Human Visual Understanding for Cognition and Manipulation - A primer for the roboticist

Martin Hjelm

Abstract—Robotic research is often built on approaches that are motivated by insights from self-examination of how we interface with the world. However, given current theories about human cognition and sensory processing, it is reasonable to assume that the internal workings of the brain are separate from how we interface with the world and ourselves. To amend some of these misconceptions arising from self-examination this article reviews human visual understanding for cognition and action, specifically manipulation.

Our focus is on identifying overarching principles such as the separation into visual processing for action and cognition, hierarchical processing of visual input, and the contextual and anticipatory nature of visual processing for action. We also provide a rudimentary exposition of previous theories about visual understanding that shows how self-examination can lead down the wrong path.

Our hope is that the article will provide insights for the robotic researcher that can help them navigate the path of self-examination, give them an overview of current theories about human visual processing, as well as provide a source for further relevant reading.

I. INTRODUCTION

A major source of inspiration for works in robotics has been the examination of different organisms, including humans. In modeling robotic cognition for human environments self-examination has been a guiding component. Self-examination can, however, be a double-edged sword.

In robotics, vision has been the major modality used for cognition and decisions regarding action. As vision is one of our primary senses it is easy to draw conclusions from self-examination of how we, ourselves, cognize about what we see. Human vision research is full of examples of theories that use ideas grounded in the workings of language and how we interface with the world. However, current models of human vision show to the contrary that the processing of visual input is significantly different from how we use vision and language to interface with the world. Fig. 1 gives a simple illustration how one can approach the intersection of language, vision, the world.

It is impossible to account for something as complex as human visual understanding within one article. We will, therefore, give a rough outline of current ideas of the human brain’s object image processing system tied together with models of internal object representation and how that connects to action, specifically to grasping. As in-depth expositions already exist [25], [71] our aim is to give a readily available source explaining main principles, strategies, and the structure of human visual understanding without too much of for the novice, confusing nomenclature used in psychological and neuroscience research.

We start with a review of human visual processing following the standard model of the two processing pathways one for semantic object recognition and one for action, fig. 2. We then proceed to give a short review of prior models of human visual understanding comparing to what self-examination tells us. We compare these models to the current models of humans vision, that is, recurrent, hierarchical processing of visual input into an increasingly invariant and linearly separable feature space, and show how it accounts for the previous models. Finally, we review vision for action. We show how the object meaning influences action representation and how that representation affects the grasping process. We also review how intention, context, and the post-grasp task influences human grasping and the visual processing.

Worth noting is that much of the understanding of the human brain comes from research done on monkeys, and it is often assumed that there are homologs, that is, equivalent functional parts, in the human brain. We will follow this idea and try to be clear about from where the experimental evidence comes as this is not always evident in the literature.
The most influential model of human image processing is that of two anatomically and functionally distinct pathways, the dorsal and ventral pathways [48] (fig.2). The dorsal named the “how” pathway links to the motor system and is thought to encode spatial information needed for interaction with the world. The ventral stream, named the “what” pathway, is thought to encode information for object recognition and general visual perception.

The reason for the “how” label of the dorsal pathway is that lesions, damaged tissue in the brain, in the ventral and dorsal cortex of primates cause degradation in object perception or spatial vision [113]. Additional evidence for the distinction between the two pathways was a human subject, D.F., with lesions in parts of the ventral pathway. D.F. had impaired object recognition and could not recognize line-drawings of objects but showed normal pre-shaping and rotation of the hand when grasping objects implying that location, orientation, size, and shape estimation of objects was intact [59], [48]. [48] put forward that both streams process the attributes of objects that are manipulated, but for different purposes.

The distinction between the two pathways should be viewed as a simplified model of visual processing in the brain. There is plenty of evidence of information sharing between the two. Much of the information encoded in each pathway is used by the other in such things as shape perception, object detection, and intentional visuomotor action [39], [49], [72], [84], [107], [106], [116].

We can outline a general model of the current understanding of visual processing under the two pathways as follows (fig.2). The visual input from the retinas is sent to the lateral geniculate nucleus (LGN) which combines the input from the two retinas and their different receptors. It forwards the visual stream to the primary visual cortex (V1) which processes features such as orientation, direction, and color. V1 forwards the information to area V2 where it splits into the two pathways the ventral and dorsal.

The ventral pathway proceeds into area V4 and the inferior-temporal (IT) cortex which is considered the end of the ventral pathway. The IT contains several areas that activate during visual input of among others faces, body parts, scenes, and different shapes.

The dorsal pathway continues onto area V3 and the caudal intraparietal area (CIP), and then onto the anterior intraparietal cortex (AIP), ending in the primary motor cortex (M1), thus transforming visual input into action. Apart from the feed-forwarding the visual processing pathways also contain feedback projections allowing earlier visual areas to receive processed information from the later stages [68].

We illustrate and explain the flow of visual input and processing more thoroughly in fig.4.

## II. HUMAN VISUAL PROCESSING

### A. The Ventral Pathway

The ventral stream, the “what” pathway, is considered to encode, among other things, information related to object identity, that is, both category and specific object identity. The word stream indicates a feed-forward visual processing network. The predominant idea has been that the network creates a hierarchy of more abstract representations further down the stream which are increasingly invariant to translation and rotation. However, there is plenty of evidence of connections between the early and later stages of visual processing that indicates that visual processing is a process of continuous refinement.

Recent models, therefore, point towards a recurrent and highly interactive network. A review [68] suggest that the
Fig. 4: Simplified structure of the visual processing of primates aggregated from [25], [71], [49], [22], [77], [33]. The model is extremely simplified and the visual processing connects to many more areas than given here, in addition, there are plenty of recurrent connections between the areas. For in-depth models see the referred papers. An approximate number of neurons per area is shown beneath each area box for the ventral pathway (from [33]). Visual input flows from the two retinas to the LGN where it is combined into one visual stream. The primary visual cortex (V1) computes features such as edges, gratings, line endings, motion, color, and absolute disparity. The features in V2 are similar to the ones in V1 with the addition of simpler contours and computation of relative disparity. In V2 the visual stream is split into the dorsal and ventral pathways. The ventral stream goes onto V4 which computes features such as orientation, color, and simple shapes. There is an increasing invariance and a luminance-invariant coding of hue. V4 also responds to contours from difference in motion. V4 projects to the inferior temporal cortex (IT) which is responsible for among other things object categorization. The dorsal stream continues on to V3 which computes color, shading, and 2D orientation. This information is forwarded to the CIP which computes surface orientations, and disparity based and perspective based orientation cues. Features are viewer-centered, local, and directed towards graspable features. The information in the CIP is forwarded to the AIP which together with the PMv, which contains movement primitives for grasping movements, plans the grasping action.
tive abilities. Visual neuroscience models, on the other hand, typically focus on explaining one specific phenomenon. Accounting for all models and phenomena as well as experimental evidence is beyond this paper. We will, therefore, limit the focus to models concerning central abilities of human object recognition - the ability to categorize, abstract, and identify - starting with some of the major models from neuropsychology.

A full model of human vision needs to explain viewpoint invariance at the basic category level, that is, invariance under the transformation of retinal position, scale, luminance, deformation, clutter, context, etc. It also needs to account for reduced viewpoint invariance for novel objects. Experiments on humans and monkeys [77] show that recognition drops for view disparities of depth-rotated objects larger than 30°. However, when presented with two views 75°–120° apart the monkeys interpolated them to give almost perfect recognition for any view between the two.

Further on, a full model also needs to explain categorization, abstraction of objects into invariant features, and the generalization into prototypical representations of objects in a category. Finally, it needs to account for different levels of categorization for one and the same object. This means, for example, being able to explain our ability to discriminate between, canine, dog, Terrier, and a Terrier named Rocky.

The abstraction of object features means decomposing objects into meaningful entities, categories of their own, and their spatial relations, an internal ontology. These subordinate categories are not necessarily necessary for categorization of the object itself — but as discussed above — are important for reasoning and conveying information about a category.

Identification means the ability to match visual input to a specific object from memory. To complicate matters, object identity can be viewed as a sub-category with cardinality one [95], [33]. If we would have one shared representation for all object recognition it would need to account for all the category memberships from superordinate to identity.

1) The Invariant Decomposable Parts Perspective: Early theories of vision modeled objects as decomposable into smaller invariants parts that preserved the relational structure, but not the underlying metric between the parts [111]. Biederman [15], for example, suggested decomposing objects into geons, deformable, prototypical parts such as cones, cuboids, cylinders, etc., that together with a relational structure can represent objects (fig. 5).

The decomposable part models as initially formulated were not tied to any experimental data [88], [89]. We should see them in the context of how we as humans reason and abstract objects to communicate about them. The major criticism of the decomposable part model is its inability to account for rotation, that is, invariant features and the relational structure might not be detectable from a view occluding them but the object might still be identifiable. A decomposable part based model must also account for the level of granularity in the decomposition it needs to categorize the object correctly which introduces additional complexity [77]. If we simplify and consider the deformable parts model a tree graph then the number of possible graphs for n nodes will grow exponentially as \( n^{n^2} \). Finally, further complications arise from the segmentation and relational structuring having to happen interchangeably as the parts need to be recognized and fit into a relational structure.

Ideas of decomposition are not uncommon in computer vision and have been applied with varying success. Common approaches are Bag-of-Words models [29] and deformable parts models [42]. Works in grasping have also used decomposition strategies. [83] represented objects as decomposable into a set of geometric primitives where each primitive has known pre-planned grasps. And [2] represents objects as graphs where they associate each node with a set of pre-learned grasps.

2) The Multiple Viewpoints Perspective: A more recent model of human object recognition, supported by psychophysical and physiological data, is that of multiple viewpoints [111], [95]. It opposes the ideas of invariance and structure arguing that the brain instead store representations of objects as a set of unique viewpoints (fig. 5).

The major criticism of the multiple viewpoints model is that a small perturbation may cause a new viewpoint to significantly differ from previously stored viewpoints. Therefore, to form complete representations that can account for recognition of novel viewpoints and mental rotations, the viewpoints must be normalized and stitched together in some fashion [111]. Another shortcoming is memory capacity. Unless there is some generalization, filtering, or compression process it is unclear which viewpoints should be stored for future use. The recognition process is also difficult as the brain, during recognition, needs to match a viewpoint to viewpoint clusters of objects retained in memory.

3) The Prototype Perspective: A third related model is that of prototypes (fig. 5), that is, the summarization of within-category objects into a generalized model [34]. We can trace this idea as far back as to Plato. To recognize an object, the visual input is matched to prototypes that are kept in memory, using an invariant distance measure. The prototype model of vision has some support in experimental data. For example, experiments involving distortions of a set of simple patterns show that, when infants and adults are given sufficient exemplars of a category, they tend to abstract these into prototypical patterns [77].

Prototype models for vision are good at explaining abstractions. Yet, similarly to the decomposable parts models, they are suspiciously close to how we abstract and communicate about categories. In fact, experiments on categorization in monkeys and humans show that the strategies involved in
Fig. 5: Models of visual understanding. **Deformable parts models**, models objects into smaller invariant parts where the relational structure is preserved, but where the underlying metric between the parts is not. Here a human is represented as a set of cylinders in a relational structure. **Prototype models**, models objects as the summarization of within-category objects into a generalized model. These prototypes can take on different granularity depending on the need e.g. pictogram vs. a more human-like model. **Multiple viewpoints models**, models objects as the association or stitching together of multiple viewpoints of an object. A novel object is then matched to a viewpoint cluster.

**Fig. 6:** Hierarchical Transformations Models. The visual input passes through the visual cortex, which performs complex multidimensional transformations making the transformed input increasingly invariant and specific. For basic categorization, the model in [33] suggest a final representation that is linearly separable as illustrated in the figure.

**Deformable Parts Model**

**Prototype Models**

**Multiple Viewpoints Models**

**Object Model**

**View 1**

**View 2**

**View 3**

Prototypes models have problems in accounting for scaling, rotation, and translation when matching the image to stored prototypes as these operations are all very taxing for biological systems [100]. Prototypes are also inherently coded for generalization. This means that a prototype based system will use many different prototypes for different generalizations under different contexts ranging from the ability to depict individual exemplars to summarizing basic categories. This leads to the same problems faced by the multiple viewpoints model an explosion in the number of prototypes.

4) Recent Ideas - Representational Transformations: Recent ideas of visual understanding focus on tying together the neural aspect of vision with higher-level cognition. Models of vision in computational biology are similar in spirit to the deep neural networks models used in machine learning. They characterize image recognition as a computational feed-forward hierarchical network ending in the inferior temporal cortex (IT) which is generally considered the end of the ventral pathway [115], [95], [32], [33], [58], [91], [109], [108], [100].

The feedforward network continuously refines the retinal images through linear and nonlinear transformations into complex multidimensional representations that are increasingly invariant to the position on the retina [95] (fig.6). The feedforward network model is essentially a version of the multiple viewpoints model which has replaced the stitching mechanism by transformations that facilitate categorization and identification by separation in space.

The transformations of these models vary from model to model. In [33] they are both high-dimensional and low-dimensional projections correlating size wise with the neuronal populations of the different cortices in the ventral pathway. The authors suggest that each neuronal subpopulation tries to achieve a transformation, using nonlinear functions such as logical-gates, max-pooling, and thresholding of neuronal firing rates. These transformations flatten the object manifold together with some form of learning rule that concentrates the response to input areas where the object is usually found. The final representation is an untangling of the object manifolds that make them separable by a hyperplane [32]. The model learns the parameters in an unsupervised fashion from the temporal contiguity of objects on the retina. We can find these construction principles in some form or other in most hierarchical models e.g. [100].

The descriptors produced by these models must account
for the different phenomena observed in human vision as outlined previously, as well as the speed of human basic image categorization which is less than 200 ms [95], [33]. One way of evaluating these computational models of human vision is on standard computer vision benchmark datasets. However, it has been argued that these datasets are difficult to use for evaluating promising models since they have low variation in viewpoint, position, size, etc., both for intra-class and between-class categories, and contain contexts that covary with the object category [91], [100].

These models build on neurological evidence that recognition is not done by matching to a single neuron but to a range of them. Neurons in IT seems to encode features such as shape and other low-level properties of the object rather than a complete representation [7] and [33] notes that the weighted sum of intervals of spiking patterns appears to be enough to explain object pose variations.

Additional findings in studies of primates [19], show that for familiar objects some of the neurons will encode viewpoint invariant information, responding to all views of an object and that most other neurons respond to specific viewpoints. The authors hypothesize that the view-dependent neurons form associated clusters that influence certain neurons to become view-invariant. These object responsive neurons then allow for rapid object recognition for familiar objects.

Recordings of IT neurons in monkeys also show that increasing familiarity with an object correlates with an increase in neurons encoding for the object [89], [19]; implying that familiarity refines the internal representation. Experiments on primates have also shown the plasticity of neurons in the temporal cortex when exposed to novel stimuli of the same category. In the experiment, monkeys were first exposed to familiar faces 5-15 times where the recorded neurons showed a stable response. When introduced to novel faces the same recorded neurons altered their response to a relative degree. This flexibility in altering the response suggests that category encodings are continuously updated in a rapid fashion to improve categorization [115].

From a machine learning perspective, the idea of feature invariance and multiple views are not a dichotomy. The untangling will by necessity have to discard these that are not relevant. Multiple views of the same or similar objects are actually necessary to find the most efficient untangling. The untangled representations will have to be close in space for it to be useful. From this perspective, the normalization and interpolation of the multiple viewpoints model will not be a problem since the untangling will automatically facilitate it. It is important to note that the multiple viewpoints of an object are not stored per se but it is the parameters of the network that are the compressed storage form.

The hierarchal nature of the networks also makes it possible to form different representations for different tasks. For example, subordinate categories can be represented higher up in the hierarchy since they need fine-grained discrimination. It is also not inconceivable that the brain uses these representations to build the prototypes and parts-based models that we use as abstractions when reasoning about categories. For a discussion on the advantages of feature hierarchy systems see [100].

C. Embodied Cognition - Categories & Semantic Memory

An important part of object understanding is the semantic memory, that is, facts, ideas, and concepts that we can recall at an instance. In its most straightforward form, this manifests itself as a deeper understanding of the meaning of words, for example, objects and their properties. Storing of such information does not come as discrete entities, as the number of categories is infinite. The semantic memory is, therefore, best characterized by parsimonious, flexible, intertwined, and shared feature spaces of overlapping categories [81].

A large body of evidence suggests that the brain stores properties of objects close to where the functional unit for recognizing them are [81], [80]. For example, color is stored close to or in the area of the brain responsible for the perception of color and knowledge about tool use is stored close to or in motor-related regions. This means that category and object-specific information should come from a weighted accumulation of information from the different property-based regions [80]. This accumulation is suggested to converge in high-level convergence zones that are far away from the primary sensorimotor cortices [16].

Experiments show that mentioning words denoting objects triggers activity in areas of the brain where it first learned the properties of the object. Memories can thus be triggered by reactivation of the neural pattern elicited when learning about the object. Greatly simplified, this implies that the concept of, for example, a cat triggers the sensor modalities that involves the recognition of a cat. Further on, concepts can have different meanings given the current context, implying that they should be dependent on the convergence of different sensor modalities.

Some researchers have in light of this proposed models of the brain as performing mental simulations when cognizing [44], [8]. This idea is backed up by evidence of mirror neurons [97]. Mirror neurons are neurons that activate when we think about a task, see or hear a word denoting a task, and when we see someone else perform the task. For example, seeing someone perform a grasping action invokes areas in the brain of the perceiver associated with motor commands of grasping, even mirroring the specific grasp that the person is performing.

Given this, and plenty more experimental evidence [9], it has been argued that to understand a concept we must ground the meaning in sensorimotor input and that the actual understanding of a concept is, in fact, sensorimotor simulation. This idea is usually referred to as the embodied
cognition hypothesis or grounded cognition [9], [10], [44], [81], [92], where cognition according to this model manifests itself in form of simulations, situated action, and bodily states [9]. In essence, this is a model for solving the symbolic grounding problem [53].

[66], [92] argues that concepts, as physically realized in the brain, are distributed representations connected via action-perception circuits (APC) that links the necessary sensorimotor modalities and higher convergence areas. The APCs are learned through exploration by finding correlates in congruent activation of sensor modalities.

Critics of grounded cognition come from the traditional cognitivist viewpoint. They consider concepts as amodal, that is, abstract symbols separate from the sensorimotor system. We can think of the separation as a recognizing unit manipulating symbols for planning and a sensorimotor system infusing the symbols with meaning. For example, [79] argues that sensorimotor activation can be epiphenomenal, a byproduct of symbolic manipulation. Patients with lesions in motoric regions can for example reason about the concept of a tool even though they are not able to use it. As such, the amodal viewpoint is that the abstract concept triggers the sensorimotor simulations.

Nonetheless, studies of patients with various types of motor damage show impairment in comprehending action words such as tool use. [16] suggest that the sensorimotor activations are hierarchical, modular, situational, and frequency dependent. We can then explain the double dissociation given above, that is often used as an argument against embodied cognition, as a degradation in the functionality of the structure. For a recent discussion on the topic of amodal and embodied cognition see [10].

1) The Dorsal Pathway: The dorsal pathway processes visual input for action, parsing objects and scenes in a person-centered reference frame. Research on vision has mainly concerned itself with cognition and not how vision guides action [47], [49]. Understanding the processing of vision for action is therefore not as developed as that of vision for cognition.

Current understanding of the dorsal stream is similar to the model of the ventral stream as a series of transformations of the visual input to representations that facilitate action planning and execution. Some have even suggested that features in the dorsal pathway are computed in a feedforward hierarchy similar to the ventral pathway [101]. The visual inputs flow from V1 to V2, and on to V3, that projects to areas involved in action planning and execution. The visual flow is illustrated in fig.4.

More recent models of the dorsal pathway suggest that it gives rise to three distinct pathways supporting spatial working memory, visually guided action, and spatial navigation [69]. The three pathways, parieto-prefrontal, parieto-premotor, and parieto-medial temporal, all found in the posterior parietal cortex integrates information from the central and peripheral visual fields, forming reference frames relative to the body and to the eyes. The pathways connect a range of functions such as spatial working memory, the top-down guidance of eye-moment, optical flow, depth information, world and object space reference frames, navigation, and the reaching and grasping of objects [69].

The dorsal stream is generally not thought to encode for objects in a view-invariant manner as in the ventral stream. However, see [39] for a review of the evidence of viewpoint invariance in the dorsal stream, as well as a discussion on different cues processed in the two streams and their integration in object perception and understanding. Viewpoints in the dorsal stream are instead interpreted as different objects [60]. They are not parsed for global contextual interpretation as in the ventral stream but provide an encoding that favors ease of visuomotor transformations for tracking, reaching, and grasping [25]. This sensitivity to viewpoint makes sense since grasping is an object centered action. The dynamics and the local shape of the object are central to physically performing the reaching and grasping action. However, as we shall see contextual information plays a big role in planning and choosing which motor commands to perform.

2) Ventral Stream Influence on Grasp Planning: As outlined above, the dorsal processing concerns itself with visuospatial transformations used for actions such as grasping, disregarding semantic knowledge. The ventral pathway, on the other hand, is thought to only influence motor planning indirectly.

Experiments with the patient D.F. showed, for example, inability to infer properties of size, shape, and orientation verbally or manually but showed normal pre-shaping and inability to infer properties of size, shape, and orientation verbally or manually but showed normal pre-shaping and rotation of the hand when grasping objects [59]. This and other studies have been taken as evidence for the separation into the two different representations catering to action and conceptual understanding.

The observations from D.F. are not all consistent with the idea of perception-action separation. For example, D.F. did not use visual cues when modulating grasp force something which would have had to come from the ventral pathway as this should be highly dependent on the object and its material [107]. Further on, D.F.”s ability to grasp objects correctly are reliant on a specific set of visual cues, and when those cues were perturbed she would fail more frequently than healthy subjects. In [107] the authors argue that this is evidence that the ventral stream processes additional depth and distance cues which are then used in the grasping process. This is echoed in a review by [86]. There the authors suggest that the dorsal pathway encodes primarily for absolute disparity while the ventral system is concerned with relative disparity. [105] argues further that observations of the dorsal and

If damage X to the brain affects functionality A but not functionality B and damage Y does not affect functionality A but affects functionality B then the parts of the brain associated with these functionalities are considered to be double dissociated. Double dissociation is stronger evidence of the independence of location in the brain of these different functionalities.
ventral streams should be built on the premise of integration instead of separation. They argue that D.F.’s degradation should be seen as if she lost specific visual cues that are reliable under certain circumstances and tasks. As such she would have to rely on the accumulation of less reliable cues to guide recognition and action.

Yet in recent experiments on binocular disparity in macaque monkeys, it is concluded that relative disparity exists in both visual streams, although serving different purposes [70]. The authors propose that the ventral stream uses relative disparity to judge the shape of objects. This would explain D.F.’s troubles in discerning spatially adjacent surfaces since relative disparity is more accurate than absolute [93]. The dorsal stream uses relative disparity to aid in the segmentation of moving features. This implies that interaction with static objects relies on ventral stream information for more delicate manipulation.

There is further evidence of dorsal-ventral cross-talk. An fMRI study [3] found somatosensory activation in parts of the ventral pathway implying that tactile information might be coupled with visual object knowledge. Others have found that recognition of tool use integrates information both from object attributes stored in the ventral stream and from motor-based properties in the dorsal stream [24] in accordance with the idea that memory of categories and attributes are stored close to the area for detection [81]. Areas close to the AIP, the area that is responsible for transforming visuospatial features into hand configurations, are also active during action and objection recognition which means they might provide information about functional properties of the object. Further on, a recent analysis of fMRI data found that the ventral pathway responds to weight or textural density as part of the visual processing for grasping [45].

For reviews and discussions on the ventral and dorsal separation see [47], [107], [105].

D. Summary

The prevalent model of human vision is that of the two pathways, one for conceptual answering what it is we see, and one for action answering how we should do what we want to do. One should not view the separation as absolutely distinct as there is plenty of evidence of crosstalk that helps solve the how or what questions, [47], [107], [105].

The ventral pathway performs basic level categorization. It is modeled as a feedforward network where representations along the network are refined along the cortical visual areas, becoming more invariant to scale, luminance, position, etc. The feedforward models are based on a schema of neuronal functionality and the idea of temporal firing rates as representations. Despite their intuitive and simple form, the basic feedforward networks only model a fraction of visual understanding. Visual cognition requires constant recalibration in the form of attention and refinement implying that a complete model of vision will have to take into account the existing feedback projections along the ventral pathway. It will also have to go beyond basic recognition explaining abstraction, deeper visual understanding, etc. There is plenty of arguments against framing visual understanding as solely consisting of object recognition [26].

Further on, converging evidence points to that humans ground concepts in sensorimotor input in some form or other, as opposed to being amodal. The grounded concepts bridges object properties with possible affordances and motor programs that perform the affordance.

The dorsal pathway handles spatial understanding for interacting with objects. It transforms visual input into representations for planning and execution of actions in the motor cortex. Representations in the dorsal pathway are in general not view-invariant and the dorsal pathway does not store representations of graspable objects for long, most probably due to the temporal aspect of actions.

There is plenty of evidence of cross-talk between the two streams where representations in the ventral pathway are thought to influence, for example, grasp planning and other activities reliant on semantic knowledge.

III. Human Grasping

Neuroscience has yet to solve, on a broader level, how perceptual inputs guide actions [23]. There is a large body of work on prehension in monkeys [96], however, the human physiology and everyday actions are somewhat different from monkeys, and the putative homologs in humans are still not fully understood [22]. We give a simplified outline of the visual processing for grasping in primates in fig.4. For an in-depth exposition of the areas in the brain, that are active during grasping, and the flow of information see [25].

The visual information in grasping comes majorly from the dorsal stream. V3 projects into the intraparietal sulcus (IPS). Experiments on macaques show that the IPS processes visual stream for action-perception coordination [50], that is, arm and eye movements. The IPS contains the caudal intraparietal sulcus (CIP) which process 3D features, axis, and surface orientation, from the information in V3, in a view-centered manner [25].

CIP connects to the anterior intraparietal area (AIP) which is thought to be central to grasp planning. Neurons in the AIP discharge during object manipulation, object observation, and even to be sensitive to manipulation during dark and light luminance conditions. [30] found that AIP neurons, in monkeys, respond preferentially to specific manipulations of specific objects in addition to being selective for shape, size, and orientation.

The AIP is thus thought to perform visuomotor transformations of forwarded visuospatial object features. It transforms these features, such as surface orientation in depth and texture gradients into grasp plans which it then forwards to
the motor cortex for execution. The AIP is also active during
the grasping process where the evidence points to it being
critical for monitoring and recalibrating grasp movements
[25].

The AIP connects to the premotor cortex. Part of the pre-
motor cortex is the ventral premotor cortex (PMv) which
contains area F5. F5 fires during specific object-related
hand movements and in the presence of a 3D object [50].
Recordings also show some F5 neurons discharging for en-
destate goals [98]. Experiments in [96] found sets of neurons
discharge in these regions during specific types of prehensile
movements suggesting that these combinations of neurons
are a motor vocabulary for elementary motor acts. The first
discovery of mirror neurons was in F5. Experiments showed
activation in F5 when a Macaques was observing other actors
perform grasp actions.

PMv neurons in monkeys are selective for the type of re-
quired prehension for grasping an object, that is, the grasping
action as a whole not controlling for the individual digits,
together with the applied force. Experiments on monkeys
have in fact found a striking accuracy, 89%, in predicting
grasping actions based on the activity in the premotor cortex
[49], see also [38].

The PMv receives information from the AIP and is thought
to output a representation activating motor programs of the
object affordance which is then combined with other visual
cues to configure and orient the hand. This information
is then forwarded to the primary motor cortex (M1) for
execution [23], [49].

fMRI studies also suggest that the human homolog of the
PMv integrates additional modalities such as somatosensory
[35]. The authors suggest that there are different areas
responsible for precision and power grips, where precision
grips might use somatosensory information from the poste-
rior parietal cortex. The use of more tactile information in
precision grips is sensible. They tend to be complex and fol-
lowed by in-hand manipulation which is much more reliant
on tactile feedback. In addition, [35] also found that precision
and power grips activate different parts of the human cortex.
The precision grip activated a larger combination of cortical
areas especially the PMv while power grips associated more
with M1. This seems to be in accordance with the notion that
precision grasps require more planning and coordination than
power grips.

A. Grasp Planning and Execution

Human grasping can be characterized by a set of phases
[78]. We illustrate the grasping movement in fig. 7.

The first phase is concerned with finding a suitable plan of
execution. In general, this means choosing a grasp position
on the object, pairing it with an initial estimate of the hand
configuration that will fit the local geometry of the object,
and then adding the proper motor commands that involve the
reaching and grasping movement.

The second phase involves executing the motor commands
for the reaching movement and pre-shaping of the hand to
comply with the local geometry of the object at the chosen
grasp position. During this phase, there is a continuous
recalibration of the trajectory and the hand configuration,
where the hand reaches a maximum aperture around 60-70%
through the reaching movement correlating with the size of
the object [22].

The third phase is during and at contact with the object where
hand reconfigurations are made to stabilize and maintain the
grasp. This phase is dominated by the aggregation of sensor
modalities such as tactile, visual, auditory, and proprioceptive
working together to give feedback about the stability of the
grasp and how that stability is maintained.

We will concern ourselves with the initial phase, the plan-
ning, as this article’s main focus is on how the visual
understanding influences the grasp planning process.

B. Effects of Task and Object Properties on Grasp Planning.

Many factors affect the planning of a grasp. The post-grasp
task, that is, what one intends to do with the object, is
central to planning with respect to the reaching movement
[5], [36], hand configuration [85], [102], placement [61],
and the applied load and prehensile force upon contact
[43]. In addition, the properties of the object also affect
grasp planning, placement, and load forces. Apart from the
shape of the object, estimations of dynamics, weight, and
texture are the predominant factors in planning, through
slow-changing priors that guide the initial plans. We give
a number task-specific grasps in fig. 8 to illustrate how task
might affect grasp placement.

C. Task & Semantic Memory

Human grasp planning is seemingly preemptive in that it con-
tinuously updates and computes potential grasping actions
and affordances [13]. Before initializing the grasping action
the eyes typically focus its attention on parts of the scene that
it anticipates being the focus of an action. Experiments show
that the eyes fixate on a set of landmarks that are central
to the task [63]. These landmarks are most likely used to
anticipate potential grasp configurations and actions.

Once set on a target object for grasping, experiments show
that the eye fixations show a preference for regions where
the brain intends to place the index finger of the grasping
hand indicating hand-eye coordination in planning [13]. [13]
even suggest that it might be possible to predict which object
manipulation is about to take place given the current fixation
point and object.

This anticipatory behavior also manifests itself as subcon-
scious computations of potential actions for objects found in
Fig. 7: A sequence of snapshots of the reaching movement for grasping a cylinder-shaped object. Notice how the pre-shape develops, with the grasp aperture increasing during the reaching movement, correlating with the shape of the object, and then decreases as the hand reaches the object. We also note that the actor places the grasp at the mid-section on the object as to get a stable grasp for picking up the object as opposed to if the actor intended to give the object to someone where a top-grasp would be more convenient.

the vicinity. In a series of experiments, [112] showed that humans using different grasp types to signal the category of objects had faster response time with object compatible grasps. This led the authors to suggest that the brain also represent objects in general motor responses that are potentiated irrespective of the agent’s intentions, that is, the brain is subconsciously computing potential action possibilities.

A later fMRI study [51] showed grasp types compatible with the object indeed activated the parietal, dorsal premotor, and inferior frontal cortex. Another fMRI study by [24], where participants named the categories of pictures depicting objects, also showed activation in ventral premotor areas, specifically for pictures of tools. These motor response representations led the authors of [37], [112] to coin the term micro-affordances to denote possible grasping actions not necessarily involved in just one type of affordance.

Planning of the grasp also considers the post-grasp dynamics. Experiments show that at least for simpler tasks [55], the chosen grasp is part of a broader strategy for maximizing control at the end of the task sequence, a so-called “end-state comfort”. This effect has been shown in a range of works from Rosenbaum and others [102], [54].

The initial realization came from observing a waiter filling glasses with water. The waiter grasped an upside-down standing glass with the thumb in the direction of the opening of the glass, rotated it, filled it with water, and put it down, thumb facing up. Rosenbaum noted, that the waiter chose the initial awkward posture for a less awkward post-grasp posture. After initial experiments, the optimization strategy was named the end-state comfort effect. Further analysis, however, indicated that humans choose grasps that optimize the control exerted over the grasped object when it is most needed. Additional experiments involving handing-over of objects showed that humans choose awkward postures to enable the receiver to perform an action with the object.
The actor thus actively takes another actor’s intentions into account.

Task also affect the speed of the reaching movement and hand shaping [65], [5]. Experiments involving grasping the same object for different tasks [5] showed that when the end task required greater control the pre-shaping was more gradual and the reaching movement of the hand was much slower. In the simpler end task, the subjects formed the hand shape directly to comply with the place for a grasp while in the complex task, the pre-shaping happened gradually during the reaching movement. In sequent experiments, [4] showed that using the same object but for different actions affected reaching duration such that it was markedly slower if no task followed the grasp. These results suggest, again, that the grasp planning anticipates the end-state. The authors explain the longer reaching time for the no-task grasp as relying more on tactile feedback as opposed to when there is a post-grasp task that requires planning and taking dynamic constraints into account.

Grasp placement for more complex tasks also appears to involve semantic memory. [28] showed in experiments, involving objects with handles rotated in different orientations, that when the subjects were simultaneously involved in a memory retrieval task they tended to pick up the object by the nearest point regardless of the distance to the handle. However, when the memory retrieval task only involved spatial or verbal working memory components, the subjects the grasps landed on the handles with higher likelihood regardless of orientation.

These findings indicate the importance of memory retrieval for performing more complex grasping procedures. It also implies that humans perform the simple act of reaching and grasping automatically without the involvement of semantic memory. Additional evidence of the involvement of memory in the grasping process comes from [82]. The authors showed that objects of familiar size modified both reaching and hand amplitude. This effect was even greater when they removed binocular cues implying an increase in reliance on memory cues.

Representations in the brain of objects are also affected by task [52], [21], [114]. [52] performed an fMRI study of twenty-five subjects that carried out six different tasks that required judging physical properties: fixation, color, tilt, or conceptual properties: content, movement, size. First, they showed the subjects an object and then tasked them with judging a property of the object. The study showed that the object context strongly affected the response in the ventral pathway such that it was easier to decode which object the subjects judged within a task compared to across-task. This was also taken as further evidence of the top-down modulation of visual processing as the task affected object processing.

Similar experiments in [114] showed that task affected processing in the dorsal stream while the ventral stream was less affected and where the early visual regions showed a higher encoding for category than task. Further on, the experiments also showed that the filtering out of salient task-irrelevant features was greater in the dorsal pathway indicating the stream’s relevance for parsing visual input into action.

D. Shape

The shape of the object affects grasp placement by determining the center of gravity as well as offering places for support. For example, in fig. 8 it is easy to see how the pinky finger uses the curvature of the bottle as a stabilizing factor. Experiments in [103] on two differently shaped plastic water bottles involving the task of pouring and moving exposed effects of task and object properties on the grasp performance. The bottles used in the experiment consisted of one ordinary cylindrical shaped bottle and one bottle with concave constriction similar to the bottle in fig.8. The bottles were either half-full or full.

In the experiments, the subjects grasped the full bottles higher up than the half-full and more internally towards the center of gravity. The same effect was observed for the pouring actions versus the moving action. The grasps made for pouring were placed higher up and more towards the center of gravity. The shape affected the grip apertures by generating smaller apertures for the moving action of the full concave bottle. Task also affected the movement time where the moving action was faster than pouring.

These results are evidence of the anticipatory nature of grasping. The grasp planning phase clearly took into consideration both the shape, in terms of the digit placement, and the estimated weight of the bottles, to determine how they would affect the post-grasp task. The authors suggested that the reason for the moving action eliciting a faster reaching movement is likely due to it requiring less precision and calibration.

Similar experiments in [5], involving placing an object inside differently sized niches, also showed this effect. The reaching movements made for niches that required less precision were faster and the pre-shaping of the hand reached its final shape almost immediately opposed to the grasps for niches that required more precision. This is in line with the fMRI results [35] described earlier which showed that precision grips generate larger neuronal activity compared to power grips. This is sensible as demanding post-grasp tasks are more difficult to plan and are likely to require more recalibration during the reaching movement.

Additional evidence of how task affects digit placement comes from experiments in [27]. The experiments involved pouring and lifting a common glass juice bottle and showed that the task and the weight of the bottle significantly affected digit placement. For example, the pouring task consistently showed greater distance between thumb and index finger, something the authors suggest was to facilitate the rotating movement of the bottle. We have illustrated a similar grasp
Fig. 8: Task-specific grasps for the tasks: drinking, drinking, giving, giving, picking up, pouring. Clearly, task is the major factor in deciding approach vector, grip position, and grip configuration. Notice also how the pinky finger in the first two images acts as stabilizing factor by being situated underneath the curvature of the bottle. A grasp higher up without the pinky finger stabilization will be much more unstable. We mostly likely learn this type of stabilization by repeated interaction implying that this type of grasp is to some extent reliant on semantic memory.

Shape is also a factor when computing the applied grip force. [62] showed in a set of experiments of precision grips on an object, which changed curvature unpredictably between trials, that humans use the curvature and kinematics estimated by vision to predict the required movements and grip forces that produce a stable grasp. The experiments also showed that anesthesia had little impact on the adaptation of the grip force indicating that visual cues are the predominant variable in grip force estimation. However, vision was of little help to the anesthetized subjects in modulating the grip forces to balance friction. This implies that past the contact phase tactile feedback is the biggest factor in modulating the grip force.

E. Size and Material

A classic experiment by primary school physics teachers is to show two objects of different size and material, and ask which falls the fastest. Whereupon most students, not familiar or sometimes even familiar with the laws of gravity, answers the larger or by material seemingly heavier one. Priors on object weight also play an important role in computing load forces needed for lifting and performing actions with objects.

Humans base their prior on the size and material of the object. Experiments involving objects whose surface displays a material different from the interior showed that subjects misjudged weight and applied erroneous load forces. [11], [20] tasked humans with lifting cubes of varying sizes, and with different surface and interior materials (brass and wood in [11], and metal, wood, and expanded polystyrene in [20]). The experiments showed that the subjects frequently misjudged object weight but learned to adapt the load force after a couple of additional interactions.

Interestingly, the prior on object weight in these experiments was seemingly stable and did not update with new information. The subjects consistently made errors when judging object weights even after receiving feedback and being asked about the object weight again. The applied load force, on the other hand, started to adapt after the first trial. The authors suggest that humans rely on two distinct representations for estimating weights. A slow-changing material-density-volume prior that we use for initial estimates of object weight. When the prior proves to be wrong the estimates tend to shift and rely to a greater extent on a combination...
of priors and sensorimotor memory.

A recent analysis of fMRI data supports the idea of these types of priors. It showed the ventral pathway responding to weight or textural density as part of the visual processing for grasping, and that these associations, in fact, are learnable [45].

Size, material, and dynamic priors are especially valuable when placing precision grips. Precisions grips require complex interaction between different load forces. They must predict both weight and friction between the fingertips and the object to prevent slippage as well as predict the dynamic behavior of the object under load forces. These types of priors have led to suggestions that humans form internal models of object dynamics. 2. Sometimes with enough training, the dynamic model even becomes specific to a single object [43].

Many of the approaches for stability prediction in robotic grasping have usually assumed knowledge of friction constants etc. These approaches are obviously not tenable and the trend is towards data-driven methods e.g. [12], [75], [1], [99]. However, the lack of reliability and resolution in robotic tactile sensors compared to humans leaves only so much room for improvement in the sophistication of the control and learning algorithms.

F. Heuristics

Experimental evidence shows that humans view objects in a holistic manner but when grasping they ignore features that are not pertinent to placing the grasp [47]. These results suggest that there are heuristics involved in grasp planning and that we can explain them in specific features of the object.

A study [40], [41] of four professionals manual laborers analyzed 7770 instances of object-task grasps of roughly 306 objects for 231 tasks collected during an 8-hour window. The analysis of a decision tree classifier fitted to the data showed 47% classification accuracy for grasp type for the attributes: dimension, mass, roundness, functional class, task constraint, grasped dimension, force, and rigidity. The most discriminative of the recorded features in predicting grasp type were: object dimension, task constraints - the degrees of freedom in rotating and translating the object, and the mass of the object.

That object dimension is a good discriminator comes as no surprise. Most tools are, for example, elongated and usually has a handle that requires a specific grasp. Analysis of the data, in fact, showed that the subjects had a clear tendency to grasp objects along the smallest dimensions of the object. The constraints features are also logical as manual labor involves repetitive tasks with specific objects with specific grasps.

Another interesting aspect of the study is that the combination of object and task constraints increased the classification accuracy significantly compared to either feature alone. This is clear evidence that categorization of required grasps needs to include both object features and features involved in the action. It is also evidence of the significant involvement and interplay of action with the object category and how the affordance of an object shapes how we categorize and cognize about it.

In another recent study [38], participants grasped objects that varied in size, elongation, and shape, using grasps with different combinations of digits plus passively viewing the objects. fMRI recordings of the subjects showed that the feature that was coded strongest for in the different brain regions was elongation followed by shape and size. The authors suggest that this reflects the importance of dimension in selecting grip configuration and wrist orientation. In addition, the results showed that the number of digits used in a grasp was a better model for explaining the activations than the type of precision grasp.

The above results show that simple features of an object might be enough to derive simple heuristics for classification and grasp planning that work well in a majority of cases. In the subsequent chapters, we will explore this idea by formulating a stack of simple features and try to learn from the data which feature works best.

G. Summary

We can decompose grasping into a set of phases summarized as planning, reaching, and contact. The planning phase is preemptive in that the mind consistently is anticipating and computing action possibilities, and their associated motor programs for objects in the surrounding. The planning is also preemptive in that it tries to predict the end-state of the task such that the grasp maximizes control over the object.

Apart from the task, placement, and force in grasp planning depend on a number of properties of the object. The properties are first and foremost shape, material, and size. Humans learn slow-changing priors of how materials respond to interaction. The elongation and size of an object are good predictors for how and where a human will place affordance-based grasps implying possible underlying heuristics for placing grasps. On the whole, the accumulated evidence suggests a complex interaction between factors of weight, material, shape, and task. Further on, it shows that humans are efficient at exploiting and estimating the involved factors to plan stable grasps that anticipate future manipulation.

IV. Discussion And Conclusion

It has been argued that,
vision began not as a system for perceiving the world, but as a system for the distal control of movement [47].

This idea contrasts strikingly with the research done in computer vision which has focused mainly on answering the what question. The main reason for this is most likely the effort involved in obtaining labeled data. Answering what is also less ambiguous than answering how in that categorization is a binary question while how spans complex interactions of body, object, and outcomes. It may also be that what is something that involves everyday conscious decisions and often is explainable in the rule-based counting of features, meanwhile, how is subconscious and thus more complicated to explain explicitly. This shows itself in that learning of actions are primarily done by imitation and sensorimotor exploration.

The focus on answering what has influenced the creation of many vision-based grasping approaches in form of feature representation and by forcing the problem into a form suitable for vision-based discrimination, e.g. [104], [73], [64], [94]. The division of labor in human vision is a strong indication that robots should use different features for action and recognition. Features for grasping, for example, need to be less focused on saliency and more focused on shape and material, and how the visual understanding of shape and material relates to the gripper configuration and force space. Data for learning features should come from interactions with shape and materials and will require more exploratory approaches as well as learning from demonstration.

This is already being explored to some extent. In [74] the authors let a set of robots perform 800,000 grasp attempts and uses the data to learn hand-eye coordination for monocular images using reinforcement learning with a convolutional neural network. [1] hypothesize that humans have an internal physics model that allows them to understand and predict how an action will affect an object and use a siamese CNN to model a similar understanding. And in [90] the authors start with a base-net that branches out into nets specialized for grasping, pushing, and pulling actions. The base-net provides the basic processing of the visual input and then receives feedback from the specialized nets on how to improve. The approach thus mimics the human visual processing in the idea of general preprocessing and then specialization. [46] explores haptic adjectives such as compressible or smooth from the fusion of visual and haptic data. For a thorough review on interactive perception and further arguments for action based perception see [17].

We also saw that human grasping is highly dependent on context and task. Research has shown that the brain generates different representations of an object depending on which task or context we view it in. Robotic grasping research, on the other hand, has traditionally focused on analytical measures of grasp stability disregarding context and task e.g. [14]. With an increased availability of grasping data and tools for 3D vision, research has moved towards data-driven grasping approaches. These methods rely in general on matching features on the object to good hand configurations where they measure good according to heuristics, matching to stored grasp-feature relations, or minimizing a machine learning loss function [18].

Even though these data-driven approaches have been successful they have failed to broach the broader subject of how object understanding and intention affects how an agent should and can manipulate objects. Grasp synthesis algorithms can heavily reduce the infinite number of grasping positions on an object that it needs to consider by taking task into account; as there is a limited set of positions for grasping an object to complete a task successfully. Humans utilize this strategy of optimizing post-grasp control sometimes placing an initial awkward grasp to optimize for the end-goal.

A handful of efforts have incorporated task in robotic grasping. [110] trained a Bayesian Network (BN) relating object properties with task, grasp, and constraint features. From the BN they could produce probabilistic maps of hand pose over the object conditioned on the task and object properties. [87] formulated a probabilistic model over task, stability, and known object models to find stable grasps. [56], [31] modularized grasping into two modules one focused on matching known grips to local properties on the object while the other computed the task probability for a gripper position given known task-specific grasps. The modularization enabled the transfer of grasps and task constraints to novel object task combinations. [6], [67] leveraged deep learning to generalize task constraints given by pixel-wise ground-truths denoting affordance bearing parts.

In addition to task-based priors, we saw that humans use priors based on material, size, and shape together with sensorimotor memory adaptation when priors are wrong. To the best of our knowledge, only [57] has approached the problem of learning priors. [57] showed how a robot can learn and utilize task-specific priors on object properties from observed task-specific grasps by a human.

To conclude, feature work in computer vision and robotics needs to have broader scopes in how they define vision. Robotics research using vision-based approaches for action needs to consider if methods developed for pure vision are a good match for the action they want the robot to achieve as primates show a preference for division and specialization of labor. Robotic grasping research and perhaps robotics in general needs to take a holistic approach to learning actions. Actions do not exist in solitude but are part of a complex behavioral machinery that contains many interdependent parts that provide useful information about each other. If roboticists can learn to incorporate these types of holistic perspectives much will be won.

REFERENCES

[1] Pulkit Agrawal, Ashvin Nair, Pieter Abbeel, Jitendra Malik, and Sergey Levine. Learning to Poke by Poking: Experiential Learning of
Intuitive Physics. In Neural Information Processing Systems, pages 5074–5082, 2016.

2] Jacopo Aleotti and Stefano Caselli. Part-based robot grasp planning from human demonstration. In IEEE International Conference on Robotics and Automation, pages 4554–4560, 2011.

3] Amir Amedi, Rafael Malach, Talma Hendler, Sharon Peled, and Ehud Zohary. Visuo-haptic object-related activation in the ventral visual pathway. Nature Neuroscience, 4(3):324–330, 2001.

4] Caterina Ansuinui, Livia Giosa, Luca Turella, Gianmarco Altoè, and Umberto Castiello. An object for an action, the same object for other actions: effects on hand shaping. Experimental Brain Research, 185(1):111–119, 2007.

5] Caterina Ansuinui, Marco Santello, Stefano Massacesi, and Umberto Castiello. Effects of End-Goal on Hand Shaping. Journal of Neurophysiology, 95(4):2456–2465, 2006.

6] Rika Antonova, Mia Kovic, Johannes A Stork, and Danica Kragic. Global Search with Bernoulli Alternation Kernel for Task-oriented Grasping Informed by Simulation. In 2nd Annual Conference on Robot Learning, pages 641–650, 2018.

7] Carlo Baldassi, Alireza Alemi-Neissi, Marino Pagan, James D DiCarlo, Riccardo Zecchina, and Davide Zoccolan. Shape Similarity, Better than Semantic Membership, Accounts for the Structure of Visual Object Representations in a Population of Monkey Inferotemporal Neurons. PLoS Computational Biology, 9(8):1–20, 2013.

8] Lawrence W Barsalou. Perceptual Symbol Systems. The Behavioral and Brain Sciences, 22:577–609—discussion 610, 1999.

9] Lawrence W Barsalou. Grounded Cognition. Annual review of psychology, 59(1):617–645, 2008.

10] Lawrence W Barsalou. On Staying Grounded and Avoiding Quixotic Dead Ends. Psychonomic bulletin & review, 23(4):1122–1142, 2016.

11] Lee A Baugh, Michelle Kao, Roland S Johansson, and J Randall Flanagan. Material evidence: interaction of well-learned priors and sensorimotor memory when lifting objects. Journal of Neurophysiology, 108(5):1262–1269, 2012.

12] Yasemin Bekiroglu, Janne Laaksonen, Jimmy A Jorgensen, Ville Kyriki, and Danica Kragic. Assessing Grasp Stability Based on Learning and Haptic Data. IEEE Transactions on Robotics, 27(3):616–629, 2011.

13] Anna Belardinelli, Madeleine Y Stepper, and Martin V Butz. It’s in the eyes: Planning precise manual actions before execution. Journal of vision, 16(1):18–18, 2016.

14] A Bicchi and V Kumar. Robotic Grasping and Contact: A Review. In IEEE International Conference on Robotics and Automation, pages 348–353, 2000.

15] Irving Biederman. Recognition-by-components: A theory of human image understanding. Psychological review, 94(2):115–117, 1987.

16] J R Binder and R H Desai. The neurobiology of semantic memory. Trends in Cognitive Sciences, 15(11):527–536, 2011.

17] Jeannette Bohg, Karol Hausman, Bharath Sankaran, Oliver Brock, Danica Kragic, Stefan Schaal, and Gaurav S Sukhatme. Interactive Perception: Leveraging Action in Perception and Perception in Action. IEEE Transactions on Robotics, 33(6):1273–1291, 2017.

18] Jeannette Bohg, A Morales, Tamim Asfour, and Danica Kragic. Data-Driven Grasp Synthesis - A Survey. IEEE transactions on robotics, 30(2):289–309, 2014.

19] M C Booth and Edmund T Rolls. View-invariant representations of familiar objects by neurons in the inferior temporal visual cortex. Cerebral Cortex, 8(6):510–523, 1998.

20] Gavin Buckingham, Jonathan S Cant, and Melvyn A Goodale. Living in A Material World: How Visual Cues to Material Properties Affect the Way That We Lift Objects and Perceive Their Weight. Journal of Neurophysiology, 102(6):3111–3118, 2009.

21] Lior Bugatus, Kevin S Weiner, and Kalanit Grill-Spector. Task alters category representations in prefrontal but not high-level visual cortex. Neuroimage, 155:437–449, 2017.

22] Umberto Castiello. The neuroscience of grasping. Nature Reviews Neuroscience, 6(9):726–736, 2005.

23] Umberto Castiello and C Begliomini. The Cortical Control of Visually Guided Grasping. The Neuroscientist, 14(2):157–170, 2007.

24] Linda L Chao and Alex Martin. Representation of manipulable man-made objects in the dorsal stream. Neuroimage, 12(4):478–484, 2000.

25] Eris Chinellato and Angel P del Pobil. The Visual Neuroscience of Robotic Grasping, volume 28 of Achieving Sensorimotor Skills through Dorsal-Ventral Stream Integration. Springer, 2016.

26] David Daniel Cox. Do we understand high-level vision? Current Opinion in Neurobiology, 25:187–193, 2014.

27] Céline Crajé, Jamie R Lukos, Caterina Ansuinui, Andrew M Gordon, and Marco Santello. The effects of task and content on digit placement on a bottle. Experimental Brain Research, 212(1):119–124, 2011.

28] Sarah H Creem and Dennis R Proufitt. Grasping objects by their handles: A necessary interaction between cognition and action. Journal of Experimental Psychology: Human Perception and Performance, 27(1):218–228, 2001.

29] Gabriella Csurka, Christopher R Dance, Lixin Fan, Jutta Willamowski, and Cédric Bray. Visual categorization with bags of keypoints. European Conference on Computer Vision, pages 1–22, 2004.

30] J C Culham. Human brain imaging reveals a parietal area specialized for grasping. In Nancy Kanwisher and John Duncan, editors, Attention and performance XX. Functional brain imaging of visual cognition, pages 417–438. Oxford University Press, 2004.

31] Renaud Detry, Jeremie Papon, and Larry Matthies. Semantic and Geometric Scene Understanding for Task-oriented Grasping of Novel Objects from a Single View. In ICRA Workshop on Learning and control for autonomous manipulation systems: the role of dimensionality reduction, 2017.

32] James J DiCarlo and David Daniel Cox. Untangling invariant object recognition. Trends in Cognitive Sciences, 11(8):333–341, 2007.

33] James J DiCarlo, Davide Zoccolan, and Nicole C Rust. How Does the Brain Solve Visual Object Recognition? Neuron, 73(3):415–434, 2012.

34] Shimon Edelman. Representation, similarity, and the chorus of prototypes. Minds and Machines, 5(1):45–68, 1995.

35] H Henrik Ehrsson, Anders Fagergren, Tomas Jonsson, G ¨oran Westling, Roland S Johansson, and Hans Forssberg. Cortical Activity in Precision- Versus Power-Grip Tasks: An fMRI Study. Journal of Neurophysiology, 83(1):528–536, 2000.

36] Staffan Ekwall and Danica Kragic. Grasp Recognition for Programming by Demonstration. In IEEE International Conference on Robotics and Automation, pages 748–753, 2005.

37] Rob Ellis and Mike Tucker. Micro-affordance: The potentiation of components of action by seen objects. British journal of psychology, 91(4):451–471, 2000.

38] Sara Fabbri, Kevin M Stubbs, Rhodri Cusack, and Jody Culham. Disentangling Representations of Object and Grasp Properties in the Human Brain. The Journal of Neuroscience, 36(29):7648–7662, 2016.

39] Reza Farivar. Dorsal-ventral integration in object recognition. Brain Research Reviews, 61(2):144–153, 2009.

40] Thomas Feix, Ian M Bullock, and Aaron M Dollar. Analysis of human grasping behavior: correlating tasks, objects and grasps. IEEE transactions on haptics, 7(4):430–441, 2014.
[41] Thomas Feix, Ian M Bullock, and Aaron M Dollar. Analysis of Human Grasping Behavior: Object Characteristics and Grasp Type. *IEEE transactions on haptics*, 7(3):311–323, 2014.

[42] Pedro F Felzenszwalb, Ross Girshick, David A McAllester, and Deva Ramanan. Object Detection with Discriminatively Trained Part-Based Models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(9):1627–1645, 2010.

[43] J Randall Flanagan and Roland S Johansson. Sensory control of object manipulation. In *Sensorimotor Control of Grasping: Physiology and Pathophysiology*, pages 141–160. Cambridge University Press, 2009.

[44] Vittorio Gallese and George Lakoff. The Brain’s concepts: the role of the Sensory-motor system in conceptual knowledge. *Cognitive neuropsychology*, 22(3):455–479, 2005.

[45] Jason P Gallivan, Jonathan S Cant, Melvyn A Goodale, and J Randall Flanagan. Representation of Object Weight in Human Ventral Visual Cortex. *Current Biology*, 24(16):1866–1873, 2017.

[46] Yang Gao, Lisa Anne Hendricks, Katherine J Kuchenbecker, and Jason P Gallivan, Jonathan S Cant, Melvyn A Goodale, and J Randall Flanagan. Eye-Hand Coordination in Object Manipulation. *The Journal of Neuroscience*, 21(17):6917–6932, 2001.

[47] Melvyn A Goodale. Transforming vision into action. *Vision research*, 51(13):1567–1587, 2011.

[48] Melvyn A Goodale and A David Milner. Separate visual pathways for perception and action. *Trends in Neurosciences*, 15(1):20–25, 1992.

[49] Scott T Grafton. The cognitive neuroscience of prehension: recent developments. *Experimental Brain Research*, 204(4):475–491, 2010.

[50] Christian Grefkes and Gereon R Fink. The functional organization of the intraparietal sulcus in humans and monkeys. *Journal of Anatomy*, 207(1):3–17, 2005.

[51] J Grèzes, Mike Tucker, J Armony, Rob Ellis, and R E Passingham. Objects automatically potentiate action: an fMRI study of implicit processing. *The European journal of neuroscience*, 17(12):2735–2740, 2003.

[52] A Harel, D J Kravitz, and C I Baker. Task context impacts visual object processing differentially across the cortex. *Proceedings of the National Academy of Sciences of the United States of America*, 111(10):962–971, 2014.

[53] Stevan Harnad. The Symbol Grounding Problem. *Physica D. Nonlinear phenomena*, 42:335–346, 1990.

[54] Oliver Herbout, Martin V Butz, and Wilfried Kunde. The contribution of cognitive, kinematic, and dynamic factors to anticipatory grasp selection. *Experimental Brain Research*, 232(6):1677–1688, 2014.

[55] Frouke Hermens, Daniel Kral, and A David A Rosenbaum. Limits of end-state planning. *Acta psychologica*, 148:148–162, 2014.

[56] Martin Hjelm, Renaud Detry, Carl Henrik Ek, and Danica Kragic. Representations for cross-task, cross-object grasp transfer. *IEEE International Conference on Robotics and Automation*, pages 5699–5704, 2014.

[57] Martin Hjelm, Carl Henrik Ek, Renaud Detry, and Danica Kragic. Learning Human Priors for Task-Constrained Grasping. In *International Conference on Computer Vision Systems*, pages 207–217, 2015.

[58] Leyla Isik, Andrea Tacchetti, and Tomaso Poggio. A fast, invariant representation for human action in the visual system. *Journal of Neurophysiology*, 119(2):631–640, 2018.

[59] Thomas W James, Jody Culham, G Keith Humphrey, A David Milner, and Melvyn A Goodale. Ventral occipital lesions impair object recognition but not object-directed grasping: an fMRI study. *Brain*, 126(11):2463–2475, 2003.

[60] Thomas W James, G Keith Humphrey, Joseph S Gati, Ravi S Menon, and Melvyn A Goodale. Differential Effects of Viewpoint on Object-Driven Activation in Dorsal and Ventral Streams. *Neuron*, 55(4):793–801, 2002.

[61] M Jeannerod. Visuomotor channels: their integration in goal-directed prehension. *Human Movement Science*, 18(2-3):201–218, 1999.

[62] Per Jenmalm, Seth Dahlstedt, and Roland S Johansson. Visual and Tactile Information About Object-Curvature Control Fingertip Forces and Grasp Kinematics in Human Dexterous Manipulation. *Journal of Neuropsychology*, 84(6):2984–2997, 2000.

[63] Roland S Johansson, Göran Westling, Anders Bäckström, and J Randall Flanagan. Eye-Hand Coordination in Object Manipulation. *The Journal of Neuroscience*, 21(17):6917–6932, 2001.

[64] E Johns, S Leutenegger, and A J Davison. Deep learning a grasp function for grasping under gripper pose uncertainty. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4461–4468, 2016.

[65] Scott Johnson Frey, Michael McCarty, and Rachel Keen. Reaching beyond spatial perception: Effects of intended future actions on visually guided prehension. *Visual Cognition*, 11(2-3):371–399, 2004.

[66] Markus Kiefer and Friedemann Pulvermuller. Conceptual representations in mind and brain: Theoretical developments, current evidence and future directions. *Cortex*, 48(7):805–825, 2012.

[67] Mia Kokic, Johannes A Stork, Joshua A Haustein, and Danica Kragic. Affordance detection for task-specific grasping using deep learning. In *IEEE-RAS International Conference on Humanoid Robotics*, pages 91–98, 2017.

[68] D J Kravitz, K S Saleem, and C I Baker. The ventral visual pathway: an expanded neural framework for the processing of object quality. *Trends in Cognitive Sciences*, 17(1):26–49, 2013.

[69] Dwight J Kravitz, Kadharbatcha S Saleem, Chris I Baker, and Mortimer Mislikin. A new neural framework for visuospatial processing. *Nature Reviews Neuroscience*, 12:217–230, 2011.

[70] K Krug and Andrew J Parker. Neurons in Dorsal Visual Area V5/MT Signal Relative Disparity. *The Journal of Neuroscience*, 31(49):17892–17904, 2011.

[71] Norbert Krüger, Peter Janssen, Sinan Kalkan, Markus Lappe, Alex Leonards, Justus H Piater, Antonio Jose Rodriguez-Sanchez, and Laurens Wiskott. Deep Hierarchies in the Primate Visual Cortex - What Can We Learn for Computer Vision? *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8):1847–1871, 2013.

[72] M A Lebedev and S P Wise. Insights into Seeing and Grasping: Distinguishing the Neural Correlates of Perception and Action. *Behavioral and Cognitive Neuroscience Reviews*, 1(2):108–129, 2002.

[73] Ian Lenz, Honglak Lee, and Ashutosh Saxena. Deep Learning for Detecting Robotic Grasps. *The International Journal of Robotics Research*, 34:705–724, 2015.

[74] Sergey Levine, Peter Pastor, Alex Krizhevsky, and Deirdre Quillen. Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection. *The International Journal of Robotics Research*, 37:421–436, 2018.

[75] M Li, Y Bekiroglu, Danica Kragic, and Aude G Billard. Learning of end-state planning. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3339–3346, 2014.

[76] N K Logothetis. Vision: a window on consciousness. *Scientific American*, 281(5):69–75, 1999.

[77] N K Logothetis and D L Sheinberg. Visual Object Recognition. *Current Biology*, 11(2-3):371–399, 1996.

[78] C L MacKenzie and T Iberall. *The Grasping Hand*. Advances in Psychology. Elsevier, 1994.
A David Milner, H C Dijkerman, Robert D McIntosh, Y Rossetti, Alex Martin and Linda L Chao. Semantic memory and the brain: structure and processes. Current Opinion in Neurobiology, 11(2):194–201, 2001.

A T Miller, S Knoop, H I Christensen, and Peter K Allen. Automatic grasp planning using shape primitives. In IEEE International Conference on Robotics and Automation, pages 1824–1829, 2003.

A David Milner, H C Dijkerman, Robert D McIntosh, Y Rossetti, and L Pisella. Delayed reaching and grasping in patients with optic ataxia. In Neural Control of Space Coding and Action Production, pages 225–242. Elsevier, 2003.

A T Miller, S Knoop, H I Christensen, and Peter K Allen. Automatic grasp planning using shape primitives. In IEEE International Conference on Robotics and Automation, pages 1824–1829, 2003.

A David Milner, H C Dijkerman, Robert D McIntosh, Y Rossetti, and L Pisella. Delayed reaching and grasping in patients with optic ataxia. In Neural Control of Space Coding and Action Production, pages 225–242. Elsevier, 2003.

A T Miller, S Knoop, H I Christensen, and Peter K Allen. Automatic grasp planning using shape primitives. In IEEE International Conference on Robotics and Automation, pages 1824–1829, 2003.

A David Milner, H C Dijkerman, Robert D McIntosh, Y Rossetti, and L Pisella. Delayed reaching and grasping in patients with optic ataxia. In Neural Control of Space Coding and Action Production, pages 225–242. Elsevier, 2003.

A T Miller, S Knoop, H I Christensen, and Peter K Allen. Automatic grasp planning using shape primitives. In IEEE International Conference on Robotics and Automation, pages 1824–1829, 2003.

A David Milner, H C Dijkerman, Robert D McIntosh, Y Rossetti, and L Pisella. Delayed reaching and grasping in patients with optic ataxia. In Neural Control of Space Coding and Action Production, pages 225–242. Elsevier, 2003.

J R Napier. The prehensile movements of the human hand. The Journal of Bone and Joint Surgery, British volume, 38-B(4):902–913, 1956.

P Neri. A Stereoscopic Look at Visual Cortex. Journal of Neurophysiology, 93(4):1823–1826, 2004.

E Nikandrovka and Ville Kyrki. Category-based task specific grasping. Robotics and Autonomous Systems, 70:25–55, 2015.

Thomas J Palmeri and Isabel Gauthier. Visual object understanding. Nature Reviews Neuroscience, 5(4):291–303, 2004.

Jessie J Peissig and Michael J Tarr. Visual object recognition: do we know more now than we did 20 years ago? Annual review of psychology, 58:75–96, 2007.

Lerrel Pinto, Dhiraj Gandhi, Yuenfeng Han, Yong-Lae Park, and Abhinav Gupta. The Curious Robot: Learning Visual Representations via Physical Interactions. In European conference on Computer Vision, pages 3–18, 2016.

Nicolas Pinto, David Daniel Cox, and James J DiCarlo. Why is Real-World Visual Object Recognition Hard? PLoS Computational Biology, 4(1):1–6, 2008.

Friedemann Pulvermüller, Rachel L Moseley, Natalia Egorova, Zubaida Shebani, and Véronique Boulenger. Motor cognition–motor semantics: Action perception theory of cognition and communication. Neuropsychologia, 55:71–84, 2014.

Jenny C A Read, Graeme P Phillipson, Ignacio Serrano-Pedraza, A David Milner, and Andrew J Parker. Stereoscopic Vision in the Absence of the Lateral Occipital Cortex. PLoS One, 5(9):1–14, 2010.

Joseph Redmon and Anelia Angelova. Real-time grasp detection using convolutional neural networks. In IEEE International Conference on Robotics and Automation, pages 1316–1322, 2015.

Maximilian Riesenhuber and Tomaso Poggio. Models of object recognition. Nature Neuroscience, 3:1199–1204, 2000.

Giacomo Rizzolatti, R Camarda, Leonardo Fogassi, M Gentilucci, Giuseppe Luppino, and M Matelli. Functional organization of inferior area 6 in the macaque monkey. Experimental Brain Research, 71(3):491–507, 1988.

Giacomo Rizzolatti, Luciano Fadiga, Vittorio Gallese, and Leonardo Fogassi. Premotor cortex and the recognition of motor actions. Brain research. Cognitive brain research, 3(2):131–141, 1996.

Magali J Rochat, Fausto Caruana, Ahmad Jezzini, Ludovic Escola, Irakli Intsikrveli, Franck Grammont, Vittorio Gallese, Giacomo Rizzolatti, and Maria Alessandra Umlita. Responses of mirror neurons in area F5 to hand and tool grasping observation. Experimental Brain Research, 204(4):605–616, 2010.

conceptual content. Journal of Physiology-Paris, 102(1-3):59–70, 2008.

Gr e gory Roger, James Steven Supancic, III, and Deva Ramanan. Understanding Everyday Hands in Action from RGB-D Images. In IEEE International Conference on Computer Vision, pages 3889–3897, 2015.

Edmund T Rolls. Invariant Visual Object and Face Recognition - Neural and Computational Bases, and a Model, VisNet. Frontiers in Computational Neuroscience, 6:35, 2012.

Edmund T Rolls and Simon M Stringer. Invariant Global Motion Recognition in the Dorsal Visual System: A Unifying Theory. Neural Computation, 19(1):139–169, 2007.

David A Rosenbaum, Kate M Chapman, Matthias Weigelt, Daniel J Weiss, and Robrecht van der Wel. Cognition, action, and object manipulation. Psychological Bulletin, 13(5):924–946, 2012.

Luisa Sartori, Elisa Straulino, and Umberto Castiello. How Objects Are Grasped: The Interplay between Affordances and End-Goals. PLoS One, 6(9):1–10, 2011.

Ashutosh Saxena, Justin Driemeyer, and Andrew Y. Ng. Robotic Grasping of Novel Objects using Vision. The International Journal of Robotics Research, 27(2):157–173, 2008.

Thomas Schenk. Visuomotor robustness is based on integration not segregation. Vision research, 50(24):2627–2632, 2010.

Thomas Schenk, V Franz, and N Bruno. Vision-for-perception and vision-for-action: Which model is compatible with the available psychophysical and neuropsychological data? Vision research, 51(8):812–818, 2011.

Thomas Schenk and Robert D McIntosh. Do we have independent visual streams for perception and action? Cognitive Neuroscience, 1(2):52–60, 2010.

T Serre, Aude Oliva, and Tomaso Poggio. A feedforward architecture accounts for rapid categorization. Proceedings of the National Academy of Sciences of the United States of America, 104(15):6424–6429, 2007.

T Serre, L Wolf, Stanley Bileschi, Maximilian Riesenhuber, and Tomaso Poggio. Robust Object Recognition with Cortex-Like Mechanisms. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(3):411–426, 2007.

Dan Song, Kai Huebner, Ville Kyrki, and Danica Kragic. Learning task constraints for robot grasping using graphical models. In IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 1579–1585, 2010.

Michael J Tarr and Quoc C Vuong. Visual Object Recognition. Stevens’ Handbook of Experimental Psychology. John Wiley & Sons, Inc., 2002.

Mike Tucker and Rob Ellis. The potentiation of grasp types during visual object categorization. Visual Cognition, 8(6):769–800, 2001.

Leslie Ungerleider and Mortimer Mishkin. Two cortical visual systems. In Analysis of Visual Behavior, pages 549–586. MIT Press, 1982.

Maryam Vaziri-Pashkam and Yaoda Xu. Goal-directed visual processing differentially impacts human ventral and dorsal visual representations. The Journal of Neuroscience, pages 3392–16, 2017.

Guy Wallis and Edmund T Rolls. Invariant Face And Object Recognition In The Visual System. Progress in Neurobiology, 51(2):167–194, 1997.

Valentinos Zachariou, Roberta Klatchy, and Marlene Behrmann. Ventral and Dorsal Visual Stream Contributions to the Perception of Object Shape and Object Location. Journal of Cognitive Neuroscience, 26(1):189–209, 2014.