

# Shared Challenges in Object Perception for Robots and Infants<sup>†</sup>

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## Abstract

Robots and humans receive partial, fragmentary hints about the world’s state through their respective sensors. In this paper, we focus on some fundamental problems in perception that have attracted the attention of researchers in both robotics and infant development: object segregation, intermodal integration, and the role of embodiment. We concentrate on identifying points of contact between the two fields, and also important questions identified in one field and not yet addressed in the other. For object segregation, both fields have examined the idea of using “key events” where perception is in some way simplified and the infant or robot acquires knowledge that can be exploited at other times. We examine this parallel research in some detail. We propose that the identification of the key events themselves constitutes a point of contact between the fields. And although the specific algorithms used in robots are not easy to relate to infant development, the overall “algorithmic skeleton” formed by the set of algorithms needed to identify and exploit key events may in fact form a basis for mutual dialogue.

**Keywords:** Infant development, robotics, object segregation, intermodal integration, embodiment.

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## 1. Introduction

Imagine if your body's sensory experience were presented to you as column after column of numbers. One number might represent the amount of light hitting a particular photoreceptor, another might be related to the pressure on a tiny patch of skin. Imagine further if you could only control your body by putting numbers in a spreadsheet, with different numbers controlling different muscles and organs in different ways.

This is how a robot experiences the world. It is also a (crude) *model* of how humans experience the world. Of course, our sensing and actuation are not encoded as numbers in the same sense, but aspects of the world and our bodies are transformed to and from internal signals that, in themselves, bear no trace of the signals' origin. For example, a neuron firing selectively to a red stimulus is not itself necessarily red. The feasibility of telepresence and virtual reality shows that this kind of model is not completely wrong-headed; if we place digital transducers between a human and the world, they can still function well.

Understanding how to build robots requires understanding in a very concrete and detailed way how it is possible to sense and respond to the world. Does this match the concerns of psychology? For work concerned with modeling phenomena that exist at a high level of abstraction, or deeply rooted in culture, history, and biology, the answer is perhaps "no". But for immediate perception of the environment, the answer must be at least partially "yes", because the problems of perception are so great that intrinsic, physical, non-cultural, non-biological, non-historical constraints must play a role. We expect that there will be commonality between how infants and successful robots operate at the information-processing level, because natural environments are of mixed, inconstant observability – there are properties of the environment that can be perceived easily under some circumstances and with great difficulty (or not at all) under others. This network of opportunities and frustrations should place limits on information processing that apply both to humans and robots with human-like sensors.

In this paper, we focus on early perceptual development in infants. The perceptual judgements infants make change over time, showing a changing sensitivity to various cues. This progression may be at least partially due to knowledge gained from experience. We identify opportunities that can be exploited by both robots and infants to perceive properties of their environment that cannot be directly perceived in other circumstances. We review some of what is known of how robots and infants can exploit such opportunities to learn to make reasonable inferences about object properties that are not directly given in the display through correlations with observable properties, grounding those inferences in prior experience. The topics we focus on are object

segregation, intermodal integration, and embodiment.

## 2. Object segregation

[Figure 1 about here.]

The world around us has structure, and to an adult appears to be made up of more-or-less well-defined objects. Perceiving the world this way sounds trivial, but from an engineering perspective, it is heart-breakingly complex. As Spelke wrote in 1990:

... the ability to organize unexpected, cluttered, and changing arrays into objects is mysterious: so mysterious that no existing mechanical vision system can accomplish this task in any general manner. (Spelke, 1990)

This is still true today. This ability to assign boundaries to objects in visually presented scenes (called “object segregation” in psychology or “object segmentation” in engineering) cannot yet be successfully automated for arbitrary object sets in unconstrained environments (see Figure 1).

There has been *algorithmic* progress; for example, given local measures of similarity between each neighboring element of a visual scene, a globally appropriate set of boundaries can be inferred in efficient and well-founded ways (see for example Felzenszwalb and Huttenlocher (2004)). Just as importantly, there is also a growing awareness of the importance of collecting and exploiting empirical *knowledge* about the statistical combinations of materials, shapes, lighting, and viewpoints that actually occur in our world (see for example Martin et al. (2004)). Of course, such knowledge can only be captured and used effectively because of algorithmic advances in machine learning, but the knowledge itself is not specified by an algorithm.

Empirical, non-algorithmic knowledge of this kind now plays a key role in machine perception tasks of all sorts. For example, face detection took a step forward with Viola and Jones (2004); the success of this work was due both to algorithmic innovation and better exploitation of knowledge (features learned from 5000 hand-labelled face examples). The success of automatic speech recognition is successful largely because of the collection and exploitation of extensive corpuses of clearly labelled phoneme or phoneme-pair examples that cover well the domain of utterances to be recognized.

These two examples clarify ways “knowledge” can play a role in machine perception. The bulk of the “knowledge” used in such systems takes the form of *labelled examples* – examples of input from the sensors (a vector of numbers), and the corresponding desired output interpretation (another vector of numbers). More-

or-less general purpose machine learning algorithms can then approximate the mapping from sensor input to desired output interpretation based on the examples (called the *training set*), and apply that approximation to novel situations (called the *test set*). Generally, this approximation will be very poor unless we transform the sensory input in a manner that highlights properties that the programmer believes may be relevant. This transformation is called *preprocessing and feature selection*. There is a great deal of infrastructure wrapped around the learning system to break the problem down into tractable parts and apply the results of learning back to the original problem. For this paper, we will group all this infrastructure and call it the ***algorithmic skeleton***. This set of carefully interlocking algorithms is designed so that, when fed with appropriate training data, it fleshes out into a functional system. Without the algorithmic skeleton, there would be no way to make sense of the training data, and without the data, perception would be crude and uninformed.

What, then, is the right algorithmic skeleton for object segregation? What set of algorithms, coupled with what kind of training data, would lead to best performance? We review suggestive work in infant development research and robotics.

[Figure 2 about here.]

## 2.1 *Segregation skills in infants*

By 4 to 5 months of age, infants can parse simple displays like the one in Figure 2 into units, based on something like a subset of static Gestalt principles – see for example Needham (1998, 2000). Initial studies indicated that infants use a collection of features to parse the displays (Needham, 1998; Needham and Baillargeon, 1997, 1998); subsequent studies suggested that object shape is the key feature that young infants use to identify boundaries between adjacent objects (Needham, 1999). Compared to adult judgements, we would expect such strategies to lead to many incorrect parsings, but they will also provide reasonable best guess interpretations of uniform objects in complex displays.

Infants do not come prepared from birth to segregate objects into units that match adult judgement. It appears that infants learn over time how object features can be used to predict object boundaries. More than twenty years ago, Kellman and Spelke (1983) suggested that infants may be born with knowledge about solid, three-dimensional objects and that this knowledge could help them interpret portions of a moving object as connected to other portions that were moving in unison. This assertion was put to the test by Slater and his colleagues (Slater et al., 1990), a test that resulted in a new conception of the neonate’s visual world. Rather than interpreting common motion as a cue to object unity, neonates appeared to interpret the visible portions

of a partly occluded object as clearly separate from each other, even when undergoing common motion. This finding was important because it revealed one way in which learning likely changes how infants interpret their visual world.

Although segregating adjacent objects present a very similar kind of perceptual problem (“are these surfaces connected or not”), the critical components of success might be quite different. Early work with adjacent objects indicated that at 3 months of age, infants tend to group all touching surfaces into a single unit (Kestenbaum et al., 1987). Subsequent experiments have revealed that soon after this point in development, infants begin to analyze the perceptual differences between adjacent surfaces and segregate surfaces with different features (but not those with similar features) into separate units (Needham 2000). 8.5 month old infants have been shown to also use information about specific objects or classes of objects to guide their judgement (Needham, Cantlon, & Ormsby, 2005).

It might be that extensive amounts of experience are required to ‘train up’ this system. However, it might also be that infants learn on the basis of relatively few exposures to key events (Baillargeon, 1999). This possibility was investigated within the context of object segregation by asking how infants’ parsing of a display would be altered by a brief prior exposure to one of the objects in the test display.

In this paradigm, a test display was used that was ambiguous to 4.5-month-old infants who had no prior experience with the display. Prior experience was then given that would help disambiguate the display for infants. This experience consisted of a brief prior exposure (visual only) to a portion of the test display. If infants used this prior experience to help them parse the test display, they should see the display as two separate objects and look reliably longer when they moved as a whole than when they move separately. Alternately, if the prior experience was ineffective in altering infants’ interpretation of the display, they should look about equally at the display, just as the infants in the initial study with no particular prior experience did (Needham and Baillargeon, 1998). Prior experiences with either portion of the test display were effective in facilitating infants’ parsing of the test display.

## *2.2 Segregation skills in robots*

This idea that *exposure to key events* could influence segregation is intuitive, and evidently operative in infants. Yet it is not generally studied or used in mechanical systems for object segregation. In this section, we attempt to reformulate robotics work by the authors in these terms.

For object segregation in robotics, we will interpret “key events” as moments in the robot’s experience where

the true boundary of an object can be reliably inferred. They offer an opportunity to determine *correlates* of the boundary that can be detected outside of the limited context of the key events themselves. Thus, with an appropriate algorithmic skeleton, information learned during key events can be applied more broadly.

Key events in infants include seeing an object in isolation or seeing objects in relative motion. In the authors' work, algorithmic skeletons have been developed for exploiting constrained analogues of these situations.

In Natale et al. (2005b), a very simple key event is used to learn about objects – *holding an object up to the face*. The robot can be handed an object or happen to grasp it, and will then hold it up close to its cameras. This gives a good view of its surface features, allowing the robot to do some learning and later correctly segregate the object out from the background visually even when out of its grasp (see Figure 3). This is similar an isolated presentation of an object, as in Needham's experiments. In real environments, true isolation is very unlikely, and actively moving an object so that it dominates the scene can be beneficial.

In Fitzpatrick and Metta (2003), the “key event” used is *hitting an object with the hand/arm*. This is a constrained form of relative object motion. In the real world, all sorts of strange motions happen which can be hard to parse, so it is simpler at least to begin with to focus on situations the robot can initiate and at least partially control. Motion caused by body impact has some technical advantages; the impactor (the arm) is understood and can be tracked, and since the moment and place of impact can be detected quite precisely, unrelated motion in the scene can be largely filtered out.

The *algorithmic skeleton* in (Fitzpatrick and Metta, 2003) processes views of the arm moving, detects impacts, and outputs boundary estimates of whatever the arm collides with based on motion. These boundaries, and what they contain, are used as training data for another algorithm, whose purpose is to estimate boundaries from visual appearance when motion information is not available. See Fitzpatrick (2003) for technical details. As a basic overview, the classes of algorithms involved are these:

1. *Behavior system*: an algorithm that drives the robot's behavior, so that it is likely to hit things. This system has a broader agenda than just this specific outcome; if
2. *Key event detection*: an algorithm that detects the key event of when the arm/hand hits an object.
3. *Training data extraction*: an algorithm that, within a key event, extracts boundary information from object motion caused by hitting.
4. *Machine learning*: an algorithm that discovers features predictive of boundaries that can be extracted in other situations without motion (in this case edge and color combinations).
5. *Application of learning*: an algorithm that actually uses those features to predict boundaries. This must

be integrated with the very first algorithm, to influence the robot's behavior in useful ways. In terms of observable behavior, the robot's ability to attend and fixate specific objects increases, since they become segregated from the background.

This skeleton gets fleshed out through learning, once the robot actually starts hitting objects and extracting specific features predictive of the boundaries of specific objects. A set of different algorithms performing analogous roles are used for the Natale et al. (2005b) example. At the algorithmic level, the technical concerns in either case are hard to relate to infant development, although in some cases there are correspondences. But at the skeletal level, the concerns are coming closer to those of infant development.

[Figure 3 about here.]

### *2.3 Specificity of knowledge gained from experience*

In the robotic learning examples in the previous section (Fitzpatrick, 2003; Natale et al., 2005b), information learned by the robot is intended to be specific to one particular object. The specificity could be varied algorithmically, by adding or removing parts of a feature's "identity". Too much specificity, and the feature will not be recognized in another context. Too little, and it will be "hallucinated" everywhere.

We return to Needham's experiments, which probed the question of generalization in the same experimental scenario described in Section 2.1.

When changes were introduced between the object seen during familiarization and that seen as part of the test display, an unexpected pattern emerged. Nearly any change in the object's features introduced between familiarization and test prevented infants from benefiting from this prior experience. So, even when infants saw a blue box with yellow squares prior to testing, and the box used in testing had white squares but was otherwise identical, they did not apply this prior experience to the parsing of the test display. However, infants did benefit from the prior exposure when it was not in the features of the object but rather in its orientation (Needham, 2001). A change in the orientation of the box from horizontally to vertically oriented led to the facilitation in parsing seen in some prior experiments. Thus, infants even as young as 4.5- to 5-months of age know that to probe whether they have seen an object before, they must attend to the object's features rather than its spatial orientation (Needham, 2001).

These results also support two additional conclusions. First, infants' object representations include detailed information about the object's features. Because infants' application of their prior experience to the parsing of

the test display was so dependent on something close to an exact match between the features, one much conclude that a highly detailed representation is formed on the initial exposure and maintained during the inter-trial-interval. Because these features are remembered and used in the absence of the initial item and in the presence of a different item, this is strong evidence for infants' representational abilities. Secondly, 4.5-month-old infants are conservative generalizers – they do not extend information from one object to another very readily. But would they extend information from a **group** of objects to a new object that is a member of that group?

#### *2.4 Generalization of knowledge gained from experience*

This question was investigated by Needham et al. (2005) in a study using the same test display and a similar procedure as in Needham (2001). Infants were given prior experiences with collections of objects, no one of which was an effective cue to the composition of the test display when seen prior to testing. A set of three similar objects seen simultaneously prior to test did facilitate 4.5-month-old infants segregation of the test display. But no subset of these three objects seen prior to testing facilitated infants' segregation of the test display. Also, not just any three objects functioned in this way – sets that had no variation within them or that were too different from the relevant test item provided no facilitation. Thus, experience with multiple objects that are varied but that are similar to the target item is important to infants' transfer of their experience to the target display.

This finding was brought into the “real” world by investigating infants' parsing of a test display consisting of a novel key ring (Needham et al., submitted). According to a strict application of organizational principles using object features, the display should be seen as composed of (at least) two separate objects – the keys on one side of the screen and the separate ring on the other side. However, to the extent that infants recognize the display as a member of a familiar category – key rings – they should group the keys and ring into a single unit that should move as a whole. The findings indicate that by 8.5 months of age, infants parse the display into a single unit, expecting the keys and ring to move together. Younger infants do not see the display as a single unit, and instead parse the keys and ring into separate units. Infants of both ages parsed an altered display, in which the identifiable portions of the key ring were hidden by patterned covers, as composed of two separate units. Together, these findings provide evidence that the studies of controlled prior exposure described in the previous section are consistent with the process as it occurs under natural circumstances. Infants' ordinary experiences present them with multiple similar exemplars of key rings, and these exposures build a representation that can then be applied to novel (and yet similar) instances of the key ring category, altering the interpretation that

would come from feature-based principles alone.

These results from infant development suggest a path for robotics to follow. There is currently no serious robotics work to point to in this area, despite its importance. Robotics work in this area could potentially aid infant psychologists since there is a strong theoretical framework in machine learning for issues of generalization.

### **3. Intermodal integration**

We have talked about “key events” in which object boundaries are easier to perceive. In general, the ease with which any particular object property can be estimated varies from situation to situation. Robots and infants can exploit the easy times to learn statistical correlates that are available in less clear-cut situations. For example, *cross-modal* signals are a particularly rich source of correlates, and have been investigated in robotics and machine perception. Most events have components that are accessible through different senses: A bouncing ball can be seen as well as heard; the position of the observer’s own hand can be seen and felt as it moves through the visual field. Although these perceptual experiences are clearly separate from each other, composing separate ‘channels’, we also recognize meaningful correspondences between the input from these channels. How these channels are related in humans is not entirely clear. Different approaches to the development of intermodal perception posit that infants’ sensory experiences are (a) unified at birth and must be differentiated from each other over development, or (b) separated at birth and must be linked through repeated pairings. Although the time frame over which either of these processes would occur has not been well defined, research findings do suggest that intermodal correspondences are detected early in development.

On what basis do infants detect these correspondences? Some of the earliest work on this topic revealed that even newborn infants look for the source of a sound (Butterworth and Castillo, 1976) and by 4 months of age have specific expectations about what they should see when they find the source of the sound (Spelke, 1976). More recent investigations of infants’ auditory-visual correspondences have identified important roles for synchrony and other amodal properties of objects – properties that can be detected across multiple perceptual modalities. An impact (e.g., a ball bouncing) provides amodal information because the sound of the ball hitting the surface is coincident with a sudden change in direction of the ball’s path of motion. Some researchers have argued (Bahrick) that detection and use of amodal object properties serves to bootstrap the use of more idiosyncratic properties (e.g., the kind of sound made by an object when it hits a surface). Bahrick & Lickliter have shown that babies (and bobwhite quail) learn better and faster from multimodal stimulation (see their Intermodal Redundancy Hypothesis (Bahrick and Lickliter, 2000)).

In robotics, amodal properties such as *location* have been used – for example, sound localization can aid visual detection of a talking person. *Timing* has also been used. Prince and Hollich (2005) develop specific models of audio-visual synchrony detection and evaluates compatibility with infant performance. Arsenio and Fitzpatrick (2005) exploit the specific timing cue of *regular repetition* to form correspondences across sensor modalities. From an engineering perspective, the redundant information supplied by repetition makes this form of timing information easier to detect reliably than synchrony of a single event in the presence of background activity. However, in the model of Lewkowicz (2000), the ordering during infant development is opposite. This suggests the engineers just haven't found a good enough algorithm, or regular repetition just doesn't happen enough to be important.

#### 4. The role of embodiment

The study of perception in biological systems cannot neglect the role of the body in the generation of the sensory information reaching the brain. The morphology of the body affects perception in numerous ways. In primates, for example, the visual information that reaches the visual cortex has a non-uniform distribution, due to the peculiar arrangement and size of the photoreceptors in the retina. In many species the outer ears and the head filter the sound in a way that facilitate auditory localization. The intrinsic elasticity of the muscles acts as a low pass filter during the interaction between the limbs and the environment.

Through the body the brain performs actions to explore the environment and collect information about its properties and rules. In their experiments with human subjects Lederman and Klatzky (Lederman and Klatzky, 1987) have identified a set of stereotyped hand movements (*exploratory procedures*) that adults use when haptically exploring objects to determine properties like weight, shape, texture and temperature. Lederman and Klatzky show that to each property can be associated a preferential exploratory procedure which is, if not required, at least optimal for its identification.

These observations support the theory that motor development and the body play an important role in perceptual development in infancy (Bushnell and Boudreau, 1993). Proper control of at least the head, the arm and the hand is required before infants can reliably and repetitively engage in interaction with objects. During the first months of life the inability of infants to perform skillful movements with the hand would prevent them from haptically exploring the environment and perceive properties of objects like weight, volume, hardness and shape. But, even more surprisingly, motor development could affect the developmental course of object visual perception (like three dimensional shape). Further support to this theory comes from the recent experiment by

Needham and colleagues (A. Needham and Peterman, 2002), where the ability of pre-reaching infants to grasp objects was artificially anticipated by means of mittens with palms covered with velcro that stuck to some toys prepared by the experimenters. The results showed that those infants whose grasping ability had been enhanced by the glove, were more interested in objects than a reference group of the same age that developed 'normally'. This suggests that, although artificial, the boost in motor development produced by the glove anticipated the infants' interest towards objects.

Exploiting actions for learning and perception requires the ability to match actions with the agents that caused it. The sense of agency (Jeannerod, 2002) gives humans the sense of ownership of their actions and implies the existence of an internal representation of the body. Although some sort of self-recognition is already present at birth, at least in the form of a simple hand-eye coordination (van der Meer et al., 1995), it is during the first months of development that infants learn to recognize their body as a separate entity acting in the world (Rochat and Striano, 2000). It is believed that to develop this ability infants exploit correlations across different sensorial channels (combined double touch/correlation between proprioception and vision).

In robotics we have the possibility to study the link between action and perception, and its implications on the realization of artificial systems. Robots, like infants, can exploit the physical interaction with the environment to enrich and control their sensorial experience. However these abilities do not come for free. Very much like an infant, the robot must first learn to identify and control its body, so that the interaction with the environment is meaningful and, at least to a certain extent, safe. Indeed, motor control is challenging especially when it involves the physical interaction between the robot and the world.

Inspired by the developmental psychology literature, roboticists have begun to investigate the problem of self-recognition in robotics (Gold and Scassellati, 2005; Metta and Fitzpatrick, 2003; Natale et al., 2005b; Yoshikawa et al., 2003). Although different in several aspects, in all these work the robot looks for intermodal similarities and invariances to identify its body from the rest of the world. In the work of Yoshikawa (Yoshikawa et al., 2003) the rationale is that for any given posture the body of the robot is invariant with respect to the rest of the world. The correlation between visual information and proprioceptive feedback is learned by a neural network which is trained to predict the position of the arms in the visual field. Gold and Scassellati (Gold and Scassellati, 2005) solve the self-recognition problem by exploiting knowledge of the time elapsing between the actions of the robot and the associated sensorial feedback. In the work of Metta and Fitzpatrick (Metta and Fitzpatrick, 2003) and Natale et al. (Natale et al., 2005b) actions are instead used to generate visual motion with a known pattern. Similarities in the proprioceptive and visual flow are searched to visually identify

the hand of the robot. Periodicity in this case enhances and simplifies the identification. The robot learns a multimodal representation of its hand that allows a robust identification in the visual field.

In our experience with robots we identified three scenarios in which the body proved to be useful in solving perceptual tasks:

1. *direct exploration*: the body in this case is the interface to extract information about the objects. For example in (Natale et al., 2004) haptic information was employed to distinguish object of different shape, a task that would be much more difficult if performed visually. In (Torres-Jara et al., 2005) the robot learned to recognize a few objects by using the sound they generate upon contact with the fingers.
2. *controlled exploration*: use the body to perform actions to simplify perception. The robot can deliberately generate redundant information by performing periodic actions in the environment.
3. *the body as a reference frame*: during action the hand is the place where important events are most likely to occur. The ability to direct the attention of the robot towards the hand is particularly helpful during learning; in (Natale et al., 2005b) we show how this ability allows the robot to learn a visual model of the objects it manages to grasp by simply inspecting the hand when touch is detected on the palm (see Figure 3). In similar situations the same behavior could allow the robot to direct the gaze to the hand if something unexpected touches it. Eye-hand coordination seems thus important to establish a link between different sensory channels like touch and vision.

## 5. Conclusions

In the field of humanoid robotics, researchers have a special respect and admiration for the abilities of infants. They watch their newborn children with particular interest, and their spouses have to constantly be alert for the tell-tale signs of them running an ad-hoc experiment. It can be depressing to compare the outcome of a five-year, multi-million-euro/dollar/yen project with what an infant can do after four months. Infants are so clearly doing what we want to robots to do; is there any way to learn from research on infant development? Conversely, can infant development research be illuminated by the struggles faced by robotics, perhaps pointing out fundamental perceptual difficulties taken for granted? Is there a way to create a model of development which applies both to infants and robots? It seems possible that similar sensorial constraints and opportunities will mold both the unfolding of an infant's sensitivities to different cues, and the organization of the set of algorithms used by robots to achieve sophisticated perception. So, at least at the level of identifying "key events" and mutually

reinforcing cues, a shared model is possible. Of course, there is a lot that would not fit in the model, and this is as it should be. It would be solely concerned with the class of functional, information-driven constraints. We have not in this paper developed such a model; that would be premature. We have at identified some points of connection that could grow into much more. We hope the paper will serve as one more link in the growing contact between the fields.

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## List of Figures

1	Object segregation is difficult for machines . . . . .	17
2	Object segregation is not always well-defined . . . . .	18
3	Exploitation of key moments in robotics . . . . .	19

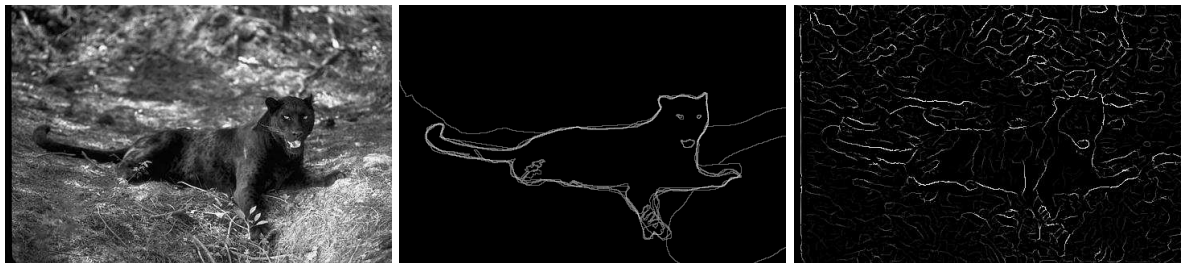


Figure 1: An example from Martin et al. (2004), to highlight the difficulties of bottom-up segmentation. For the image shown on the left, humans see the definite boundaries shown in white in the middle image. The best machine segmentation of a set of algorithms gives the result shown on this right – a mess. This seems a very difficult scene to segment without having some training at least for the specific kinds of materials in the scene.

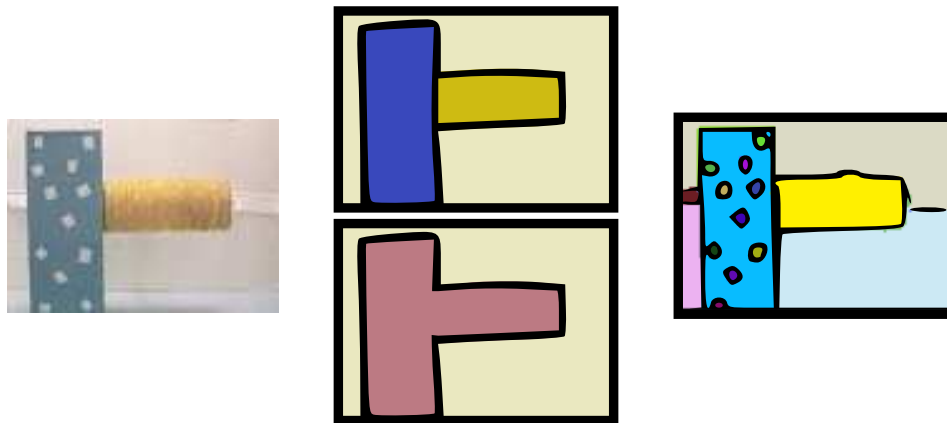


Figure 2: Object segregation is not necessarily well-defined. On the left, there is a simple scenario, taken from Needham (2001), showing a rectangle attached to a yellow tube. Two plausible ways to segregate this scene are shown in the middle, depending on whether the tube and rectangle make up a single object. For comparison, automatically acquired boundaries are shown on the right, produced using the algorithm in Felzenszwalb and Huttenlocher (2004). This algorithm does *image segmentation*, seeking to produce regions that correspond to whole objects (such as the yellow tube) or at least to object parts (such all the blue rectangle and all the small white patches on its surface, and various parts of the background). Ideally, regions that extend across object boundaries are avoided. Image segmentation is less ambitious than object segregation, and allows context information to be factored in as a higher level process operating on a region level rather than pixel level.

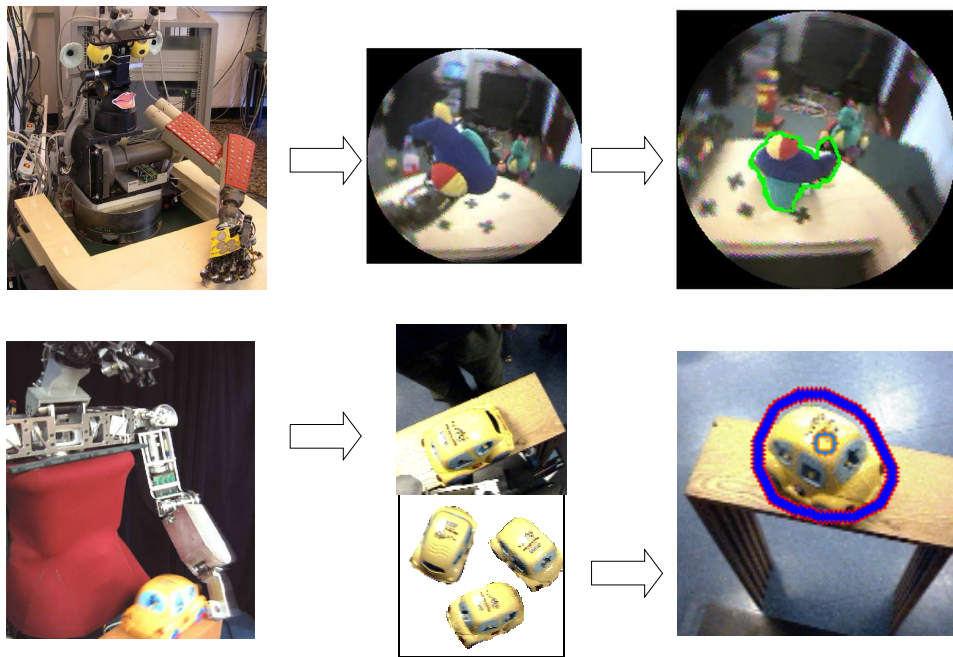


Figure 3: The upper row shows object segregation by the robot “Babybot” based on prior experience. The robot explores the visual appearances of an object that it has grasped; the information collected in this way is used later on to segment the object (Natale et al., 2005b). Left: the robot. Middle: the robot’s view when holding up an object. Right: later segmentation of the object. The lower row shows the robot “Cog” detecting object boundaries experimentally by poking (Fitzpatrick, 2003). During object motion, it finds features of the object that contrast with other objects, and that are stable with respect to certain geometric transformations. These features are then used to jointly detect and segment the object in future views. Left: the robot. Middle: segmentations of a poked object. Right: later segmentation of the object on a similarly-colored table.