model is learned, it can be used to find the object in new, previously unseen contexts.

A robot can generate the necessary data through interaction with the environment. For example, Krainin et al. [88] present an approach where a robot autonomously builds an object model while holding the object in its hand. The object model is completed by executing actions informed by next best view planning. Kenney et al. [59] push an object on the plane and accumulate visual data to build a model of the object.

There are also approaches that build an object model from haptic sensory data, e.g. by Dragiev et al. [37], Allen and Bajcsy [33], Bohg et al. [59], Ilonen et al. [89], Björkman et al. [90] show examples that initialize a model from visual data and then further augment it with tactile data. Sinapov et al. [59] present a method where a robot grasps, lifts and shakes objects to build a multi-modal object model.

F. Object Pose Estimation

Interactive perception has also been applied to the problem of object pose estimation. Related approaches focus on reducing object pose uncertainty by either touching or moving it.

Koval et al. [78] employ manifold particle filters for this purpose. Javdani et al. [56] use information-theoretic criteria such as information gain to actively reduce the uncertainty of the object pose. In addition to reducing uncertainty, they also provide optimality guarantees for their policy.

G. Grasp Planning

Cluttered scenes and premature object interactions used to be considered as obstacles for grasp planning that had to be avoided by all means. In contrast, Interactive Perception approaches in this domain take advantage of the robot’s ability to move objects out of the way or to explore them to create more successful plans even in clutter or under partial information.

Hsiao et al. [81] use proximity sensors to estimate the local surface orientation to select a good grasp. Dragiev et al. [87] devise a grasp controller for objects of unknown shape which combines both exploration and exploitation actions. Object shape is represented by a Gaussian Process implicit surface. Exploration of the shape is performed using tactile sensors on the robot hand. Once the object model is sufficiently well known, the hand does not prematurely collide with the real object during grasping attempts.

H. Manipulation Skill Learning

In some cases the goal of Interactive Perception is to accomplish a particular manipulation skill. This manipulation skill is generally a combination of some of the pre-specified goals.

To learn a manipulation skill Kappler et al. [66], Pastor et al. [65] represent the task as a sequence of demonstrated behaviors encoded in a manipulation graph. This graph provides a strong prior on how the actions should be sequenced to accomplish the task. Lee et al. [64] uses a set of kinesthetic demonstrations to learn the right variable-impedance control strategy. Cusumano-Towner et al. [63] propose a planning approach that uses a previously-learned Hidden Markov Model to fold clothes.

The approaches discussed above can be thought of as methods that capture the regularity of complex manipulation behaviors in $S \times A \times t$ by learning them via demonstration.
I. State Representation Learning

In the majority of the IP approaches, the representation of sensory data and latent variables are pre-specified based on prior knowledge about the system and task. There are however some approaches that learn these representations. Most notable are Jonschkowski and Brock [71], Levine et al. [74], Wahlström et al. [73]. All of them learn some mapping from raw, high-dimensional sensory input (in this case images) to a lower-dimensional state representation. All of these example approaches fix the structure of this mapping, e.g. linear mapping with task-specific regularizers [71] or Convolutional Neural Networks [74, 73]. The parameters of this mapping are learned from data.

V. Taxonomy of Interactive Perception

In this section, we identify a number of important aspects that characterize existing IP approaches. These are additional to the two benefits of CNS and APR and independent of the specific application of an approach. We use these aspects to taxonomize and group approaches in the Tables 8 and 9. In the following, each table column is described in detail in a subsection along with example approaches. We use paper sets to refer to groups of similar approaches that address the same application, e.g. either object segmentation or manipulation skill learning. We split paper sets further into approaches that either exploit CNS or APR. We also list papers separately that do not pursue a unique goal, e.g. they perform both Object Segmentation and Recognition.

1) Commonalities and differences between CNS and APR: Approaches that exploit the novel sensory signal (CNS) also rely on regularities in the sensory response to an interaction. In its most basic form, this regularity is usually linked to some assumed characteristic of the environment that thereby restricts the expected response of the world to an arbitrary action. Even more useful to robust perception and manipulation is to also include prior knowledge about the response to a specific interaction (APR).

Fig. 7. Spectrum of the extent to which knowledge about the Action Perception Regularity (APR) is exploited by IP approaches. Example problems are plotted along the x-axis. Their placement depends on how much prior knowledge about the interaction in the environment is commonly used in existing approaches towards them.

For example, approaches towards basic visual object tracking or optical flow use very weak priors to regularize the solution space without incorporating knowledge about the specific interaction that caused the novel sensory response (CNS). Similar to that, approaches towards motion-based object segmentation often rely on interpreting a novel sensory response caused by an arbitrary interaction (CNS). Approaches towards object pose estimation often choose an action that is expected to provide the most informative sensory signal (APR).

1) How is the signal in $S \times A \times t$ leveraged?

An IP approach leverages at least one of the two aforementioned benefits: (i) it exploits a novel sensory signal that is due to some time-varying, forceful interaction (CNS) or (ii) also leverages prior knowledge about the regularity in the combined space of sensory data and action parameters over time $S \times A \times t$ for predicting or interpreting this signal (APR).
### Goals & Paper Set ID

| Papers | How is the signal in $S \times A \times t$ leveraged? | What priors are employed? | Does the approach perform action selection? | What is the objective: perception, manipulation or both? | Are multiple sensor modalities exploited? | How is uncertainty modeled and used? |
|--------|--------------------------------------------------|---------------------------|--------------------------------------------|------------------------------------------------|--------------------------------------|----------------------------------|
| [61] [11] [12] | APR | RO [61], OD, AP | M [61], x [11] [12] | P [11] [61], [12] | x(Vision) | no dynamics [12], SDM [61], SOM [11], EU [61], [11] |
| 53 55 54 44 49 56 50 51 45 52 46 109 | CNS | RO, PM 54 55 56 50 51 45 49 56 50 51 45 52 46 109, OD 54, AP 44 49 56 50 51 45 | x 53 55 54 44 49 56 50 51 45 52 46 109 | P 53 55 54 44 49 56 50 51 45 52 46 M 109 | x(Vision) | no dynamic model, DOM 53, 54, 56 50, 51, 45 52, 46, SOM 55, 44 49, 109, EU 49, 109 |
| 47 48 | APR | AP | M | P | x(Vision) | SDM, SOM, EU |
| 57 | CNS | RO, AP, PM | M | P | x(Vision) | no dynamic model, DOM |
| 53 | APR | RO, AP | G | P | x(Vision) | DDM, SOM, EU |
| 43 | CNS | AO | x | P | x(Vision) | no dynamics, SOM |
| 100, 103 99 96 95 110 | CNS | AO | x 103 99 96 95 110, M 100 | P | x(Vision) | no dynamics [103], SOM [99], SDM [96, 100], EU [43, 103, 99, 96, 110] |
| 94, 102 97 98 101 | APR | AO, PM 97 | M 98, 101, G 94, 102, 97 | P 98, 101, B 94, 102, 97 | x(Vision, Tactile) 98, (Force/Torque or Joint Positions, Visual Odometry)[94, 97, 101], x(Vision) 97, 101 | SDM 98, 101, SOM 98, 101, EU 98, 101, DDM 94, 102, 97, DOM 94, 102, 97 |
| 36 79 78 | APR | RO, PM, OD, SD 78 | x 78, M 36, G 79 | P 36, 78, M 79 | x(Tactile) 36, 78, x(Vision) 79 | static environment 36, SDM 79, 78, SOM 36, 78, DOM 79, EU 58, 78 |
| 77 | CNS | RO, PM, OD | x | P | x(Vision) | SDM, EU, DOM |
| 76 | APR | RO, PM, AP | x | P | x(Vision, Tactile) | SDM, EU, SOM |
| 75 | APR | RO, AP, OD | x | P | x(Force/Torque) | DDM, DOM |
| 82, 111, 112 | CNS | RO 82, 111, OD 82, 111, AP 82, 111, DO 112 | x 111, G 112, (dependent on the algorithm in 82) | P 82, M 111, 112 | x(Vision) | no dynamics, DOM 111, SOM 82, 112, EU 112 |

Fig. 8. Taxonomy of Interactive Perception approaches - Part I

- **Create Novel Signals (CNS) vs Action Perception Regularity (APR)**
- A prior is a source of information that aids in the interpretation of the sensor signal by rejecting noise, possibly by projecting the signal into a lower dimensional space. RO-rigid objects, AP-action primitives, PM-planar motion, OD-object database, SD-simple dynamics, AO-articulated objects, DO-deformable objects.
- Alternatively, it can rely on some hard-coded action or just interpret/exploit the interaction induced by something/someone else. M=myopic/greedy, PH=variable planning horizon, G=global policy
- Does the approach use multiple modalities? If so, which ones?
- Is uncertainty explicitly represented? How is it used? DDM-deterministic dynamics model, SDM-stochastic dynamics model, DOM-deterministic observation model, SOM-stochastic observation model, EU-estimates uncertainty
| Goals & Paper Set ID | Papers | How is the signal in $S \times A \times t$ leveraged? | What priors are employed? | Does the approach perform action selection? | What is the objective: perception, manipulation or both? | Are multiple sensor modalities exploited? | How is uncertainty modeled and used? |
|----------------------|--------|-----------------------------------------------|-----------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| Grasp Planning II    | [83]   | APR                                           | RO, AP          | $\checkmark$                     | (Proximity Sensors $\checkmark$) | (Vision $\checkmark$) | no dynamic model, DOM, SOM, EU |
| Grasp Planning - Pose Estimation | [81] | APR                                           | RO, AP          | $\checkmark$                     | (Vision, Tactile)              | no dynamics, DOM, SOM, EU |
| Haptic Property Estimation I | [92] | CNS                                           | RO, AP, OD, PM, AP | $\checkmark$                     | (Vision, Tactile)              | no dynamics model, SOM, EU |
| Haptic Property Estimation II | [41] | APR                                           | PM, AP, OD      | $\checkmark$                     | (Vision, Tactile)              | no dynamics model, SOM, EU |
| Multimodal Object Model Learning I | [93] | CNS                                           | RO, AP, PM      | $\checkmark$                     | (Vision, Tactile)              | no dynamics model, SOM, EU |
| Multimodal Object Model Learning II | [37, 88, 59] | APR                                        | RO, AP          | $\checkmark$                     | (Vision, Tactile)              | no dynamics model, SOM, EU |
| Multimodal Object Model Learning - Object Recognition | [59, 62] | CNS                                           | RO, AP          | $\checkmark$                     | (Vision, Audio, Tactile)       | no dynamics model, SOM, EU |
| Multimodal Object Model Learning - Grasp Planning | [87] | APR                                           | RO              | $\checkmark$                     | (Vision, Tactile)              | no dynamics model, SOM, EU |
| Manipulation Skill Learning | [66] | APR                                           | OD, RO, DO      | $\checkmark$                     | (Vision, Internal torques)     | no dynamics model, SOM, EU |
| Manipulation Skill Learning - State Representation Learning | [73] | APR                                           | OD, RO          | $\checkmark$                     | (Vision, Joint Pos.)           | DOM, SDM, SD, EU |
| State Representation Learning | [71] | APR                                           | SD, AP, PM, RO  | $\checkmark$                     | (Vision, Tactile)              | DDM, DOM |
| State Representation Learning - Object Dynamics Learning | [70] | APR                                           | AP, PM, RO, OD  | $\checkmark$                     | (Vision, Tactile)              | DDM, DOM |

Fig. 9. Taxonomy of Interactive Perception approaches - Part 2

*Create Novel Signals (CNS) vs Action Perception Regularity (APR)
*A prior is a source of information that aids in the interpretation of the sensor signal by rejecting noise, possibly by projecting the signal into a lower dimensional space. RO-rigid objects, AP-action primitives, PM-planar motion, OD-object database, SD-simple dynamics, AO-articulated objects, DO-deformable objects.
*Alternatively, it can rely on some hard-coded action or just interpret/exploit the interaction induced by something/someone else. M=myopic/greedy, PH=variable planning horizon, G=global policy
*Does the approach use multiple modalities? If so, which ones?
*Is uncertainty explicitly represented? How is it used? DDM-deterministic dynamics model, SDM-stochastic dynamics model, DOM-deterministic observation model, SOM-stochastic observation model, EU-estimates uncertainty
torques if given this prior information on the structure of the space $S \times A \times t$ and data from interaction. Sinapov et al. \cite{59,60}, Sinapov and Stoytchev \cite{62} let a robot interact with a set of objects that are characterized by different attributes such as rigid or deformable, heavy or light, slippery or not. Features computed on the different sensor modalities serve as the basis to learn object similarity. The authors show that this task is eased when the learning process is conditioned on joint torques and the different interaction behaviors. They also use the knowledge of the interaction in \cite{62,60} to correlate various sensor modalities in the $S \times A \times t$.

Zhang and Trinkle \cite{76}, Koval et al. \cite{78} track object pose using visual and tactile data while a robot is pushing this object on a plane. Zhang and Trinkle \cite{76} solve a non-linear complementarity problem within their dynamics model to predict object motion given the control input. At the same time, they use observations of the object during interaction for estimating parameters of this model such as the friction parameters. Koval et al. \cite{78} assume knowledge of a lower-dimensional manifold that describes the different contact states between a specific object and hand during a push motion. Hypotheses about future object poses are constrained to lie on this manifold. Hausman et al. \cite{68}, Hsiao et al. \cite{113} condition on the action to drive the estimation process. Hsiao et al. \cite{113} estimate the belief state by conditioning the observations on the expected action outcomes. Hausman et al. \cite{68} adopt a similar approach to estimate the distribution of possible articulation models based on action outcomes.

B. What priors are employed?

To devise an IP system means to interpret and/or deliberately generate a signal in the $S \times A \times t$. The regularity of this signal can be programmed into the system as a prior incorporating knowledge of the task; it can be learned from scratch or the system can pick up these regularities using a mixture of both priors and learning. Therefore an important component of any IP system is this regularity and how it is encoded and exploited for performing a perception and/or manipulation task.

1) Priors on the Dynamics: Interactive Perception requires knowledge of how actions change the state of the environment. Encoding this kind of regularity can be done in a dynamics model i.e. the model for predicting the evolution of the environment after a certain action has been applied. Dependent on the number of objects in the environment, this prediction may be very costly to compute. Furthermore, due to uncertainty and noise in robot-object and object-object interactions, the effects of the interactions are stochastic.

a) Given/Specified/Engineered Priors: There are many approaches that rely on priors which simplify the dynamics model and thereby make it less costly to predict the effect of an action. Examples of commonly used priors are the occurrence of only rigid objects (RO), of articulated objects (AO) with a discrete set of links or of only deformable objects (DO). Another prior includes the availability of a set of action primitives (AP) such as push, pull, grasp, etc. These action primitives are assumed to be accurately executed without failure. Many approaches assume that object motion is restricted to a plane (PM) or other simplifications of the scene dynamics (SD), e.g. quasi-static motion during multi-contact interaction between objects. In this section, each prior will be explained in more detail by using one or several example approaches that exploit them.

Of the highlighted priors some are more commonly used than others. For instance apart from papers in paper set (Object Segmentation II, Object Segmentation - Object Recognition II, Haptic Property Estimation II) almost all other approaches make assumptions about the nature of objects in the environment, i.e. they assume that all objects present in the environment belong exclusively to one of three classes: rigid, articulated or deformable.

The majority of approaches in Interactive Perception assume that the objects are rigid (RO). Only approaches concerned with estimating an articulation model assume the existence of articulated objects. Similarly, Levine et al. \cite{112}, Cusumano-Towner et al. \cite{63}, Lee et al. \cite{64} in paper set Manipulation Skill Learning are unique in that they are the only ones that deal with the manipulation of deformable objects (DO).

Many approaches in the paper set Object Segmentation I utilize the planar motion prior (PM). In instances such as Gupta and Sukhatme \cite{50}, this prior is used for scene segmentation where all the objects in the scene are assumed to lie on a table plane. In other approaches e.g. \cite{50,51,45,52,46} in Object Segmentation I, \cite{53} in Multimodal Object Model Learning I and \cite{59,90} in Multimodal Object Model Learning II the planar motion assumption is used not only for scene segmentation, but also to track the movement of objects in the environment.

Then there are approaches which make additional simplifying assumptions about the dynamics of the system (SD). For instance Koval et al. \cite{80} assume that the object being manipulated has quasi-static dynamics and moves only on a plane (PM). Such an assumption becomes particularly useful in cases where action selection is performed via a multi-step planning procedure because it simplifies the forward prediction of object motion.

b) Learned Priors: There are approaches that learn a dynamics model of the environment given an action. Some of these let the robot learn this autonomously through trial and error. Early approaches towards this are by Christiansen et al. \cite{79}, Metta and Fitzpatrick \cite{54} that learn a simple mapping from the current state and action to a most likely outcome. \cite{79} demonstrate this in a tray-tilting task for bringing the object lying on this tray into a desired configuration. \cite{54} demonstrate their approach in an object pushing behavior and learn the response of an object to a certain push direction. Both of them model the non-determinism of the response of the object to an action. More recent approaches are presented by Levine et al. \cite{67}, Han et al. \cite{68}, Wahlström et al. \cite{73} where the authors learn the mapping from current state to next best action in a policy search framework. Kappler et al. \cite{66}, Pastor et al. \cite{65}, Lee et al. \cite{64} bootstrap the search process through trial and error by demonstrating actions.

2) Priors on the Observations: Regularities can also be encoded in the observation model that relates the state of the system to the raw sensory signals. Thereby it can predict the observation given the current state estimate. Only if this relationship is known, an IP robot can gain information from observations. This information may be about some quantity of interest that needs to be either estimated or directly provide the distance to some goal state.

a) Given/Specified/Engineered Observation Models: Traditionally, the relationship between the state and raw sensory signals is hand-designed based on some expert knowledge. One example are models of multi-view or perspective geometry for camera sensors \cite{14,124}. Often, approaches also assume access to an object database (OD) that allows them to predict how the objects will be observed through a given sensor, e.g. by Chu et al. \cite{42}.

b) Learned State Representations: More recently, we see more approaches that learn a suitable, task-specific state representation directly from observations. Examples include Jon-
C. Does the approach perform action selection?

Knowledge about the structure of $S \times A \times t$ can also be exploited to select appropriate actions. A good action will reveal as much information as possible and at the same time bring the system as close as possible to the manipulation goal. If we know something about the structure of $S \times A \times t$, we can perform action selection so as to make the resulting sensor information as meaningful as possible. The agent must balance between exploration (performing an action to improve perception as much as possible) and exploitation (performing an action that maximizes progress towards the manipulation goal).

1) Problem Formulation: For optimal action selection, the IP agent needs to know a policy that given the current state estimate returns the optimal action or sequence of actions to take. Here, optimal means that the selected actions yield a maximum expected reward to the IP agent. The specific definition of the reward function heavily depends on the particular task of the robot. If it is a purely perceptual task, actions are often rewarded when they reduce the uncertainty about the current state, costs associated with the system, etc. Levine et al. [71] demonstrate such an approach to action selection for interactive perception. Another way of finding global policies is to formulate them as POMDPs. In practice the solution to such problems is intractable to find the optimal policy of the corresponding POMDP. Therefore, there exist many methods that find approximate solutions to this problem [77].

PSRs are another formalism for action selection. Here, the system dynamics are represented directly by observable quantities in the form of a set of tests instead of over some latent state representation as in POMDPs [128, 129, 130].

3) Planning Horizon: Action selection methods can be categorized based on the number of steps they look ahead in time. There are approaches that have a single step look ahead which are called myopic or greedy (M). Here the agent’s actions are optimized for rewards in the next time step given the current state of the system. Most approaches to interactive perception that exploit the knowledge of the outcome of an action in $S \times A \times t$ are myopic (M). Myopic approaches do not have to cope with the evolution of complex system dynamics or observation models beyond a single step. Hence this considerably reduces the size of the possible solution space. Examples of such approaches can be seen in paper sets Object Segmentation II [98, 101], in Articulation Model Estimation II [73] and in the paper set Pose Estimation.

Then, there are approaches which look multiple steps ahead in time to inform their action selection process. These multi-step look-ahead solutions decide an optimal course of action also based on the current state of the system. The time horizon for these multi-step look-aheads can either be fixed or variable. In either case, the time horizons are generally dictated by a budget, examples of which include computational resources, uncertainty about the current state, costs associated with the system, etc. For instance, a popular multi-step look ahead approach relies on the assumption that the maximum likelihood estimate (MLE) observation will be obtained in the future. This way, one can predict the behavior of the system within the time horizon and use it to select an action. Overall we label such approaches to action selection as planning horizon approaches (PH). Examples of these approaches include [81, 83].

Another set of methods tries to find global policies that specify the action that should be applied at any point in time for any state. We categorize such approaches as methods that have global policies (GP) Among these, there are approaches that take into account all possible distributions over the state space (beliefs) and offer globally optimal policies. These policies account for stochastic belief system dynamics, i.e. they maintain probabilities over the possible current states and probable outcomes given an action. Such methods are often solved by formulating them as POMDPs. In practice the solution to such problems is intractable and are often solved by approximate offline methods. Javdani et al. [56], Koval et al. [80] demonstrate such an approach to action selection for interactive perception. Another way of finding global policies uses reinforcement learning which provides a methodology to improve a policy over time. An example of a specific policy search method is presented by Levine et al. [67], Han et al. [68], Levine et al. [74].

Apart from planning based approaches that perform action selection, there are approaches that focus on low-level control. In these approaches, the control input is computed online for the next cycle based on a global control law. We also classify these methods as global-policy (GP) approaches as they compute the

As mentioned earlier, a realistic dynamics model should be stochastic to account for uncertainty in sensing and execution. In this case, to find the optimal sequence of actions the agent has to form an expectation over all the possible future outcomes of an action. The dynamical system can then be modeled as an MDP. Finding the optimal sequence of actions can be achieved through approaches such as value or policy iteration [126].

In an MDP, we assume that the state of the system is directly observable. However in a realistic scenario, the robot can only observe its environment through noisy sensors. This can be modeled with a POMDP where the agent has to maintain a probability distribution over the possible states, i.e. the belief, based on an observation model. For most real-world problems, it is intractable to find the optimal policy of the corresponding POMDP. Therefore, there exist many methods that find approximate solutions to this problem [77].
next control input based on control law that is global, e.g. the feedback matrix in Linear Gaussian Controllers. The actions are generated at a high frequency and operate on low-level control commands. Examples of these approaches include [94, 102, 84, 87, 37].

4) Granularity of Actions: Action selection can be performed at various granularities. For example, a method may either select the next best control input or an entire high-level action. The next best controls can be low-level motor torques that are sent to the robot in the next control cycle. The corresponding action selection loop is executed at a very high frequency and is dependent on the immediate feedback from different sensors [94, 102, 84, 87, 37].

High-level action primitives are generally used in approaches that do not require reasoning about fine motor control such as pushing or grasping actions that are represented by motion primitives. In such cases, reasoning about observations is purely dependent on the outcome of high-level actions. There are numerous approaches that utilize high-level actions for interactive perception. Examples include: Burragán et al. [100] and the following authors in paper set Object Segmentation I: Fitzpatrick and Metta [53], Metta and Fitzpatrick [54], Kenney et al. [55] and Bergström et al. [44], Sturm et al. [95], Pillai et al. [99], Martin Martin and Brock [96].

D. What is the objective: Perception, Manipulation or Both?

Approaches to Interactive Perception may pursue a perception or a manipulation goal and in some cases both (see Fig. 4). Object segmentation, recognition and pose estimation, multimodal object model learning and articulation model estimation are examples of areas where interactive perception is utilized to service perception.

Then there are interactive perception approaches whose primary objective is to achieve a manipulation goal (e.g. grasping or learning manipulation skills). For instance Kappler et al. [66], Pastor et al. [65], exploit regularities in $S \times A \times t$ to enable better action selection. The robot compares the observed perceptual signal with the expected perceptual signal given the current manipulation primitive. It then picks controls that drive the system towards the expected signal. Similarly, Koval et al. [78], Kaelbling and Lozano-Pérez [81], Platt et al. [83] exploit the regularities in $S \times A \times t$ to facilitate task oriented grasping, i.e locate and grasp an object of interest.

The final thread of interactive perception approaches include a combination of both perception and manipulation. For instance, Dragiev et al. [87], Koval et al. [80] simultaneously improve perception (object model reconstruction or pose estimation, respectively) and select better actions under uncertainty (efficient grasping). In Jain and Kemp [94], Karayiannidis et al. [102] in paper set Articulation Model Estimation II, the knowledge about the regularity in both the observations and dynamics in $S \times A \times t$ is used to improve articulation model estimation as well as to enable better control. In the case of Karayiannidis et al. [102], the control input is directly incorporated into the state estimation procedure. In contrast, Jain and Kemp [94] use the position of the end effector in the articulation mechanism estimation. The manipulation goal in both these approaches is to enable a robot to open doors and drawers.

E. Are multiple sensor modalities exploited?

Some approaches exploit multiple modalities in the $S \times A \times t$ space, whereas other approaches restrict themselves to a single informative modality. The various sensing modalities can be broadly categorized into contact and non-contact sensing. Examples of non-contact sensing include vision, proximity sensors, sonar, etc. Contact sensing is primarily realized via tactile sensors and force-torque sensors. Approaches that only use tactile sensing include the works of Chu et al. [42], Koval et al. [78, 80], Javdani et al. [36]. There are also approaches that use both contact and non-contact sensing to inform the signal in the $S \times A \times t$ space. These include some of the works listed in paper sets Articulation Model Estimation II, Pose Estimation - Object Dynamics Learning II, Multimodal Object Model Learning I & II and Manipulation Skill Learning in Tables 8 and 9.

F. How is uncertainty modeled and used?

In Interactive Perception tasks, there are many sources of uncertainty about the quantity of interest. One of them is the noisy sensors through which an agent can only partially observe the current state of the world. Another is the dynamics of the environment in response to an interaction. Some approaches towards Interactive Perception model this uncertainty in either their observations and/or the dynamics model of the system. Depending on their choice, there are a wide variety of options for estimating the quantity of interest from a signal in $S \times A \times t$. For updating the current estimate, some approaches use recursive state estimation and maintain a full posterior distribution over the variable of interest, e.g. [76, 90, 78]. Others frame their problem in terms of energy minimization in a graphical model and only maintain the maximum a posteriori (MAP) solution from frame to frame, e.g. [44]. An MLE of the variable of interest is computed in approaches that do not maintain a distribution over possible states. Examples are clustering methods that assign fixed labels [56, 50, 51, 53] to the variable of interest. More recently non-parametric approaches have also been utilized. For instance Boularias et al. [86] use kernel density estimation.

Methods that model uncertainty of the variable(s) of interest can cope better with noisy observations or dynamics, but they become slower to compute as the size of the solution space grows. This creates a natural trade-off between modeling uncertainty and computational speed. The above choices also have implications for action selection. If we maintain a full distribution over the quantity of interest, then computing a policy that takes the stochasticity in the dynamics and observation models into account is generally intractable [25]. If an approach assumes a known state, the dynamical system can also be modeled by an MDP with stochastic dynamics given an action. The least computationally demanding model for action selection is the one that neglects any noise in the observations or dynamics. However, it might also be the least robust depending on the true variance in the real dynamical system that the agent tries to control.

Based on the above, we propose four labels for IP approaches with respect to their way of modeling and incorporating uncertainty in estimation and manipulation tasks. Approaches that assume deterministic dynamics are labeled (DDM), stochastic dynamics (SDM), deterministic observations (DOM), stochastic observations (SOM) and approaches that estimate uncertainty are labeled (EU).

Fitzpatrick and Metta [53], Metta and Fitzpatrick [54], Kenney et al. [55] propose example approaches that assume no stochasticity in the system, and model both the dynamics and observations deterministically. Then there are approaches that assume deterministic observations but do not model the dynamics at all. These are listed in paper set Object Segmentation.
I which include the works of Chang et al. [56], Gupta and Sukhatme [50], Hausman et al. [51, 45], Kuzmic and Ude [52], Schiebener et al. [46]. Then there are approaches that model only stochastic observations but no dynamics because they assume that the environment is static upon interaction, e.g. Hsiao et al. [84]. Most approaches that assume both stochastic dynamics and observations have some form of uncertainty estimation technique implemented to account for the stochasticity in the system. An approach that assumes stochasticity in its observations but does not estimate uncertainty is Chu et al. [42]. Here the authors train a max-margin classifier to assign labels to stochastic observations.

VI. DISCUSSION AND OPEN QUESTIONS

A. Remaining Challenges

If Interactive Perception is about merging perception and manipulation into a single activity then the natural question arises of how to balance these components. When have manipulation actions (that are in service of perception) elicited sufficient information about the world such that manipulation actions can succeed that are in service of a manipulation goal? This question bears significant similarities with the exploration/exploitation trade-off encountered in reinforcement learning. One can further ask: how can manipulation actions be found that combine these two objectives—achieving a goal and obtaining information—in such a way that desirable criteria about the resulting sequence of actions (time, effort, risk, etc.) are optimized?

When performing manipulation tasks, humans aptly combine different sources of information, including prior knowledge about the world and the task, visual information, haptic feedback, and acoustic signals. Research in Interactive Perception is currently mostly concerned with visual information. New algorithms are necessary to extend IP towards a multi-modal framework, where modalities are selected and balanced so as to maximally inform manipulation with the least amount of effort, while achieving a desired degree of certainty. Furthermore, for every sensory channel, one might differentiate between passively (e.g. just look), actively (e.g. change vantage point to look), and interactively (e.g. observe interaction with the world) acquired information. Each of these is associated with a different cost but also with a different expected information gain. In addition to adequately mining information from multiple modalities, Interactive Perception must be able to decide in which of these different ways the modality should be leveraged.

Also at the lower levels of perception significant changes might be required. It is conceivable that existing representations of sensory data are not ideal for Interactive Perception. Given the focus on dynamic scenes with multiple moving objects, occlusions, lighting changes, and new objects appearing and old ones disappearing — does it make sense to tailor visual features and corresponding tracking methods to the requirements of Interactive Perception? Are there fundamental processing steps, similar to edge or corner detection, that are highly relevant in the context of Interactive Perception but have not seen a significant need in other applications of computer vision? The same for haptic or acoustic feedback: when combined with other modalities in the context of Interactive Perception, what might be the right features or representations we should focus on?

B. A Framework for Interactive Perception?

All of the aforementioned arguments indicate that Interactive Perception might require a departure from existing perception frameworks, as they can be found in applications outside of robotics, such as surveillance, image retrieval, etc. In Interactive Perception, manipulation is an integral component of perception. The perceptual process must continuously trade off multiple sensor modalities that might each be passive, active, or interactive. There is no stand-alone perceptual process and not only a single aspect of the environment that must be extracted from the sensor stream as the optimization objectives may change when the robot faces different tasks over its lifetime.

After the review of existing work in the field, we conclude that there is yet no framework that can address all the challenges in Interactive Perception. There are however candidates that represent the regularity in $S \times A \times t$ in a way that caters to a particular challenge encountered in IP. For instance, Krüger et al. [131] present a concept that allows to symbolically represent continuous sensory-motor experience: Object-Action Complexes (OACs). The concept’s current instantiations through the examples in [131] are focused on learning and detecting affordances [1] which describe the relationship between a certain situation (often including an object) and the action that it allows.

Other popular formalisms lend themselves particularly well to the problem of optimal action selection (see Section V-C). Examples include MDPs, POMDPs, PSRs or Multi-armed bandits. They rely on different assumptions (e.g. Markov Assumptions, observable state) and make different algorithmic choices (e.g. probabilistic modeling). Approaches that rely on these decision-making frameworks often assume the availability of transition, observation and reward functions and the possibility to analytically compute the optimal action.

For complex real-world problems this is often not the case and information about the world can only be collected through interaction. The data collected in this way is then used to update the relevant models. The problem of selecting the next best action may be based on submodularity [36], the variance in a Gaussian Process [37, 39] or the Bhattacharyya coefficient between two normal distributions [40, 41].

Reinforcement learning [126] is also a common choice to learn a policy for action selection under these complex conditions. Many approaches assume the availability of some reliable state estimator (e.g. by using motion capture or marker-based systems) where the state is of relatively low dimension and hand-designed. Particularly relevant to Interactive Perception are recent approaches that directly learn a state representation from data and employ reinforcement learning on this learned state representation [74, 71, 20].

All these formalisms have been used to solve particular sub-problems encountered in the context of Interactive Perception. We do not claim that this list is complete. However, the wealth of very different approaches suggests that there is currently not one framework for IP that can address all the relevant challenges. It is an open question what such a framework would be and how it could enable coordinated progress by developing adequate subcomponents.

C. New Application Areas

The majority of the work that is included in this survey is concerned with Interactive Perception for manipulating and grasping objects in the environment. In the context of the recent Darpa Robotics Challenge (DRC) we have also seen a need to bridge the gap between perception and action in whole-body, multi-contact motion planning and control. The ability to physically explore unstructured environments (such as those encountered in disaster sites) are of utmost importance for the safety and robustness of a robot. Probing and poking not
only with your hands but also your legs can also help extract more information. Currently, these robots extensively rely on teleoperation and carefully designed user interfaces. We argue that they can achieve a much higher degree of autonomy if they rely on Interactive Perception.

VII. Summary

This survey paper provides an overview on the current state of the art in Interactive Perception research. In addition to presenting the benefits of IP, we discuss various criteria for categorizing existing work. We also include a set of problems such as object segmentation, manipulation skills and object dynamics learning that are commonly eased using concepts of interactive perception.

We identify and define the two main aspects of Interactive Perception: (i) Any type of forceful interaction with the environment creates a new type of informative sensory signal that would otherwise not be present and (ii) any prior knowledge about the nature of the interaction supports the interpretation of the signal in the Cartesian product space of $S \times A \times t$. We use these two crucial aspects of IP as criteria to include a paper as related or not. Furthermore, we compare IP to existing perception approaches and named a few formalisms that allow to capture an IP problem.

We hope that this taxonomy helps to establish benchmarks for comparing various approaches and to identify open problems.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their insightful comments and all the cited authors who provided feedback upon our request. They would also like to sincerely thank Aleksandra Waltos for providing the visuals in Figures 5 and 6.

This research is supported in part by National Science Foundation grants IIS-1205249, IIS-1017134, EECS-0926052, the Office of Naval Research, the Okawa Foundation, and the Max-Planck-Society. It is also supported by grant BR 2248/3-1 by the German Science Foundation (DFG), and grant H2020-ICT-645599 on Soft Manipulation (Soma) by the European Commission. The authors would also like to thank Swedish Research Council and Swedish Foundation for Strategic Research. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

REFERENCES

[1] J. J. Gibson, The Ecological Approach to Visual Perception. Houghton Mifflin, 1979.
[2] J. K. O’Regan and A. Noé, “A sensorimotor account of vision and visual consciousness,” Behavioral and Brain Sciences, vol. 24, pp. 939–973, 2001.
[3] A. Noé, Action in Perception. The MIT Press, 2004.
[4] R. Held and A. Hein, “Movement-produced stimulation in the development of visually guided behaviour,” Journal of comparative and physiological Psychology, no. 56, pp. 872–876, October 1963.
[5] J. J. Gibson, The senses considered as percep tual systems. Boston: Houghton Mifflin, 1966.
[6] M. Everingham, L. Gool, C. K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (voc) challenge,” Int. J. Comput. Vision, vol. 88, no. 2, pp. 303–338, Jun. 2010.
[7] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, “ImageNet Large Scale Visual Recognition Challenge,” International Journal of Computer Vision (IJCV), vol. 115, no. 3, pp. 211–252, 2015.
[8] T.-Y. Lin, M. Maire, S. J. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, “Microsoft COCO: Common Objects in Context,” in Computer Vision – ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V, 2014, pp. 740–755.
[9] M. A. Erdmann and M. T. Mason, “An exploration of sensorless manipulation,” IEEE Journal on Robotics and Automation, vol. 4, no. 4, pp. 369–379, Aug 1988.
[10] M. Dogar, K. Hsiao, M. Ciocarlie, and S. Srinivasa, “Physics-based grasp planning through clutter,” in Proceedings of Robotics: Science and Systems, Sydney, Australia, July 2012.
[11] H. Kjellström, J. Romero, and D. Kragic, “Visual object-action recognition: Inferring object affordances from human demonstration,” Computer Vision and Image Understanding, pp. 81–90, 2010.
[12] M. Cai, K. M. Kitani, and Y. Sato, “Understanding hand-object manipulation with grasp types and object attributes,” in Proceedings of Robotics: Science and Systems, Ann Arbor, Michigan, June 2016.
[13] T. Xue, M. Rubinstein, C. Liu, and W. T. Freeman, “A computational approach for obstruction-free photography,” ACM Trans. Graph., vol. 34, no. 4, pp. 97:1–97:11, Jul. 2015.
[14] J. Aloimonos, I. Weiss, and A. Bandyopadhyay, “Active vision,” International Journal of Computer Vision, vol. 1, pp. 333–356, 1988.
[15] R. Bajcsy, “Active perception,” Proceedings of IEEE Special issue on Computer Vision, vol. 76, no. 7, August 1988.
[16] D. H. Ballard, “Animate vision,” Artificial intelligence, vol. 48, no. 1, pp. 57–86, 1991.
[17] K. Pahlavan, T. Uhlin, and J.-O. Eklundh, “Active vision as a methodology,” Active perception, pp. 19–46, 1993.
[18] P. M. Sharkey, D. W. Murray, P. F. Maclachlan, and J. P. Brooker, “Hardware Development of the Yorick Series of Active Vision Systems,” Microprocessors and Microsystems, vol. 21, no. 6, pp. 363–375, Mar. 1998.
[19] T. Astfors, K. Welke, P. Azad, A. Ude, and R. Dillmann, “The Karlsruhe Humanoid Head,” in IEEE/RAS International Conference on Humanoid Robots (Humanoids). IEEE, Dec. 2008, pp. 447–453.
[20] L. Itti and C. Koch, “Computational modelling of visual attention,” Nature Reviews Neuroscience, vol. 2, no. 3, pp. 194–203, Mar 2001.
[21] J. K. Tsotsos, S. M. Culhane, W. Y. K. Wai, Y. Lai, N. Davis, and F. Nullo, “Modeling visual attention via selective tuning,” Artificial Intelligence, vol. 78, no. 12, pp. 507–545, 1995, special Volume on Computer Vision.
[22] R. Bajcsy, Y. Aloimonos, and J. K. Tsotsos, “Revisiting active perception,” CoRR, vol. abs/1603.02729, 2016.
[23] L. Natale, G. Metta, and G. Sandini, “Learning haptic representation of objects,” in International Conference on Intelligent Manipulation and Grasping, July 2004.
[24] G. Sandini, F. Gandolfi, E. Grosso, and M. Tistarelli, Vision during Action. Lawrence Erlbaum Associates, Inc, 1993, ch. 4.
[25] C. J. Tsikos and R. K. Bajcsy, “Segmentation via manipulation,” GRASP, University of Pennsylvania, Tech. Rep., 1988.
[26] C. J. Tsikos and R. Bajcsy, “Segmentation via manipulation,” IEEE T. Robotics and Automation, vol. 7, no. 3, pp. 306–319, 1991.
[27] R. Bajcsy, Active Perception and Exploratory Robotics. Berlin, Heidelberg: Springer Berlin Heidelberg, 1993, pp. 3–20.
[28] R. Bajcsy and P. R. Sinha, “Exploration of surfaces for robot mobility,” in Proceedings of the Fourth International Conference on CAD, CAM, Robotics and Factories of the Future. Tata McGraw-Hill, December 1989.
[29] M. Salgamicoff and R. Bajcsy, “Sensorimotor learning using active perception in continuous domains,” in AAAI Fall Symposium on Sensory Aspects of Robot Intelligence, November 1991.
[30] H. R. Nicholls and M. H. Lee, “A survey of robot tactile sensing technology,” The International Journal of Robotics Research,
G. E. Loeb and J. A. Fishel, “Bayesian action & perception,” Cognition and Brain Theory, vol. 7, no. 2, pp. 199–214, 1984.

P. Allen and R. Bajcsy, “Two sensors are better than one: Example of integration of vision and touch,” in International Symposium on Robotics Research (ISRR), France, October 1985.

A. Petrovskaya and O. Khatib, “Global localization of objects via touch,” Trans. Roh., vol. 27, no. 3, pp. 569–585, Jun. 2011.

J. Hebert, T. Howard, N. Hudson, J. Ma, and J. Burdick, “The next best touch for model-based localization,” in Robotics and Automation (ICRA), 2013 IEEE International Conference on, May 2013, pp. 99–106.

S. Javdani, M. Klingensmith, J. A. Bagnell, N. S. Pollard, and S. S. Srinivasa, “Efficient touch based localization through submodularity,” in Robotics and Automation (ICRA), 2013 IEEE International Conference on, 2013, pp. 1828–1835.

S. Dragev, M. Toussaint, and M. Gienger, “Gaussian process implicit surfaces for shape estimation and grasping,” in Robotics and Automation (ICRA), 2011 IEEE International Conference on, May 2011, pp. 2845–2850.

V. Kim, M. Choi, Y. Kim, F. Liu, H. Moon, J. Koo, and H. Choi, “Exploration of unknown object by active touch of robot hand,” International Journal of Control, Automation and Systems, vol. 12, no. 2, pp. 406–414, 2014.

J. Bohg, M. Johnson-Roberson, M. Björkmann, and D. Kragic, “Strategies for multi-modal scene exploration,” in Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, October 2010.

J. Fishel and G. Loeb, “Bayesian exploration for intelligent identification of textures,” Frontiers in Neurorobotics, vol. 6, 2012.

G. E. Loeb and J. A. Fishel, “Bayesian action & perception: Representing the world in the brain,” Frontiers in Neuroscience, vol. 8, 2014.

V. Chu, T. McMahan, L. Riano, C. G. McDonald, Q. He, J. M. Perez-Tejada, M. Arrigo, T. Darrell, and K. J. Kuchenbecker, “Robotic learning of haptic adjectives through physical interaction,” Robotics and Autonomous Systems, vol. 63, pp. 279–292, 2015.

D. Katz and O. Brock, “Interactive segmentation of articulated objects in 3d,” in Workshop on Mobile Manipulation at ICRA 2011, 2011.

N. Bergström, C. H. Ek, M. Björkmann, and D. Kragic, “Scene understanding through autonomous interactive perception,” in ICVS, 2011, pp. 153–162.

K. Hausman, D. Pangeric, Z.-C. Márton, F. Bálint-Benczédi, C. Bersh, M. Gupta, G. Sukhatme, and M. Beetz, “Interactive segmentation of textured and textureless objects,” in Handling Uncertainty and Networked Structure in Robot Control. Springer International Publishing, 2015, pp. 237–262.

D. Schiebener, A. Ude, and T. Asfour, “Physical interaction for segmentation of textured and non-textured unknown rigid objects,” in IEEE International Conference on Robotics and Automation (ICRA), 2014, pp. 0–0.

H. van Hoof, O. Kroemer, H. B. Amor, and J. Peters, “Maximally informative interaction learning for scene exploration,” in IROS, 2012, pp. 5152–5158.

H. van Hoof, O. Kroemer, and J. Peters, “Probabilistic segmentation and targeted exploration of objects in cluttered environments,” in Robotics, IEEE Transactions on, vol. 30, no. 5, 2014, pp. 1198–1209.

K. Xu, H. Huang, Y. Shi, H. Li, P. Long, J. Caichen, W. Sun, and B. Chen, “Autoscan for coupled scene reconstruction and proactive object analysis,” ACM Transactions on Graphics (Proc. of SIGGRAPH Asia), vol. 34, no. 6, 2015.

M. Gupta and G. S. Sukhatme, “Using manipulation primitives for brick sorting in clutter,” in International Conference on Robotics and Automation, May 2012.

K. Hausman, F. Balint-Benczedi, D. Pangercic, Z.-C. Marton, R. Ueda, K. Okada, and M. Beetz, “Tracking-based interactive segmentation of textureless objects,” in IEEE International Conference on Robotics and Automation (ICRA), Karlsruhe, Germany, May 6–10 2013.

E. S. Kuzmic and A. Ude, “Object segmentation and learning through feature grouping and manipulation,” in Humanoids, 2010, pp. 371–378.

P. Fitzpatrick and G. Metta, “Towards manipulation-driven vision,” in Intelligent Robots and Systems, 2002. IER/RSJ International Conference on, vol. 1, 2002, pp. 43–48 vol.1.

G. Metta and P. Fitzpatrick, “Early integration of vision and manipulation,” in Neural Networks, 2003. Proceedings of the International Joint Conference on, vol. 4, July 2003, pp. 2703–2708.

J. Kenney, T. Buckley, and O. Brock, “Interactive segmentation for manipulation in unstructured environments,” in ICRA, 2009, pp. 1377–1382.

L. Y. Chang, J. R. Smith, and D. Fox, “Interactive singulation of objects from a pile,” in ICRA, 2012, pp. 3875–3882.

D. Schiebener, J. Morimoto, T. Asfour, and A. Ude, “Integrating visual perception and manipulation for autonomous learning of object representations,” Adaptive Behavior, vol. 21, no. 5, pp. 325–345, 2013.

A. Ude, D. Omrten, and G. Cheng, “Making object learning and recognition an active process,” I. J. Humanoid Robotics, vol. 5, no. 2, pp. 267–286, 2008.

J. Sinapov, C. Schenck, and A. Stoytchev, “Learning relational object categories using behavioral exploration and multimodal perception,” in IEEE International Conference on Robotics and Automation (ICRA), Hongkong, China, May 31-June 7 2014.

J. Sinapov, C. Schenck, K. Staley, V. Sukhoy, and A. Stoytchev, “Grounding semantic categories in behavioral interactions: Experiments with 100 objects,” Robotics and Autonomous Systems, vol. 62, no. 5, pp. 632 − 645, 2014, special Issue Semantic Perception, Mapping and Exploration.

K. Hausman, C. Corcos, J. Müller, F. Sha, and G. Sukhatme, “Towards interactive object recognition,” in IROS 2014 Workshop on Robots in Clutter: Perception and Interaction in Clutter, Chicago, IL, USA, September 2014.

J. Sinapov and A. Stoytchev, “Grounded object individuation by a humanoid robot,” in Robotics and Automation (ICRA), 2013 IEEE International Conference on, May 2013, pp. 4981−4988.

M. Cusumano-Towner, A. Singh, S. Miller, J. F. O’Brien, and P. Abbeel, “Bringing clothing into desired configurations with limited perception,” in IEEE International Conference on Robotics and Automation, ICRA 2011, Shanghai, China, 9-13 May 2011, pp. 3893–3900.

A. X. Lee, H. Lu, A. Gupta, S. Levine, and P. Abbeel, “Learning force-based manipulation of deformable objects from multiple demonstrations,” in IEEE International Conference on Robotics and Automation, ICRA, 2015, Seattle, WA, USA, 26-30 May, 2015, pp. 177–184.

P. Pastor, L. Rigotti, M. Kalakrishnan, and S. Schaal, “Online movement adaptation based on previous sensor experiences,” in Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on. IEEE, 2011, pp. 365–371.

D. Kappler, P. Pastor, M. Kalakrishnan, M. Wültchich, and S. Schaal, “Data-driven online decision making for autonomous manipulation,” in Proceedings of Robotics: Science and Systems, Rome, Italy, 2015.

S. Levine, N. Wagenert, and P. Abbeel, “Learning contact-rich manipulation skills with guided policy search,” in IEEE International Conference on Robotics and Automation, ICRA 2015, Seattle, WA, USA, 26-30 May, 2015, pp. 156–163.

W. Han, S. Levine, and P. Abbeel, “Learning compound multi-step controllers under unknown dynamics,” in 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2015, Hamburg, Germany, September 28 - October 2, 2015, pp. 6435–6442.

C. Finn, I. Goodfellow, and S. Levine, “Unsupervised learning...
for physical interaction through video prediction,” in Advances in Neural Information Processing Systems 29, D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, Eds. Curran Associates, Inc., 2016, pp. 64–72.

[70] P. Agrawal, A. Nair, P. Abbeel, J. Malik, and S. Levine, “Learning to poke by poking: Experiential learning of intuitive physics,” in Advances in Neural Information Processing Systems 29, D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, Eds. Curran Associates, Inc., 2016.

[71] R. Jonschkowski and O. Brock, “Learning state representations with robotic priors,” Autonomous Robots, vol. 39, no. 3, pp. 407–428, 2015.

[72] L. Pinto, D. Gadhi, Y. Han, Y. Park, and A. Gupta, “The curious robot: Learning visual representations via physical interactions,” in Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II, 2016, pp. 3–18.

[73] N. Wahlström, T. B. Schön, and M. P. Deisenroth, “Learning deep dynamical models from image pixels,” IFAC-PapersOnLine, vol. 48, no. 28, pp. 1059 – 1064, 2015.

[74] S. Levine, C. Finn, T. Darrell, and P. Abbeel, “End-to-end training of deep visuomotor policies,” Journal of Machine Learning Research, vol. 17, no. 39, pp. 1–40, 2016.

[75] C. G. Atkeson, C. H. An, and J. M. Hollerbach, “Estimation of inertial parameters of manipulator loads and links,” The International Journal of Robotics Research, vol. 5, no. 3, pp. 101–119, 1986.

[76] L. Zhang and J. Trinkle, “The application of particle filtering to grasping acquisition with visual occlusion and tactile sensing,” in Robotics and Automation (ICRA), 2012 IEEE International Conference on, May 2012, pp. 3805–3812.

[77] J. Wu, I. Yildirim, J. J. Lim, B. Freeman, and J. Tenenbaum, “Galileo: Perceiving physical object properties by integrating a physics engine with deep learning,” in Advances in Neural Information Processing Systems 28, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds. Curran Associates, Inc., 2015, pp. 127–135.

[78] M. C. Koval, N. S. Pollard, and S. S. Srinivasa, “Pose estimation for planar contact manipulation with manifold particle filters,” The International Journal of Robotics Research, vol. 34, no. 7, pp. 922–945, 2015.

[79] A. Christiansen, M. T. Mason , and T. Mitchell, “Learning reliable manipulation strategies without initial physical models,” in IEEE International Conference on Robotics and Automation, vol. 2, May 1990, pp. 1224 – 1230.

[80] M. C. Koval, N. S. Pollard, and S. S. Srinivasa, “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty,” The International Journal of Robotics Research, vol. 35, no. 1-3, pp. 244–264, 2016.

[81] L. P. Kaelbling and T. Lozano-Pérez, “Unifying perception, estimation and action for mobile manipulation via belief space planning,” in IEEE Conference on Robotics and Automation (ICRA), 2012.

[82] M. Dogar, M. Koval, A. Tallavajhula, and S. Srinivasa, “Object search by manipulation,” Autonomous Robots, vol. 36, no. 1-2, pp. 153–167, 2014.

[83] R. Platt, L. P. Kaelbling, T. Lozano-Pérez, and R. Tedrake, “Efficient planning in non-gaussian belief spaces and its application to robot grasping,” in International Symposium on Robotics Research (ISRR), 2011.

[84] K. Hsiao, P. Nangeroni, M. Huber, A. Saxena, and A. Y. Ng, “Reactive grasping using optical proximity sensors,” in Proceedings of the 2009 IEEE International Conference on Robotics and Automation, ser. ICRA’09. Piscataway, NJ, USA: IEEE Press, 2009, pp. 4230–4237.

[85] O. Kroemer, R. Detty, J. Piater, and J. Peters, “Combining active learning and reactive control for robot grasping,” Robotics and Autonomous Systems, vol. 58, no. 9, pp. 1105–1116, 2010.

[86] A. Boularias, J. A. D. Bagnell, and A. T. Stentz, “Learning to manipulate unknown objects in clutter by reinforcement,” in Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI). AAAI, January 2015.

[87] S. Dragiev, M. Toussaint, and M. Gienger, “Uncertainty-aware grasping and tactile exploration,” in Robotics and Automation (ICRA), 2013 IEEE International Conference on, May 2013, pp. 113–119.

[88] M. Krainin, B. Curless, and D. Fox, “Autonomous generation of complete 3D object models using next best view manipulation planning,” in Proc. of the IEEE International Conference on Robotics & Automation (ICRA), 2011.

[89] J. Ilonen, J. Bohg, and V. Kyrki, “Three-dimensional object reconstruction of symmetric objects by fusing visual and tactile sensing,” I. J. Robotic Res., vol. 33, no. 2, pp. 321–341, 2014.

[90] M. Björkman, Y. Bekiroglu, V. Hogan, and D. Kragic, “Enhancing visual perception of shape through tactile glances,” in 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, Tokyo, Japan, November 3-7, 2013, pp. 3180–3186.

[91] H. Culbertson, J. Unwin, and K. J. Kuchenbecker, “Modeling and rendering realistic textures from unconstrained tool-surface interactions,” IEEE T. Haptics, vol. 7, no. 3, pp. 381–393, 2014.

[92] Y. Karayiannidis, C. Smith, F. Vina, P. ¨Ogren, and D. Kragic, “Learning dynamic tactile sensing with robust vision-based training,” Robotics, IEEE Transactions on, vol. 27, no. 3, pp. 545–557, June 2011.

[93] A. Jain and C. C. Kemp, “Pulling open doors and drawers: Coordinating an omni-directional base and a compliant arm with equilibrium point control,” in Robotics and Automation (ICRA), 2010 IEEE International Conference on. IEEE, 2010, pp. 1807–1814.

[94] J. Sturm, C. Stachniss, and W. Burgard, “A probabilistic framework for learning kinematic models of articulated objects.” J. Artif. Intell. Res.(JAIR), vol. 41, pp. 477–526, 2011.

[95] R. Martín Martín and O. Brock, “Online interactive perception of articulated objects with multi-level recursive estimation based on task-specific priors,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014.

[96] D. Katz and O. Brock, “A factorization approach to manipulation in unstructured environments,” in Robotics Research. Springer, 2011, pp. 285–300.

[97] K. Hausman, S. Niekum, S. Osentoski, and G. S. Sukhatme, “Active articulation model estimation through interactive perception,” in International Conference on Robotics and Automation, May 2015.

[98] S. Pillai, M. Walter, and S. Teller, “Learning articulated motions from visual demonstration,” in Proceedings of Robotics: Science and Systems, Berkeley, USA, July 2014.

[99] P. R. Barragán, L. P. Kaelbling, and T. Lozano-Pérez, “Interactive bayesian identification of kinematic mechanisms,” in IEEE Conference on Robotics and Automation (ICRA), 2014.

[100] S. Otte, J. Kulick, M. Toussaint, and O. Brock, “Entropy-based strategies for physical exploration of the environments degrees of freedom,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014.

[101] Y. Karayiannidis, C. Smith, F. Vina, P. ¨Ogren, and D. Kragic, “Model-free robot manipulation of doors and drawers by means of fixed-grasps,” in IEEE International Conference on Robotics and Automation, 2013, pp. 4470–4477.

[102] D. Katz, A. Orthey, and O. Brock, “Interactive perception of articulated objects,” Springer Tracts in Advanced Robotics, vol. 79, pp. 301–315, 2014.

[103] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik, “Contour detection and hierarchical image segmentation,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 33, no. 5, pp. 898–916, May 2011.

[104] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik, “Contour detection and hierarchical image segmentation,” in Advances in Neural Information Processing Systems 25, F. Pereira, C. Burges, L. Bottou, and K. Weinberger, Eds. Curran Associates, Inc., 2012, pp. 584–592.
[106] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015, pp. 3431–3440.

[107] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proceedings of the International Conference in Representation Learning (ICLR), 2015.

[108] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” in Advances in Neural Information Processing Systems 28, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds. Curran Associates, Inc., 2015, pp. 91–99.

[109] J. Pajarinen and V. Kyrki, “Decision making under uncertain segmentations,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), 2015.

[110] R. Martin-Martín, S. Höfer, and O. Brock, “An integrated approach to visual perception of articulated objects,” in Proceedings of the IEEE International Conference on Robotics and Automation, 2016.

[111] L. Natale and E. Torres-Jara, “A sensitive approach to grasping,” in Proceedings of the sixth international workshop on epigenetic robotics. Citeseer, 2006, pp. 87–94.

[112] S. Levine, P. Pastor, A. Krizhevsky, and D. Quillen, “Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection,” in International Symposium on Experimental Robotics, Tokyo, Japan, 2016.

[113] K. Hsiao, L. P. Kaelbling, and T. Lozano-Pérez, “Robust grasping under object pose uncertainty,” Autonomous Robots, vol. 31, no. 2-3, pp. 253–268, 2011.

[114] L. Pinto and A. Gupta, “Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours,” in 2016 IEEE International Conference on Robotics and Automation (ICRA), May 2016, pp. 3406–3413.

[115] T. Mar, V. Tikhanoff, G. Metta, and L. Natale, “Self-supervised learning of grasp dependent tool affordances on the icub humanoid robot,” in ICRA. IEEE, 2015, pp. 3200–3206.

[116] J. Pajarinen and V. Kyrki, “Robotic manipulation in object-action complexes,” in Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2014.

[117] L. Natale, F. Orabona, G. Metta, and G. Sandini, “Sensorimotor coordination in a baby robot: learning about objects through grasping,” in From Action to Cognition, ser. Progress in Brain Research, C. von Hofsten and K. Rosander, Eds. Elsevier, 2007, vol. 164, pp. 403 – 424.

[118] B. Browatzki, V. Tikhanoff, G. Metta, H. H. Blhoff, and C. Wallraven, “Active in-hand object recognition on a humanoid robot,” IEEE Transactions on Robotics, vol. 30, no. 5, pp. 1260–1269, Oct 2014.

[119] A. Tsuda, Y. Kakiuchi, S. Nozawa, R. Ueda, K. Okada, and M. Inaba, “Grasp, motion, view planning on dual-arm humanoid robot,” in 15th IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2014.

[120] E. Torres-Jara, L. Natale, and P. Fitzpatrick, “Tapping into touch,” pp. 79–86, 2005.

[121] D. Kraft, N. Pugeot, E. Baselski, M. Popovic, D. Kragic, S. Kalkan, F. Würgötter, and N. Krüger, “Birth of the object: Detection of objectness and extraction of object shape through object-action complexes,” I. J. Humanoid Robotics, vol. 5, no. 2, pp. 247–265, 2008.

[122] D. Omrzen, A. Ude, K. Welke, T. Asfour, and R. Dillmann, “Sensorimotor processes for learning object representations,” in 2007 7th IEEE-RAS International Conference on Humanoid Robots, November 29th - December 1st, Pittsburgh, PA, USA, 2007, pp. 143–150.

[123] D. Michal, X. Zabulis, and A. A. Argyros, “Shape from interaction,” Machine Vision Applications, vol. 25, no. 4, pp. 1077–1087, May 2014.

[124] A. Byravan and D. Fox, “S3e-nets: Learning rigid body motion using deep neural networks,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), May 2017, to appear.

[125] S. M. LaValle, Planning Algorithms. Cambridge, U.K.: Cambridge University Press, 2006, available at http://planning.cs.uiuc.edu/.

[126] J. Kober, J. A. D. Bagnell, and J. Peters, “Reinforcement learning in robotics: A survey,” International Journal of Robotics Research, July 2013.

[127] S. Singh, M. R. James, and M. R. Rudary, “Predictive state representations: A new theory for modeling dynamical systems,” in Proceedings of the 20th Conference on Uncertainty in Artificial Intelligence, ser. UAI ’04. Arlington, Virginia, United States: AUAI Press, 2004, pp. 512–519.

[128] B. Boots, S. M. Siddiqi, and G. J. Gordon, “Closing the learning-planning loop with predictive state representations,” Int. J. Rob. Res., vol. 30, no. 7, pp. 954–966, Jun. 2011.

[129] J. A. Stork, C. H. Ek, Y. Bekiroglu, and D. Kragic, “Learning predictive state representation for in-hand manipulation,” in 2015 IEEE International Conference on Robotics and Automation (ICRA), May 2015, pp. 3207–3214.

[130] N. Krüger, C. Geib, J. Piater, R. Petrick, M. Steedman, F. Würgötter, A. Ude, T. Asfour, D. Kraft, D. Omrzen, A. Agostini, and R. Dillmann, “Objectaction complexes: Grounded abstractions of sensorymotor processes,” Robotics and Autonomous Systems, vol. 59, no. 10, pp. 740 – 757, 2011.

[131] C. Atkeson, B. Babu, N. Banerjee, D. Berenson, C. Bove, X. Cui, M. DeDonato, R. Du, S. Feng, P. Franklin, M. Gennert, J. Graff, P. He, A. Jaeger, J. Kim, K. Knoedler, L. Li, C. Liu, X. Long, T. Padir, F. Polido, G. Tighe, and X. Xinjinfu, “No falls, no resets: Reliable humanoid behaviour in the darpa robotics challenge,” in 15th IEEE/RSJ International Conference on Humanoid Robots, 2015, pp. 623–630.

[132] M. Johnson, B. Shrewsbury, S. Bertrand, T. Wu, D. Duran, M. Floyd, P. Abeeles, D. Stephen, N. Mertins, A. Lesman, J. Carif, W. Riffigburgh, P. Kaveti, W. Straatman, J. Smith, M. Griffinan, B. Layton, T. de Boer, T. Koolen, P. D. Neuhauus, and J. E. Pratt, “Team ihmc’s lessons learned from the DARPA robotics challenge trials,” J. Field Robotics, vol. 32, no. 2, pp. 192–208, 2015.

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