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Learning for Coordination of Vision and Action

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We define the problem of visuomotor coordination and identify bottleneck problems in the implementation of general purpose vision and action systems. We conjecture that machine learning methods provide a general purpose mechanism for combining specific visual and action modules in a task-independent way. We also maintain that successful learning systems reflect realities of the environment, exploit context information, and identify limitations in perceptual algorithms which cannot be captured by the designer. We then propose a multi-step find-and-fetch mobile robot search and retrieval task. This task illustrates where current learning approaches provide solutions and where future research opportunities exist.

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Abstract

We define the problem of visuomotor coordination and identify bottleneck problems in the implementation of general purpose vision and action systems. We conjecture that machine learning methods provide a general purpose mechanism for combining specific visual and action modules in a task-independent way. We also maintain that successful learning systems reflect realities of the environment, exploit context information, and identify limitations in perceptual algorithms which cannot be captured by the designer. We then propose a multi-step find-and-fetch mobile robot search and retrieval task. This task illustrates where current learning approaches provide solutions and where future research opportunities exist.

1 Problem Statement, Classification, and Goals

Visuomotor coordination is an instance of the general sensorimotor coordination where sensory information is used for the control of actions. We define *visuomotor coordination* as the process of using non-contact sensing methods (primarily vision) for decision-making that controls motor outputs in order to generate desired behavior. However, the problem of ultimate interest is that of sensorimotor learning, which might include both contact and non-contact sensing modalities. Sensorimotor learning is can be considered a distinct problem from that of studying the properties of learning of vision and action separately. This is because sensorimotor systems involved feedback loops between perception and actions which may modify the world around the agent. This unique interaction is what makes visuomotor coordination a separate and distinct research area. We take notice that the above definition also includes the tasks of visually guided navigation and object recognition, and may provide principles of use to those areas.

In this paper we briefly summarize the basic issues and roadblocks to progress in the general visuomotor coordination and define key problems and potential roles for machine learning techniques.

Current systems have demonstrated visual-motor capabilities such as: navigation in an unknown obstacle-laden environment based on vision and sonar, including map-building abilities [Mataric, 1990], prototype abilities for rough terrain navigation [Simmons and Krotkov, 1991], and road following at high speeds [Dickmanns and Graefe, 1988]. Initial attempts at employing learning methodologies for road following [Pomerleau, 1989] compete with the best non-learning methods.

In the areas of knowledge-based grasp planning, much work has been done, [Cutkosky, 1989; Liu *et al.*, 1989; Tomovic *et al.*, 1986; Stansfield, 1990] using vision and tactile sensing. However, the problem of grasping/manipulating arbitrary objects is still unsolved in the general case, although initial learning results are promising [Tan, 1990; Salganicoff, 1992]

The current state of the art in visuomotor coordination is primarily shaped by two major problems: the extraction of shape and recognition from shape, which would permit obstacles and targets to be reliably identified in workspaces; and by issues in control of redundant manipulators in environments with obstacles. Vision is limited by many bottleneck problems. For example, there are no algorithms for general purpose segmentation over a variety of natural and man-made scenes with varying illumination levels and directions. Another outstanding problem is the recognition of functional categories, such as what invariants in perception and reaction to actions can be used to identify what constitutes difficult to classify objects such chair, door or a pen. By the same token, various approaches for controlling and exploiting the kinematics and dynamics of redundant manipulators have been devised, but no analytic approaches have combined kinematic, dynamic and obstacle constraints along with visual information in a general purpose and efficient fashion. Indeed, redundancy implies the use of optimization approaches, since the solutions are not unique, and therefore objective functions must be designed depending on context in an explicit fashion. Recently, very encouraging results have been obtained for these problems using learning approaches [Mel, 1991; Ritter *et al.*, 1991].

Most importantly, no approach has been devised for scaling vision and motor systems up in terms of increasing dimensionality in the state spaces and for the multi-step solutions necessary for solving important problems. Only a few systems have combined research in recognition, navigation and manipulation capabilities [Bajcsy *et al.*, 1991; Lin, 1991; Tan, 1990; Connell, 1989], and general approaches to such integration have yet to emerge.

Vision research over the past several years has yielded much progress in the development of visual modules for the extraction of task-independent, low-level features as edges, regions, shapes, texture, shading, optical flow and methods for efficient and robust feature tracking. Additionally, numerous candidate shape representations both in two and three dimensions have been devised. Unfortunately, no general-purpose high-level representations seem to be available that are useful across a wide variety of tasks. However, there is currently no principled, generally accepted architecture for combining the visual modules mentioned above in a purposive task-specific way, although this has been done successfully on a task by task basis. Therefore, we submit the following claims about the state of computer vision and the role of machine learning:

1. It is our contention that vision research has gone about as far as possible using the approach of processing using domain-independent and context-independent visual features. Although there is certainly room for improvement in particular algorithms for extraction of specific features such as edges and shape, significant progress will rely on the development of systems that can combine these lower-level features in reliable and parsimonious ways. Unfortunately, searching for combinations of visual modules that solve a given task is generally ad-hoc and not a solution of great generality. Therefore, these solutions will depend on particular task, user, and context, and will therefore be of less scientific interest.

2. We claim that learning offers the possibility of *general solutions* for *task-specific* vision and visuomotor coordination. While useful high-level visual features may necessarily be *task-specific* (e.g., a feature for recognizing the shoulder of the road), the methods for learning these features can be *task-independent.* Because learning methods can be task-independent, the scientific impact of developing such methods will be far greater than the impact of manually developing task-specific features for any single task.

3. A number of problems in vision are underdefined questions which, when more completely specified, are amenable to learning techniques. These

type of questions have no answer until one asks them in a context, *relative to a population of images*. For example, in the segmentation problem, whether a particular group of pixels *should* be interpreted as a distinct segment depends on the context and population of scenes under consideration. Once the problem is posed in this manner, machine learning techniques are the best approach. In other words, we should not try to manually program the system to recognize which combinations of features should lead to regions being merged, but should instead let the system learn it from the statistics of the population it encounters (i.e., from the context in which the vision task is embedded).

4. Finally, learning systems use real data, real sensors/manipulators, and are judged by real performance metrics. Therefore, learning systems reflect the reality of the external world and agents perceptual and action system, rather than just the designer's aspirations or hunches about those systems. For example, reality may include many aspects that cannot be captured by the designer, either because of limitations in the analytic model of the system (i.e. drift in optics resulting in chromatic abberation), or because of errors in sensing due to insufficient resolution and transduction noise, or inadequacies in algorithms. For example, different feature extraction algorithms may have differing reliabilities in different contexts (e.g., color perception in low light), and therefore, their corresponding attributes should be emphasized according to context during recognition and control. Because the results of learning reflect regularities found in real data and perceptual algorithms, they will take the relevant issues into account whether or not these were known to the designer.

2 Visuomotor Tasks and Learning Techniques

Machine learning has progressed significantly over the past decade. We currently have many workable inductive methods for learning from examples. The most successful include neural network Backpropagation and other curve-fitting methods (for learning continuous functions), and decision tree learning such as CART [Breiman *et al.*, 1984] and ID3 [Quinlan, 1986] for learning discrete-valued functions.

These techniques are robust to noise in the data, and have been demonstrated for many tasks such as learning to drive [Pomerleau, 1989], character recognition [le Cun *et al.*, 1990], learning the forward dynamics for robot arms [Atkeson, 1991], learning human-understandable rules from credit databases (e.g., ID3), and predicting complications from medical procedures [Breiman *et al.*, 1984]. In visuo-motor learning, reinforcement learning techniques such as Q-learning [Watkins, 1989] and Temporal Differencing [Sutton, 1988] have been developed for dealing with situations in which the feedback training signal is delayed (e.g., robot must perform a sequence of actions before receiving reward/feedback).

While these inductive methods work well for not-very-complex function approximation tasks, the primary limit on their applicability is that they do **not** scale up to very complex tasks. In the area of visual-motor control, they have mostly been applied in ad-hoc fashion, providing solutions in individual domains, but not providing a science of visuomotor learning.

2.1 How might machine learning help?

To ground the discussion of how learning might play a useful role in future visuo-motor systems consider the following scenario. We wish to have a generally useful robot to perform a wide variety of find-and-fetch tasks. In particular, assume that on some (future) day you purchase a robot and bring it to your home/workplace. It comes pre-programmed with perception and control routines of general use, and you now want to program it for specific tasks in your environment, such as "whenever you find my notebook in the conference room, fetch and return it to my office", "find and fetch my glasses and place them on my desk", "find and fetch dirty, empty dishes from the coffee table to the dishwasher." We are interested in *minimizing* the amount of programming of the system that must be done by each customer, and *maximizing* the competence of the system for each specialized task and environment.

Such a task underscores the potential role of learning since it is far too difficult for the end-user to program for all possible scenarios. While general capabilities can be built into the robot at the factory e.g., for path-planning and basic obstacle avoidance, other relevant information can be acquired only after it has been purchased and begins to characterize its domain. For example, it must learn how to recognize its owner's notebook, where he/she typically forgets their notebook, what a door looks like in this specific office environment, the acoustic reflectivity of walls and when to ignore echoes, how to manipulate a particular notebook, etc. This task involves navigation, recognition and manipulation, all of which require visuomotor coordination.

2.2 Obstacle Avoidance

First of all, our find-and-fetch robot must be able to move about in a non-destructive fashion. Obstacle avoidance is a necessary competence for navigation and exploration and an example of visual motor coordination. There has been a flurry of recent work in learning behaviors for low-level reactive procedures. Several researchers [Millan and Torras, 1991; Sutton, 1990] have explored dynamic programming reinforcement learning [Watkins, 1989] for learning plans in fixed obstacle environments. Prescott [Prescott and Mayhew, 1991] develops a general obstacle avoidance behavior using reinforcement learning which can be applied domain-independently. Lin [Lin, 1991] describes a learning approach for a search and docking task, and explores the role of human teleoperation and hierarchical organization to reduce learning times.

Cooperstock [J. Cooperstock and Milios, 1992] describes a system for rendezvous and manipulation which builds a model of its control actions using neural networks. Singh [Singh, 1991] describes an hierarchical decomposition architecture for reinforcement learning which allows for a transference of reinforcement models from subtasks of one task to others, which can speed learning in future cases.

2.3 Efficient Visual Search

While our find-and-fetch robot is navigating through its environment it must be searching for the desired object. Visual search is very computationally expensive, therefore search must be minimized as much as possible. One way to achieve this is by learning environment-specific information (e.g., segmentation methods that work well under the lighting conditions in this particular environment), as well as user-specific regularities (e.g., where the owner normally forgets their glasses), which will focus the search. Additionally, given a set of objects, learning methods can be applied to generate sequences of discriminatory sensing procedures that are maximally informative and of minimal cost to sense and process, such as the Cost Sensitive learning approaches of Tan [Tan, 1990]. Wixson [Wixson and Ballard, 1992] has applied reinforcement learning for learning context driven search sequences for different objects in the environment.

2.4 Learning Invariances

Additionally, recognition of objects in the environment requires the identification of invariances which facilitate identification of objects under the various imaging transformations and occlusions that occur in real environments. Recently, learning has been applied to recognition of three dimensional objects from projections [Poggio and Girosi, 1990; Intrator *et al.*, 1991] and combinations of aspect views [Basri and Ullman, 1991].

2.5 Calibration between Sensing and Action

Once our robot has identified its desired object, it must interact with the real world and manipulate that object. Since the actions executed during a visuomotor task must occur in the three-dimensional world around it, in order for the visual input to be useful in decision-making and control, some mechanism must exist for bringing the visual and motor coordinate systems in register via calibration. Traditionally, robotic systems have been decomposed into a vision system and a motor system and an attempt is made to calibrate each system separately using an analytic parameterized model of each system. In practice, this calibration approach has suffered from several disadvantages, such as the tediousness of obtaining precise measurements and calibration sources, and the fact that many of these methods do not operate on-line, and require a separate calibration phase to be undertaken.

Since the perception and action systems are based on mechanical components, inevitably, the mechanical characteristics of optical and actuator systems vary with time. It then becomes necessary to model and track the processes that lead to variations, if the system is to be robust to these changes. Learning systems are by definition adaptive, and allow this calibration to occur in a natural and transparent fashion.

Fortunately, there are several successful examples of self-calibrating learning systems. Kuperstein [Kuperstein, 1988] trained a simulated network of simple elements to compute the inverse kinematics of a simulated five degree of freedom arm from inputs derived from oculomotor and binocular disparity signals. Miller [Miller III, 1987] explored using CMAC associative memories [Albus, 1972] to learn a inverse visual Jacobian function that was used to command joint velocities for a positioning and tracking tasks in visual coordinates. Ritter [Ritter *et al.*, 1989] has developed a simulation of a manipulator with two cameras that learns to grasp objects described by a position and orientation in three-dimensional space.

All of these approaches have the advantage that no explicit model of the camera and manipulator system is necessary. These systems learn the visual Jacobian, which relates instantaneous actuator velocities to instantaneous velocities in the visual field. This visual Jacobian lumps the visual and motor calibrations together, rather than undertaking the respective calibrations separately.

2.6 Approaching and Grasping

Once our robot has identified the object it must attempt to grasp it. The grasp preshape and approach selected will depend on many factors, including the pose and shape of the object with respect to gravity, the dexterity of the gripper, the object's weight, its frictional characteristics, its supporting surfaces, the obstacles immediately around it (e.g. is their a Ming dynasty vase next to it?), and other obstacles that might interfere with it (e.g. will the extended manipulator knock over objects with its elbow?).

While there has been a tremendous amount of work in motion planning over the past few years beginning with the configuration space approaches of Lozano-Perez [Lozano-Perez, 1987], most approaches have proved inefficient in practical situations. In particular, redundant manipulators provide the flexibility necessary to avoid obstacles, but bring even greater complexity from a planning standpoint. Learning system have taken some promising first steps towards obstacle avoidance and redundancy planning. Ritter *et al.* [Ritter *et al.*, 1991] describe a system which learns the kinematics of redundant manipulators, albeit in an obstacle free environment. Mel [Mel, 1991] has developed a system that learns path planning in a cluttered two dimensional environment with a three degree-of-freedom arm by building a forward model of its actions.

Tham *et al.* [Tham and Prager, 1991] describe a reinforcement learning approach for multi-linked manipulators in obstacle filled environments. Since redundant arm solutions are non-unique, learning methods provide a mechanism for selecting good solutions based on experience and context.

Another important aspect which our find-and-fetch robot must take into account in grasping is the shape of the object as recovered from visual processing. Dunn and Segen [Dunn and Segen, 1988] have developed a system which attempts to grasp puzzle pieces and looks up successful approach orientations when the object is presented subsequently. Tan [Tan, 1990] has developed a cost sensitive learning system which attempts a set of stereotypical grasps on objects during a training phase. It attempts to build discrimination trees that take into account the tradeoff between attribute informativity and the cost of the sensing procedures to recover those attributes during the execution phase. Salganicoff [Salganicoff, 1992] has developed a robotic system for learning about grasp planning using density adaptive decision trees and projection-pursuit methods. The experimental system recovers a superquadric object *pose* and *shape* representation and attempts various grasps. It builds models that predict reinforcement for the different combined candidate grasps and approach directions which can be used decision making. Additionally, a density forgetting mechanism permits the system to adapt its reinforcement model to perceptual and action failures.

2.7 Functionality Learning

The find-and-fetch task ultimately brings up very complex problems. For example, many functional categories can only be learned through experimentation and observation. For example, what constitutes a door or doorway involves interaction with doors in terms of the different states that doors can take, i.e. open or closed, and what actions are necessary to accomplish state transitions. This learning of functional categories encompasses a huge number of tasks, such as, for example piercing or any other mechanical interaction with another object/surface.

2.8 Learning to Recognize Context Changes

Functional category learning implies observation of a controlled manipulatory action. This brings up the problem of learning to observe and recognize different *contexts*. This problem is that of recognizing state transitions which are manifested through sensory events which indicate that new dynamics are now in play [Sobh, 1991] (e.g., before grasp, no payload; then holding heavy object changes the manipulator dynamics substantially).

The formalism of Discrete-Event Dynamic Systems (DEDS) [Ozveren, 1990; Ramadge and Wonham, 1987] is a powerful technique for expressing notions of controllability, stability, observability and changing dynamics. The different nodes in a DEDS represent different contexts, each with differing dynamics.

These dynamics necessitate different control and sensing policies. For example, upon grasping an object, the hand and arm might begin to occlude the target object, therefore, the sensing policy might dictate that the camera be moved to a location with less occlusion, while the manipulator control policy should take into account the weight of the object.

Node transitions in a DEDS system occurs when certain thresholds are exceeded in monitored quantities extracted from sensory observations. Currently the transitions between different states of DEDS automatons must be set experimentally and then empirically verified. Learning techniques should be applied to learn these transition thresholds and simplify the design of these systems. Ultimately, the entire automaton might be generated via inductive learning. The generality of these methodologies could lead to high payoffs in terms of many useful applications in industrial process monitoring, automated surveillance and reconnaissance.

2.9 Efficient Exploration

Using learning systems to address the above problems imposes an important additional requirement: an efficient exploration strategy for characterizing the environment. This is because each generating each learning trial may be costly in terms of time, or equipment (e.g., Ming Dynasty Vases, street price = $30,000). We desire an exploration strategy to balance the utility and risks of information gathering versus exploiting the current models to perform the desired task well [Kaelbling, 1990; Christiansen *et al.*, 1991]. Therefore, intelligent exploration strategies are necessary. Some recent work has been undertaken by Thrun using "competence maps" [Thrun and Moller, 1991] which assess the prediction accuracy of action models in various regions of the state space and control experimentation accordingly. Moore [Moore, 1990] has developed techniques for intelligent experimentation that estimate which of a set of candidate actions are more promising given the current action model and a Gaussian distribution assumption about outcomes.

3 Summary and Recommendations

Learning for visuomotor tasks is an extremely rich problem domain, which, most importantly, has many intermediate goals which will yield tangible benefits to the research and applied communities in the long and short run.

3.1 Benefits from Learning Approaches

In the 2-5 year time frame there will be many research opportunities and we expect to see substantial progress in the following areas:

- Learning cost efficient visual search and surveillance strategies by selection of sensors and algorithms which are most discriminating in a given context. In other words, learn what to sense and where focus attention and resources at different stages in a task.

- Combining multiple visual modules for task dependent vision using learning approaches.

- Learning to observe by segmenting actions temporally and learning appropriate perceptual actions to maximize observability of processes by active vision systems.

- Selective forgetting strategies which allow learners to track changes in the environment, especially in order to allow system performance to readapt when system sensors and actuators fail.

- Learning contexts so that the environment and task can be partitioned into special cases that require different perceptual and action control strategies.

- Combined unsupervised and supervised learning of grasping based on object geometry.

- Applying reinforcement learning to subsumption architectures for perception action mapping in reactive planning and control [Mahadevan and Connell, 1992].

- Effective general purpose methods for combining teaching, exploration and exploitation in learning.

- Improved robot path planning in obstacle filled environments using learning algorithms for redundant manipulators and sensors.

- Mechanical Assembly Planning using learning by observation for task decomposition ([Ikeuchi and Suehiro, 1991; Kuniyoshi *et al.*, 1989], and specialization using reinforcement learning for each sub-action.

- Visuomotor learning techniques that do not require tracking fixtures on robot arms and explicit feature tracking because they combine the extraction of relevant features with simultaneous learning of action models.

These research described above will have immediate applications in many areas. Manufacturing processes, such as parts handling, transport, and assembly and disassembly will benefit from these results. Guard and surveillance robots can work more effectively using resource allocation methods that are learn and adapt to their task. Service robots that are similar to the find-and-fetch variety described here will certainly have many commercial and military tasks.

Prediction is more difficult in the 5-15 year time frame, but possible goals include learning context information, user specific habits and learning complex behaviors, as well as abstractions.

3.2 Recommendations

The following points summarize issues that we believe are important considerations in planning future funding for learning in vision:

1. *Machine learning can play an important role in vision:* Machine learning appears to offer significant opportunities to extend current methods for vision, especially in the area of task-specific vision. The above discussion describes a number of initial results, and a variety of suggested roles for machine learning in visuomotor learning and vision.

2. *Reasonable expectations:* We should certainly not assume that by introducing learning into visual tasks one will solve all the vision problems. Many of the short term goals enumerated above are restricted problems, but importantly, solutions to any one of these problems will have important research implications and practical use. In general, visual processing for any task is extremely **complex**, which is the reason why progress in this area has been slow. This complexity comes about from the multivariable problem of changing illumination, the observer's optics, geometry and the complexity of the environment. Furthermore the data is spatially and temporally distributed hence the data selection and reduction mechanisms are very task and context dependent. We must therefore continue study/support of basic analysis of the multivariate problem of data reduction and selection mechanisms. We must study invariances and spaces which enhance these invariances.

3. Collaboration between the Machine Learning and the Vision/Robotics Communities. Many members of the machine learning communities do not have access to the laboratory facilities needed to pursue learning for visual motor coordination. In particular the equipment costs and staff expertise necessary for designing and maintaining robotic and vision hardware is out of the reach of many machine learning groups. Therefore, in order to facilitate the interchange between these two communities we propose that cross-disciplinary postdoctoral fellowships be established to allow machine learning researchers extended visits to researchers at robotics and vision facilities.

4. A robotic competition that encourages graduate students in computer science to explore research in combining machine learning, perception and robotics. This would be held in conjunction with some major conference in either Robotics or Artificial intelligence, such as IJCAI or IEEE Robotics and Automation.

4 Summary

We have defined the problem domain of visuomotor coordination and described some basic issues and properties of the problem that make it unique. Our central claim is that machine learning offers a *task-independent* way of combining *task-dependent* features and actions. Secondarily, learning systems incorporate limitations existing in real data, sensors, actuators and perceptual processing algorithms into their solutions, rather than the expectations and approximations of designer. We then describe how the many existing subfields of machine learning for robotics and vision might be combined to solve a complicated find-and-fetch task that would be impractical to engineer and program *a priori* due to variations in domains.

We have highlighted what we consider will be productive areas of research in visuomotor learning in the next five years: including learning efficient sensing strategies, combining visual-modules; forgetting; contexts; grasping preshapes and approaches; exploration and exploitation; and mechanical assembly planning by learning from demonstration. Finally, we have identified a need for collaboration between the Machine Learning and Vision/Robotics communities and proposed extended visits between researchers in those fields so that machine learning researchers may have access to facilities necessary to pursue research in visuomotor coordination.

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