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GESTURE-BASED PROGRAMMING, PART 2: PRIMORDIAL LEARNING

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ABSTRACT:
In part one of this two-part series, we described our Gesture-Based Programming paradigm for programming by human demonstration. This paradigm depends on a pre-existing knowledge base of capabilities, collectively called "encapsulated expertise," that comprise the real-time sensorimotor primitives from which the run-time executable is constructed as well as providing the basis for interpreting the teacher's actions during programming. In this paper we present a technique based on principal components analysis, augmentable with model-based information, for learning and recognizing sensorimotor primitives. We describes simple applications of the technique to a mobile robot and a PUMA manipulator. The mobile robot learned to escape from jams while the manipulator learned guarded moves and accommodations that are composable to allow flat plate mating operations. While these initial applications are simple, they demonstrate the ability to extract primitives from demonstration, recognize the learned primitives in subsequent demonstrations, and combine and transform primitives to create different capabilities.

INTRODUCTION

Gesture-Based Programming (GBP) is a paradigm for programming rapidly deployable systems by human demonstration. A fundamental assumption on which the paradigm is based is the availability of a knowledge base of sensorimotor dexterity -- precompiled capabilities the target system already "knows." There are three basic mechanisms by which these primitives can come into existence. The first is "clairvoyance." The user (or automatic planner), acting as a god, hand codes a primitive that he/she *knows* is useful and composable. An example of this is a guarded move. The second mechanism is through assembly of lower-level primitives (i.e. Morrow and Khosla, 1995). Using a calculus analogy, algebraic primitives may form the basis for calculus, but arithmetic primitives form the basis for algebra. Finally, there is learning.

In this paper, we present a learning approach for extracting sensorimotor primitives from teleoperated manipulations that is a natural extension of an autonomous sensor calibration technique called *Shape from Motion* (Voyles et al, 1995a). Calibration is, afterall, a form of learning. One wants to "learn" the transformation from the sensor's input space to the output space. Most traditional calibration techniques (such as least-squares) do not pose it as a learning problem, however. Shape from Motion calibration extracts the "shape" of an input/output mapping that results from random "motion" of the input through the sensor space. The result is calibration of the sensor with little or no knowledge of the loads applied to the sensor. It became apparent that Shape from Motion could be applied to other types of learning problems, as well.

Shape from Motion is based on the extraction of an eigenspace representation of the input/output mapping by SVD to derive principle components. In the case of force/torque sensor calibration (described in Voyles et al, 1995a), the principle components analysis (PCA) is constraint-directed, so model-based information can be incorporated into the learning process. Because the underlying representation (a set of eigenvectors) is linear, it is limited to learning linear, or at least piece-wise linear, interactions. The drawback is the difficult task of segmenting the observations into linear, learnable subtasks. The advantage is the representation provides not only a mechanism to learn the primitives, but natural mechanisms for identifying primitives in subsequent observations and combining and transforming existing primitives into new primitives. These are abilities many other learning approaches have difficulty demonstrating.

PRIOR WORK

We are interested in developing a primitive representation which supports acquisition, integration, and transformation of sensorimotor primitives. Previous work in learning robot skills is relevant to this effort because it provides potential primitive acquisition techniques and because primitives learned by techniques other than primordial learning may also be used in the execution phase of our system. The idea is to relate primitives to recurring subgoals of complex tasks and to reuse primitives in the construction of complex task strategies, whatever the origin of the primitives may be.

Yang et al (1994) have applied hidden markov models to skill modelling and learning from telerobotics. The skills learned are manipulator positioning tasks without force or vision feedback. Pook and Ballard (1992) performed similar work.

Along these lines of skill acquisition by supervised learning is ALVINN, an artificial neural network for vehicle steering (Pomerleau, 1992). ALVINN has demonstrated robust mastery over a wide range of vehicles and road types by observing a human drive the vehicle on the target road type. For the purpose of comparison, Hancock and Thorpe (1995) developed ELVIS, a PCA-based vehicle steerer to operate on the same vehicles. The success of ELVIS provided additional impetus to complete this work.

Several researchers have applied reinforcement learning methods to the recovery of a peg insertion skill. Simons et al (1982) learn how to interpret a force feedback vector to generate corrective actions for a peg insertion which has an aligned insertion axis. Gullapalli et al (1992) learned close tolerance peg insertion using a neural network and a critic function, but the result is specific to hole location.

PRIMORDIAL LEARNING

Primordial Learning refers more to a way of thinking than to a specific algorithm; it refers to learning fundamental interactions, or mappings, with no prior knowledge. It's like an infant that learns gross motor control by flailing. The infant is aware of "sensor and actuator ports," but has no comprehension of their connection to the body or to the outside world. Some might say primordial learning is non-parametric learning. Some might call it unsupervised learning. The implementations in this paper can be called principle components analysis. Yet, all these terms, broad and narrow, are, in one way or another, inaccurate in describing our work in its entirety, from autonomous sensor calibration to mobile robot behaviors, hence the new terminology.

Mobile Robot Primitives

The infant analogy provided not just the impetus for the name, but the impetus for the first application. Somewhat as a lark, the challenge was made to create a mobile robot that could learn to "crawl" before the newborn infant of the first author could do so. The term "crawl" was interpreted loosely to mean "purposefully motivate" so as not to exclude the creation of a wheeled vehicle as opposed to a much more mechanically complex legged vehicle.

This sort of robot learning has been suggested for mobile robots before and prior work and detailed results from our experiments can be found in Voyles, et al (1995b). To summarize, we applied primordial learning to the MK-V, a three-wheeled, non-holonomic mobile robot. Sensors include wheel encoders, a compass, bump sensors and motor current sensors. The drive and steering motors have three-valued -- forward-off-reverse -- commands with no closed-loop controllers on velocity or position. For this initial experiment there are no redundant groups of very similar and correlated sense elements such as a visual retina (as in Hancock and Thorpe, 1995) or sonar ring.

The shape from motion technique allows the robot to develop an internal representation of teleoperated interaction to produce "meaningful" externalized behavior. We do not use an explicit objective function or provide a reinforcement signal, but the learned result is explicitly dependent on the teleoperated interactions presented by the teacher. For training, we teleoperated the robot in a cluttered environment allowing it to wander while bumping into obstacles and jamming the wheels.

The training data consists of a matrix of input/output vectors sampled periodically during teleoperation. The input/output vector is composed of the actuator commands concatenated to the sensor data. The mean of this vector, $\mathbf{a}$, over the entire sequence was subtracted out to normalize the data values. Next, the matrix was batch-processed using SVD to extract the eigenvectors and the largest n eigenvectors were selected using the largest ratio of adjacent singular values as the threshold for n. This test assumes there is a group of "significant" eigenvectors, $\mathbf{e}_i$, with similar singular values and then there's a bunch of noise with small singular values. Examining the ratios of adjacent, ordered singular values indicates the dividing line between the groups. For run-time operation, the new sensor image, $\mathbf{x}$, is projected onto the eigenspace as described in Hancock and Thorpe (1995):

$$\mathbf{v} = \mathbf{a} + \sum_{i=1}^{n} ((\mathbf{x} - sensor(\mathbf{a})) \bullet sensor(\mathbf{e}_i))\,\mathbf{e}_i \tag{1}$$

Using this technique, the real robot successfully achieved both wandering behavior and escaped stalls and collisions without highly redundant or correlated sensors and with no algorithmic structure imposed on the learned result. Plots demonstrating the MK-V learned when to steer and reverse direction in order to free itself appear in Voyles, et al (1995b).

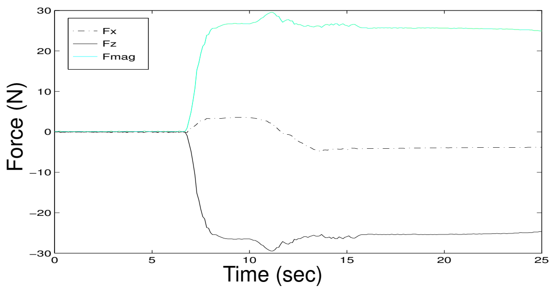

Figure 1: Autonomous operation of the learned, one-dimensional guarded move.

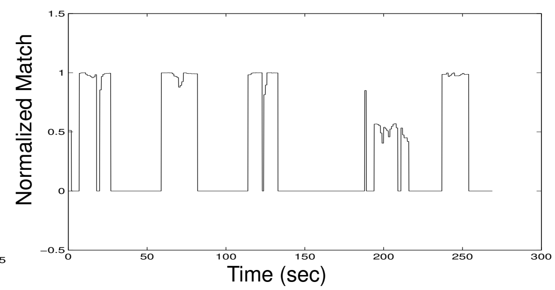

Figure 2: Goodness of match determined by automatic skill identification algorithm.

PUMA Manipulator Primitives

While the application on the MK-V mobile robot started out as a lark, learning sensorimotor primitives for robot manipulation skills has long been a serious goal of our lab. Automatic generation of usable primitives is a necessary technology demonstration for the credibility of GBP. Because the skill base can incorporate primitives from a variety of sources, it is not necessary to generate all primitives automatically. Nonetheless, it is important to show proof-of-concept of the end-to-end system.

Guarded Move. As a first demonstration, we attempted to learn a one-dimensional guarded move. Although this is a fairly trivial primitive that can easily be hand-coded, it is not as obvious how to robustly identify it during human demonstration. This is the strength of an integrated approach like shape from motion primordial learning; it provides primitive identification and transformation as well as basic learning.

To learn *zguard* -- a guarded move along the z-axis -- we teleoperated a PUMA robot with a 6-DoF force/torque sensor so that it came into contact with a table while moving along the approach (z) axis of the end effector. We repeated this one-dimensional guarded move ten times, logging data only during the guarded move, not during the retraction phase when the end effector was moved away from the surface. The robot was controlled by a cartesian velocity controller, teleoperation input was provided by a 6-DoF trackball, and operator feedback was visual as well as a graphical display of the real-time force/torque components.

The input/output vector from which the data matrix for training was generated consisted of the useful data -- 6 measured force components, the total force and torque magnitudes, and 6 commanded cartesian velocities -- plus some irrelevant data -- 3 cartesian position elements and 9 cartesian orientation elements. We used the same algorithm for extraction of the eigenvectors as used on the MK-V.

The output of the training was a primitive of one eigenvector that performed very well. Figure 1 shows the measured force components as the guarded move primitive autonomously acquires a hard surface. 25N was the target force threshold applied during training and this can be varied by scaling the output portion of the extracted eigenvector. The primitive worked equivalently in all trials performed regardless of region of workspace, orientation of the end effector, compliance of the surface, or external perturbations. Analysis of the components of the eigenvector support this. The primitive is looking at the z-component of force as well as the total magnitude of the force.

To identify instances of the primitive from demonstration data, we run the training algorithm on windowed batches of run-time data and examine the parallelism between the extracted eigenspace and the eigenspace representation of the primitive. The dot product gives a quantified measure of eigenvector parallelism that we compare to a high threshold for presence or absence of the primitive.

To test the recognizer, we randomly moved the robot around the workspace, occasionally coming into contact with surfaces. The resulting goodness-of-fit is plotted in Figure 2. The identification algorithm accurately picked out every instance of a guarded move in z and rejecting every instance of random motion or random contact, including guarded moves along other axes. The occasional dropouts to zero are inconsequential as this fitness measure is but one input to the gesture interpretation network of the GBP system.

Edge-to-Surface Alignment. The guarded move is a "move until force threshold" operation. Movement is an explicit part of the goal. Alignment operations, on the other hand, only move in order to accommodate. Since no explicit motion is part of the primitive, it is difficult to teleoperate. What we'd like to do is use the previously learned guarded move to bring the edge and surface together while we teleoperate only the alignment primitive. The problem is the learned result would include both primitive operations, since there is no way to separate the sensor stream into "guarded move" and "alignment" portions. However, the eigenspace representation provides a convenient mechanism for separating the two after learning, if they are truly elemental and decoupled.

Learning the *yroll* alignment task -- alignment of an edge to a surface by accommodating rotationally around the y-axis -- was accomplished in the same manner as the *zguard* primitive with the exception that *zguard* was running during the teleoperation phase. This complicated the eigenvector extraction, as well. We expect the *zguard* eigenvector to appear in the new set of trained vectors and, in fact, it does. Using our standard ratio of eigenvalues test, only one eigenvector is extracted during training and its dot product with *zguard* is 0.9993, indicating it is the *zguard* primitive.

To extract the alignment primitive, we must look to the next significant group of eigenvectors. Ignoring the *zguard* eigenvector produces a set of four eigenvectors that very nicely implement the desired accommodation operation. Combining the *zguard* and *yroll* primitives by superposition produced behavior that reliably pressed a line against a table. Simple superposition of eigenvectors allows for decomposition and recomposition of the primitives at least in this case of decoupled operations.

Surface-to-Surface Alignment. The above decoupled primitives can be combined to produce more complex behavior. Combining *zguard*, *xroll*, and *yroll* produces a "skill" that allows two surfaces to be pressed together. An experimental run of these three primitives is shown doing just that in Figure 3 and Figure 4.

CONCLUSIONS

We have described shape from motion primordial learning, a learning technique based on principle components analysis that has been successfully applied to extracting and identifying robotic sensorimotor primitives from teleoperated actions of both mobile robots and manipulators. By incorporating model-based information, we have also applied it to nearly autonomous calibration of force/torque sensors with equal or greater accuracy than the traditional least-squares technique (data in Voyles et al, 1995a).

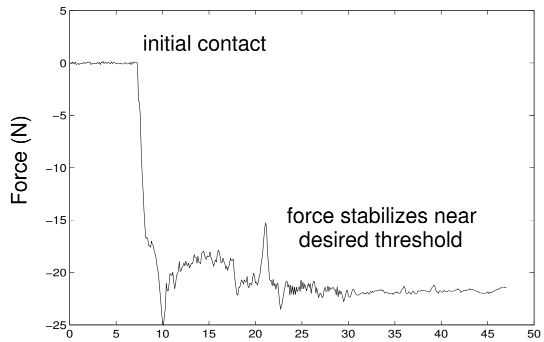

Figure 3: Force in z-axis as zguard, xroll, and yroll cooperate to press one surface against another.

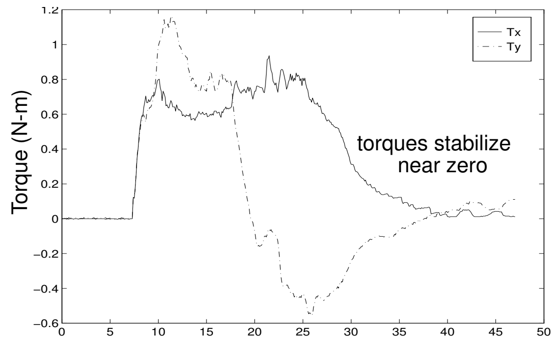

Figure 4: Torque around x- and y-axes as zguard, xroll, and yroll cooperate.

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