Learning by Watching: Extracting Reusable Task Knowledge from Visual Observation of Human Performance

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***Abstract*—A novel task instruction method for future intelligent robots is presented. In our method, a robot learns reusable task plans by watching a human perform assembly tasks. Functional units and working algorithms for visual recognition and analysis of human action sequences are presented. The overall system is model based and integrated at the symbolic level. Temporal segmentation of a continuous task performance into meaningful units and identification of each operation is processed in real time by concurrent recognition processes under active attention control. Dependency among assembly operations in the recognized action sequence is analyzed, which results in a hierarchical task plan describing the higher level structure of the task. In another workspace with a different initial state, the system re-instantiates and executes the task plan to accomplish an equivalent goal. The effectiveness of our method is supported by experimental results with block assembly tasks.**

I. Introduction

FUTURE INTELLIGENT ROBOTS are expected to work with humans in unstructured environments. In such situations, a wide variety of task instructions will be given to the robots under the following conditions:

1) The end-users have working knowledge of the target tasks but are novice at programming or operating robots.
2) Well-equipped programming facilities or expert robot programmers may not be accessible.
3) The time and the effort required for task instruction is strictly limited.
4) The environment is uncontrollable. Special fixtures or feeders are not available.
5) The end result of the instruction should be highly reusable.
6) The end-users must not be exposed to any danger.

Unfortunately, existing methods of robot programming are not directly applicable to the above situation. This paper presents a framework, a design, and implementation of a novel functionality for future intelligent robots called "learning by watching." With this functionality, the robots will intelligently acquire reusable task knowledge quickly and safely by watching without disturbance human workers perform tasks.

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A. Existing Methods for Task Instruction

Until now, basically four approaches to robot programming have been pursued; teaching by guiding, text programming, off-line simulation-based programming, and inductive-learning.

Although text programming is suitable for sophisticated applications, it requires special skills and much effort to write complete robot programs. This problem motivated the development of task level robot languages [1]–[3]. But it turned out that application of a general purpose task planner to practical domains results in an explosion in the number of declarations and computational time.

Off-line simulation-based programming [4]–[6] techniques integrate direct teaching in a simulated world, text programming and model-based motion planners on a common platform. These techniques are quite powerful, but it requires expensive special-purpose hardware such as a high-resolution graphics display and a 3-D pointer. Moreover, a user must supply a complete discription of the real world to the system. This is a costly procedure.

With inductive learning, a robot can learn appropriate motion and sensing strategies through trial and error [7]. This imposes the least burden on the user, but it is not adequate for instructing complex task structures to robots. Rather, this method is useful for adding refinements to other methods.

"Teaching by guiding" is a straightforward method in which a human instructor achieves the desired task by operating a robot manipulator in the real world while its motion is recorded. This has been the most widely practiced retraining method for industrial robots for the following reasons: it requires no additional hardware, no expertise in computer programming, no extra effort such as close analysis of the task and no complete description of the workspace structure.

Despite its fitness to field robot programming, teaching by guiding suffers from serious drawbacks concerning flexibility, robustness, sensor utilization and safety. It forces the user to accomplish the task using real manipulators, which is exhausting, often leads to wrong moves, and can sometimes be risky. The result is very hard to modify or debug, and is not transferable to different manipulators or workspace states. Furthermore, the method cannot handle sophisticated sensor interactions.

Several efforts have been made to cope with these problems by improving or extending the method. This is done by gathering sensory information during task instruction and embedding

sensor utilization codes into template programs by interacting with the user [8], extracting dynamic control rules for a particular assembly motion from the position and force data of human performance [9], integrating task level languages and direct teaching through masterslave manipulators [10]. Despite these efforts, achieving robustness and flexibility while maximizing the merits of teaching by guiding is still an open problem.

B. Teaching by Showing

The original concept of teaching by guiding has several noteworthy features:

1) *Direct:* The instructor directly performs the target task while watching the actual workspace. This is intuitive and does not spoil the working knowledge about the task.
2) *Tacit:* No explicit statements about the target task or the workspace need to be made.
3) *Inexpensive:* No extra hardware is required.

There is room for improvement for item 1, this is because operating a real manipulator to achieve a task imposes an extra burden on the instructor. If we can solve this problem and retain items 2 and 3, an ideal framework of task instruction for the next generation robots will be near at hand.

Obviously, the most natural form of task performance by a human instructor is to perform the task in the usual manner, e.g., using his/her own hands. The robot should extract knowledge from the task's performance without disturbing it. A passive remote sensor, vision, is the best device for this purpose. It is envisaged that vision will be part of the standard equipment in future intelligent robots. Visual recognition of human actions is becoming feasible due to recent development in vision algorithms and processors.

Moreover, optimal values of motion parameters such as trajectory and velocity of the manipulator depend on the configuration of the workspace and the structure of the manipulator. In contrast, task plans described in terms of more abstract and qualitative representation of assembly operations such as pick and place are of high reusability.

We have proposed a novel framework of task instruction called "teaching by showing" [11]. It consists of five phases:

1) *Presentation:* The instructor shows the target task to the system by performing it with his/her hands. The instructor needs to perform the task only once from start to end without pausing.
2) *Recognition:* The system observes the performance by vision and constructs a symbolic description of the task. Recognition must be completely automatic and in real time in order to keep up with the performance of the task by the instructor.
3) *Analysis:* The system analyzes the task description and extracts higher structures such as a goal hierarchy and dependency among operations.
4) *Generation:* For a given target workspace the system recognizes the initial configuration of the objects, modifies and instantiates the task description, and generates an executable robot program.
5) *Execution:* The program is executed to accomplish the task with a manipulator.

Our method is direct, tacit, and inexpensive. Also, the method is quick and safe due to single continuous presentation in a nearby workspace with undisturbing observation by the robot. The method is flexible because the task is described symbolically, allowing re-instantiation and modification in various situations.

C. Learning by Watching

Realization of visual recognition and interpretation of human action sequences is of critical importance to the development of teaching by showing.

Early attempts at this problem were made on simple figures moving around in two-dimensional world [12]–[14].

A progress concerning teaching data has been made: A learning system was built that extracts complex task structures from manipulator command sequences issued by a human operator [15]. And a telerobotic system that recognizes pick-and-place sequences from force/joint data was developed [16].

Recently, several attempts have been made that conform to the "teaching by showing" framework: An "assembly plan from observation" system [17] extracted fine motion sequences from transitions among face contact states acquired by a range sensor. And integration of a symbolic recognizer and a playback module using visual servo was attempted for two dimensional pick and place operations [18].

However, none of these systems dealt with real time visual recognition of continuous human action sequences in the three dimensional world. Classical recognition techniques must be reconsidered under real time constraints. Runtime temporal segmentation of the task into meaningful units becomes crucial when a continuous flow of actions is given. Moreover, integration with higher level processing such as task planning or generalization needs to be considered.

II. System Design

An overview of the system [19], [20] is shown in Fig. 1. The overall structure reflects the framework of "teaching by showing" presented in Section I-B.

A. Required Functions

Learning by watching consists of three major functions that must be integrated as a unity: seeing, understanding, and doing. Our approach is to connect these at the symbolic level. From this viewpoint, each function can be specified as follows:[1]

1) Seeing:

1) Recognizing the initial state and construct the environment model.
2) Finding and tracking the hand.
3) Visual search for the target of operation.
4) Detecting meaningful changes around the target and describe them qualitatively.

[1] This paper puts emphasis on "seeing" and "understanding."

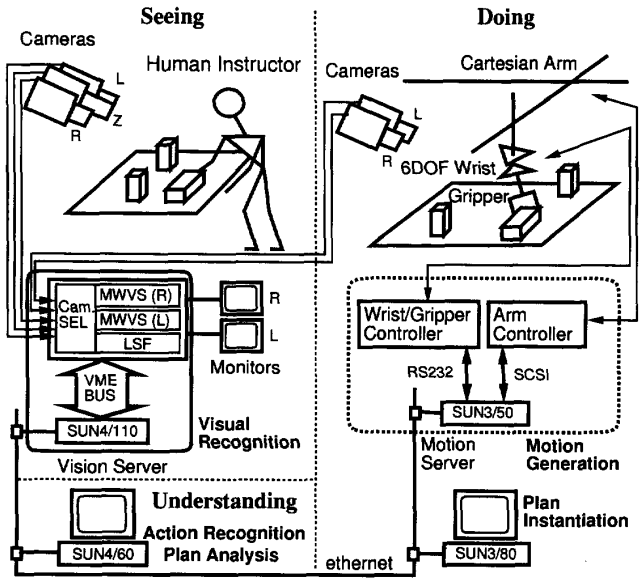


Fig. 1. Overview and hardware configuration of the system.

2) Understanding:

1) Segmentation of the continuous task performance into meaningful unit operations.
2) Classification of operations based on motion types, target objects, and effects on the targets.
3) Dependency analysis of a task procedure to extract subprocedures consisting of mutually dependent operations.
4) Bottom-up plan inference. Generate higher-level operators for each subprocedure and gather target objects and state change descriptions from the lower-level operators.

3) Doing:

1) Instantiation of the task plan. Recognize the given intial state. Match the result with the stored task plan to produce goal positions for each operation.
2) Path planning and generation of motion commands.
3) Sensor feedback for guiding motions.
4) Error detection by vision and recovery actions.[2]

B. Experimental Setup

The hardware setup of the system is shown in Fig. 1. The system consists of three parts (divided by dotted lines in the figure) for seeing, understanding and doing.

1) Camera Configuration: Task presentation is monitored by three monochrome video cameras (two for stereo and one for zoom-in) connected to a network-based robot vision server [21]. Another stereo pair of cameras are used for monitoring task execution.

In our experiments, each stereo pair of cameras was configured as the baseline being about 240 mm, and the distance to the worktable being about one meter. External parameters of each camera were calibrated by taking a line image of a precisely shaped block placed at the origin of theworld coordinates and matching it with the geometric model using Lowe's method [22].

2) Vision Server: A special vision hardware is connected to a host workstation via a VME bus. The host runs a server process that accepts commands, controls the vision hardware and transmits the extracted data via a socket connection over an Ethernet network. The vision hardware consists of a high speed Line Segment Finder (LSF) [23] and a Multi Window Vision System (MWVS) [24]. The LSF extracts lists of connected line segments from a gray scale image (256 × 256 pixels) within 200 msec. The MWVS hardware is multi processor. It extracts various image features at video rate from within rectangular "windows" of specified size, sampling rate, and location. It can handle up to 32 windows in parallel for continuous tracking and detection of features.

3) High-Level Processing Servers: Two workstations are dedicated to recognition of actions, plan analysis, and plan instantiation. The action recognizer consists of an action model, an environment model, and an attention stack. It extracts visual features by actively controlling the vision server and generates a symbolic description of the action sequence in near real time. The plan analyzer extracts high level task structures from the action sequence. The acquired plan is matched against the environment model, which is re-initialized by visual recognition of the execution environment. Then, motion commands for the manipulator are generated and sent to the motion server. The programs are written in an object-oriented style using EUSLISP, an object-oriented Lisp environment with geometric modeling facilities [25].

4) Motion Server: A Cartesian-type arm with a 6 DOF parallel-link wrist mechanism [26] supporting a parallel-jaw gripper is used for task execution. This manipulator is controlled by a dedicated CPU board (for the wrist) and a PC

[2]The function of "doing" will be discussed only briefly. Items 3 and 4 in "doing" are not yet implemented.

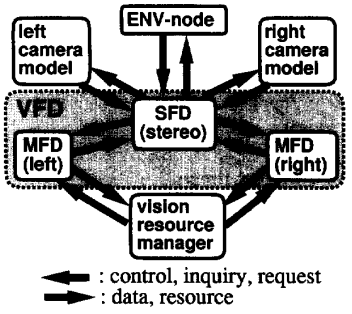


Fig. 2. Vision Processing Elements. ENV-node: ENVironment model node. VFD: Visual Feature Detector. SFD: Stereo Feature Detector. MFD: Monocular Feature Detector. The camera models and the vision resource manager are shared by all VFD's. The arrows are realized as sending messages (black) and return values (gray).

(for the arm) running servo and command interpreters. The host workstation interprets robot commands from the Ethernet network, performs the necessary coordinate transformations and sends primitive instructions to the manipulator controller.

III. Active Vision for Observing Actions

Restricting the amount of visual information while retaining the important portions is the key to real time recognition of human action sequences. There are two axes for a restriction scheme: 1) use of regions of interest (windows) and 2) selecting specific features to extract. Both should be actively controlled [27] with regard to the task context.

A. Visual Feature Detectors

The vision processing consists of the modules shown in Fig. 2. They are implemented as EUSLISP objects.

A Visual Feature Detector (henceforth, VFD) represents a unit of vision processing as a combination of visual attention and a feature extraction algorithm. As long as the hardware resource allows, any number of VFD's can be created and used in parallel during recognition. Five types of VFD's are used in our system; motion-detector, object-finder, sil-finder, change-detector, and coplanar-detector. The algorithms are described in the following subsections.

An ENVironment model node (ENV-node) is an element of the environment model (see Section IV-A) that sends requests to a VFD and receives detected features.

The left/right camera models maintain calibrated camera models and computes forward/backward projection, such as a view-line from a screen point.

The vision resource manager maintains the vision hardware resource (the windows and the processors in the MWVS). On request from the MFD's, it allocates/initializes/frees a specified amount of windows/processors and returns a control handle.

A VFD is programmed as a Stereo Feature Detector (SFD) class and a Monocular Feature Detector (MFD) class. When an ENV-node needs a VFD, it instantiates one SFD. The SFD then instantiates two MFD's for the left and the right images.

We have one generic VFD that describes common functions. For each specific visual feature, a VFD is defined as a subclass of the generic VFD with additional procedures for feature extraction.[3]

TABLE I
External Interface of a VFD (Each Method Is Invoked When a Corresponding Message Is Received from an ENV-Node; the Result Is Sent Back to the ENV-Node)

Method	Function
:attention	Watch the specified 3-D region
:srate	Set a sampling rate
:start	Start detecting
:stop	Stop detecting
:found	Feature found since last query
:target	3-D position of the target
:reset	Clear the internal state
:free	Release hardware resource

A generic SFD provides methods for stereo integration of the 2-D image features obtained from the left and right MFD's, such as epipolar planes, stereo matching, triangulation (the least square crosspoint between the binocular view lines), etc.

A generic SFD also provides a standard interface for an ENV-node, as shown in Table I. All the methods are invoked by sending messages from the ENV-node to the SFD. The method ":attention" takes a 3-D geometrical model as an argument. It computes projected 2-D regions for the left and the right cameras, and directs the MFD's to set the windows on the regions. Feature extraction is controlled by ":start" and ":stop." And the result is requested using ":found" and ":target." This interface is common to all the feature types.

An MFD is a combination of 1) visual windows in the MWVS, 2) vision algorithm for extracting a specific feature, and 3) an internal state memory for remembering the detected features temporarily. When it is created, it requests the vision resource manager to allocate necessary hardware resource. If no resource is available, an error is returned.

B. Recognizing the Initial State

To initialize the environment model, it is necessary to find and measure the positions of all objects in the workspace prior to the commencement of the task. An object-finder implements this function.

A coarse to fine method is used for spatial segmentation. First, take a very coarse image of the whole workspace to find representative points on object silhouettes. Then in progressively finer images, check the neighborhood of each point/region to grow/shrink, merge or shape more precisely. Finally, stereo correspondence is determined for the regions in the right and left images, and the three dimensional positions of the region centers are calculated. In our experimental setup, allowing only rectangular blocks as samples, the measurement error was several millimeters. This is sufficient for qualitative action recognition.

Line images are extracted from each segmented region to match against known geometric models using Lowe's method [22]. This provides a shape name for each object and its precise position and orientation. Our implementation consumes more

[3]The common functions are inherited from the generic VFD.

than fifteen seconds for computing one to one matching. And the total computational time is proportional to a product of the number of objects and the number of object models. This time consuming step is optional since it is possible to supply a shape name for each segmented region manually. Shape recognition is not our goal.

C. Finding and Tracking the Hand

It is important to track the position of the hand in real time because the position and the velocity of the hand plays a significant role in task recognition. Since the hand frequently changes its shape or touches one object after another, simple feature tracking (e.g., correlation, edge, center of mass) easily fails or captures the wrong target. Robustness is the key issue in hand tracking and as a tradeoff, precise measurement of finger postures is neglected. This does not harm the recognition process since such information is not very useful in recognition of assembly operations. Even in a fine motion such as part mating, information of finger configuration is much less important compared to the configuration of manipulated objects.

1) Finding the Hand by Temporal Image Subtraction: A motion-detector finds the hand moving by continuously computing temporal differences over the entire image.

Each successive image is first subsampled and stored into an image buffer at fixed intervals. Here we use a double buffering technique. Each image is then locally averaged and subsampled again in order to reduce noise and filter out small false targets.[4] Finally, the previous image (in the other buffer) is subtracted from the current image. If any point in the result has a gray value over threshold, the motion detector sets a status flag (found), computes the center of mass of the significant points, and immediately invokes a hand-tracker and places it at the center of mass.

Temporal differentiation is continued on as a parallel background process to help robust hand tracking (see Section V-A).

2) Feature Tracking Using Feedback Control: Simple feature tracking is implemented as a following video rate cycle: 1) Acquire a window subimage into memory, 2) Apply a specified image preprocessing to the subimage, 3) Compute the position of a feature point, 4) Do positional control of the window.

For Step 2, our system provides various types of edge extraction (Robinson's and Roberts' filters, orientation selective filters, and gradient labeled edge detection), edge junction extraction, binary thresholding, and their combinations.

Step 3 selects a single feature point within the preprocessed subimage using either of center of mass, X-Y projection peaks, or min./max. graylevel pixel.

Step 4 moves the center of the window to a goal point $\mathbf{g}$ computed as follows: $\mathbf{g} = \mathbf{f} + \mathbf{d}$ where $\mathbf{f}$ denotes the feature point, and $\mathbf{d}$ denotes a preset *offset* vector. The positional vectors, $\mathbf{g}$ and $\mathbf{f}$, have their origin at the current center position of the window.

Besides tracking, a window with only Step 1–3 can be used to continuously or momentarily watch and detect a feature. A sil-finder continuously extracts a silhouette feature (the center of mass of a binarized area).

[4] Currently, the interval is 83.5 msec and a subsampled final pixel corresponds to 60 H × 40 V pixels in the input image.

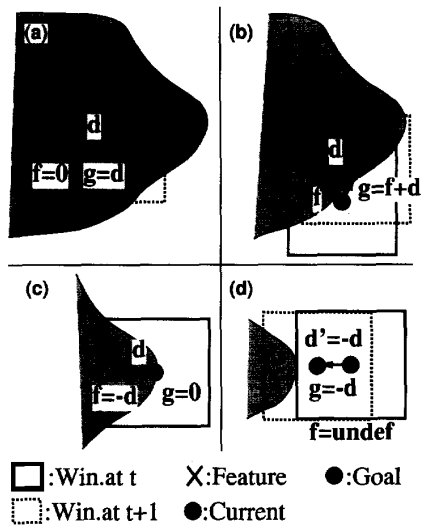


Fig. 3. Tracking control. (a) The window moves by $\mathbf{d}$ (to the right) when the feature point is at the center. (b) The window moves along the edge toward protuberance. (c) The window at a stable position. (d) When no feature is detected, the offset vector is reversed ($\mathbf{d} = -\mathbf{d}$) for local recovery.

Fig. 3 shows typical behavior of a simple feature tracker. The offset vector adds two useful characteristics to the tracker: 1) Local search and stable tracking of an end point of a locally convex shape. The offset vector defines a local axis for measuring convexity. 2) Local recovery for recapturing the lost target. This is achieved by an automatic inversion of the offset vector when no feature is detected within the window.

The intensity of an offset vector is chosen as a result of a trade-off between stability (smaller intensity is preferred) and search speed (larger intensity is preferred). A typical value is half the distance from the window center to the window frame measured in the direction of the offset vector.

3) Tracking with a Group of Windows Under Coordinated Control: Introducing coordinated control, multiple simple feature trackers can be organized into a group with a variable structure. This group of trackers functions as a composite tracker capturing a combination of image features from a deformable object.

Fig. 4(a) illustrates a hand-tracker superimposed on a silhouette of a hand. The structure of the hand-tracker is shown in (b). Each rectangular frame denotes a visual window and a three-letter label in top left corner denotes the type of image feature to extract: "GGE" for a center of mass of a binarized silhouette, and "EGE" and "EGW" for a center of mass of an edge with its brightest side on the east (right) or west (left), respectively.

The coordinated control of the multiple windows of a hand-tracker is achieved through a combination of two processes: 1) Dynamic update of offset vectors, and 2) Imposing mutual constraints on the window motion.

An offset vector for a window can be specified using a relative position of the window with regard to another window,

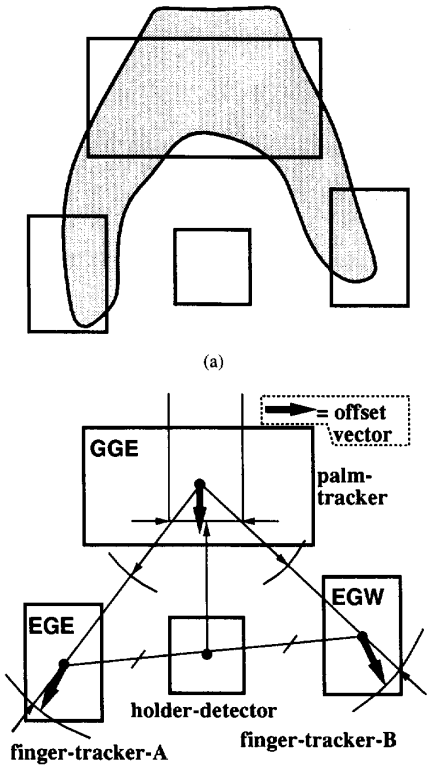


Fig. 4. Structure of a hand-tracker. Arrangement on a hand shape is shown in (a). Tracked features and the control structure are shown in (b).

or to a center of mass of a specified group of windows. In this case, our system automatically computes and updates the offset vector at video rate. For example, we can place two trackers (feature type GGE) on both ends of a stick-like shape, and specify an offset vector for each window as pointing to an opposite direction from the other window. Then, the two windows cooperatively tracks the stick ends even when the stick rotates.

In our hand-tracker (Fig. 4), the offset vector for each finger-tracker is set as pointing to an opposite direction from the palm-tracker. As described in the previous section, if any of the finger-trackers loses its target, its offset vector is immediately reversed for local recovery. Moreover, whenever the whole hand-tracker is re-positioned by the motion detector, the two finger-trackers are initially placed on both sides of the palm-tracker. Then as a result of the offset tracking, the finger-trackers trace down the outer edges of the hand and reach the fingertips.

In our system, motion of each tracking window can be constrained using 1) a distance range from a certain reference point; 2) an orientation range specified by a reference point and two angles; 3) a rectangular area specified with regard to a reference point; and 4) arbitrary combination of all of these constraints. A reference point can be either a fixed absolute coordinates, the position of another window, or the center of mass of a specified group of windows. In the latter two cases, the reference point is automatically updated at video rate.

Our hand-tracker uses the window motion constraints to reflect a simplified 2-D mechanical structure of a hand (Fig. 4). The two finger-trackers are constrained by distance range from the palm-tracker and can not move too close to each other. The holder-detector is kept in the middle of the finger-trackers to represent the position of the hand. It can be used to continuously extract an image feature to check for a grasped object.[5] The vertical position of the palm-tracker cannot be lower than a preset distance above the holder-detector and the horizontal position is constrained by a short distance range in respect to the holder-detector.

All the processing described above is done at video rate by the MWVS. Interactions among the constraints and the offset vectors provide robustness to the hand-tracker. It does not fail even if the hand changes its posture and/or touches other objects.

D. Detecting Meaningful Changes

Tracking the hand is not sufficient for classifying assembly operations. For example, the hand may follow quite similar trajectories during a pick or a place operation.

In theory, measuring precise postures of the fingers might help recognizing grasp and ungrasp operations. But, from our preliminary experiments, we decided that this approach is unrealistic for our purpose. During assembly operations, the fingers are often occluded by or touches the other objects. So it is very difficult to reliably measure the 3-D positions and postures of all the fingers in real time using vision.

Alternatively, we pay attention to a manipulated object and its neighbors. Every meaningful assembly operation changes the state of those objects. And such changes are generally easier to detect by vision.

1) Detecting Qualitative Changes: Pick and place operations move objects from one place to another. So, if we restrict our attention to a spatial region that contains an object being picked up or a region where a grasped object is to be placed, we can define three types of qualitative changes for classifying operations: 1) An object has disappeared, which means the object was picked up. 2) An object has appeared, which means the object was placed. 3) No change, which means the hand has approached an object or the worktable, or even touched it, but did neither pick nor place.

These events can be detected by differentiating two snapshot images of the target region extracted at the start and the end time points of an operation. We implemented this method as a "change-detector." The change-detector returns either of the three qualitative values (appeared, disappeared, no-change) based on image subtraction and area thresholding. In addition, the detector returns a 3-D measurement of the center of changed area based on stereo triangulation.

Aligning two faces to achieve a coplanar state is one of the important fine operations in assembly tasks. We developed a "coplanar-detector" that extracts edges from a local region around the two faces and checks for characteristic types of junctions (Fig. 5) that only occur in the coplanar state.

[5] This function is not used in our current system, because it is useless when the hand rotates around the vertical axis.

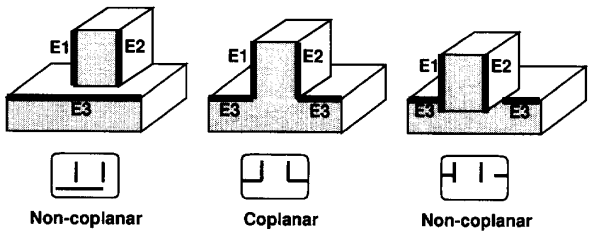


Fig. 5. Characteristic features (in round boxes) of coplanar/non-coplanar relations.

E. Guided Visual Search

In order to detect a change, it is important to find the target region of an operation and take the first snapshot before the hand or the object being held actually touches the target. In other words, controlling the visual attention in time and space is crucial for snapshot based change detection.

The time control is done as a part of a "temporal segmentation" procedure in the higher recognition process (see Section V-A), based on a qualitative change of the hand movement and the guided visual search described below.

The spatial control is done by a guided visual search. It is a procedure that detects the target of an operation before the operation completes.

The procedure uses both visual information and the environment model. It consists of the following steps:

1) *Initial setup:* Set a virtual 3-D attention region at the current position of the hand in the environment model (Fig. 6(1)). The region is chosen as: A default rectangular prism[6] if the hand is empty, or else a circumscribed box of the grasped object.[7] Instantiate a sil-finder and send it an "attention" message with the 3-D attention region.

   Based on the velocity and pose of the hand, determine a search orientation in which the target of operation is likely to be found. A step length is defined as the segment of a line of the search orientation intersecting with the attention region. Prepare a search step vector with the chosen direction and length.[8] The vector is projected for the right and left views to set the 2-D search step vectors.

   Set up a termination condition. In the environment model, compute the distance between the initial point and the surface of the worktable[9] in terms of the number of search steps. Choose the minimum of the step count and a fixed preset limit.[10] Store it as the cycle limit.

2) *Search:* Repeat moving the sil-finder windows by the 2-D search step until either, 1) the sil-finder reports an existence of a silhoutte, or 2) the number of cycles exceeds the limit (Fig. 6(2)).

[6]Currently, 50 mm(W) × 50 mm(D) × 45 mm(H).

[7]The fact that the hand is or is not holding an object is retrieved from the environment model as a result of recognizing previous actions.

[8]In our current implementation, the direction is fixed as perpendicular downward and so the magnitude is set as the vertical length of the attention region.

[9]The table is painted black and therefore invisible.

[10]Currently set to 4.

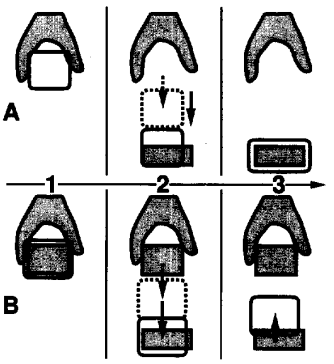


Fig. 6. Guided Visual Search. (a) When the hand is empty. (b) When the hand is holding a block. 1–3: Temporal order.

   If the cycle is terminated due to Condition 1), proceed to Step 3. Otherwise, just return control to the higher process. In the latter case, no event is generated and the temporal segmentation cue (qualitative movement change) is discarded.

3) *Post processing:* Something was found, so look it up in the environment mode: Set the attention region at the reported 3-D position, and find an object-model that intersects with the attention region.

   If no object model is found, just return control to the higher process. The visual cue that is not confirmed by the environment model is thrown away.

   If an intersecting object model is found, report to the higher process that the target of operation is found. Then place a snapshot region according to the current state of the hand: 1) If the hand is empty, set the region to cover the target object (Fig. 6(a-3)). 2) Otherwise, set the region at the place just above the found target with the approximate size of the grasped object (Fig. 6(b-3)).

This procedure uses simple visual cues for speedy detection, spatial information from the environment model for guiding the search and confirmation, and temporal context from the action model for correct setting of the attention region. The effectiveness of the method is based on the on-line update of the environment model and the action model to reflect the current task state.

The entire visual search procedure takes about 200–300 msec.

IV. Structure of the Action Recognizer

The action recognizer consists of an action model, an environment model, and an attention stack (Fig. 7). The entire system is implemented by object-oriented programming. Each primitive element (node) of the recognizer is implemented as an object with internal state and associated methods (embedded procedures). Most of the processing is done by passing messages among the nodes.

A. The Environment Model

The environment model consists of *partial description* nodes (ENV-nodes), which form a coarse to fine hierarchy. During

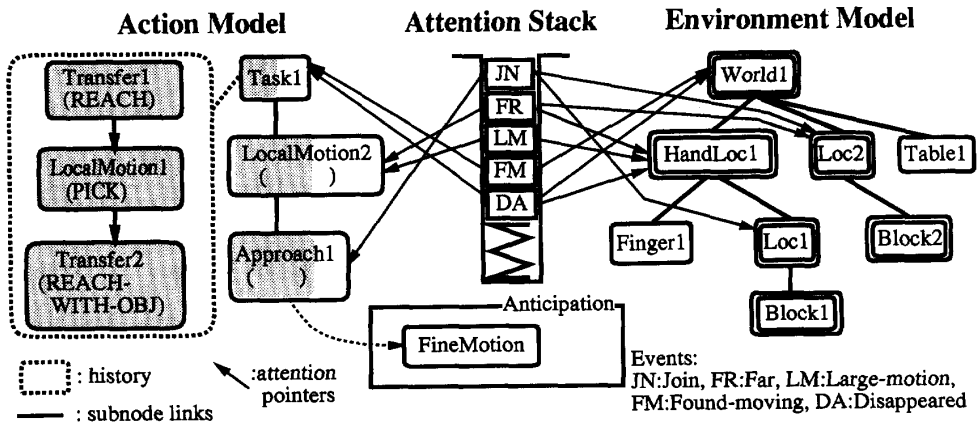


Fig. 7. Structure of the action recognizer.

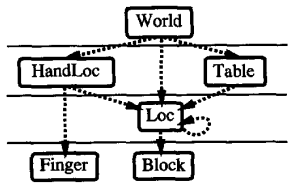


Fig. 8. Environment model node (ENV-node) classes. Hierarchical levels are denoted by solid horizontal lines. Possible subnode relations are denoted by dotted arrows.

action recognition, the nodes and the connecting links are dynamically generated or updated to reflect the current state of the workspace. The types of nodes, possible links between them, and the levels of hierarchy are shown in Fig. 8. A dotted arrow in the figures means there can be a "subnode" link that represents a positional dependency between the two nodes, e.g., holding, supporting, etc.

Table II shows an example of an instantiated ENV-node (HandLoc). Each node has slots for current position (`position`), a geometric model of the describing region (`geomodel`), and links (`parent` and `subnodes`) to other nodes. The `event-table` translates each incoming event query to a self method call that interrogates a VFD, interprets the obtained data using current state description and then, depending on the result, returns a qualitative event. The `detector-table` associates each event detection method with a VFD, which is dynamically generated by the ENV-node. Table III lists the currently defined visual events.

The description is partial in the sense of spatial extent, coarseness, and types of information. The class "World" represents the whole workspace coarsely, using only the "HandLoc," "Loc," and "Table" nodes as entries. An object-finder and a motion-detector is associated with this node.

The "HandLoc" (Table II) represents a simplified concept of the hand, e.g., its spatial extent, the position and the velocity of the hand, and whether it is holding an object. Here, we assume the sole function of the hand is to grasp objects. So we define the center of the hand at the middle point between the thumb and the index finger (the position of the holder-detector in the hand-tracker). Also, we use a rectangular prism with its center placed at the center of the hand to represent its spatial extent. Its size is not very important, since it is used only as a default attention region representing uncertainty for visual search procedure described in Section III-E.

TABLE II
SLOTS AND CONTENTS OF AN INSTANTIATED ENV-NODE; ALL THE NUMERICAL DATA ARE IN MM

Slot	Content
type	HandLoc
name	HandLoc1
parent	World1
subnodes	(Loc1)
position	#f(138 225 174)
geomodel	50 (w) × 50 (d) × 45 (h) prism
attention-region	Rectangular prism
attention-nodes	(NR, SM)
event-table	:Near → :visual-search :Small-motion → :motion-feature
detector-table	:visual-search → sil-finder :motion-finder → hand-tracker
relation	(Holding Loc1)

The HandLoc node computes qualitative motion feature values using 3-D velocity data from the hand-tracker. The values and thresholds used are shown in Table IV.[11] One of the two different speed range, $V_L^1 < v < V_H^1$ or $V_L^2 < v < V_H^2$, can be selected by sending either :small-motion or :Large-motion as an event query message to the HandLoc node.

The "Loc" represents a partial state of a *place* which contains one block. Its `geomodel` is a rectangular prism that encloses the block. It describes position, size, and support relations, but no orientation.

Geometrical models for "Block" nodes are chosen by the initial state recognition process from a shape database that is provided manually. And their positions and orientations are initialized by the object-finder. Currently, finger models are

[11] In our current system, $V_L^1 = 10, V_H^1 = V_L^2 = 50, V_H^2 = 10000$ [mm/s]. And $A_D = 75, A_U = 120$ [deg], both angles measured from a perpendicular downward orientation.

TABLE III
QUALITATIVE VISUAL EVENTS. EACH EVENT IS DETECTED BY A CORRESPONDING ENV-NODE USING THE SPECIFIED DETECTOR.

Event type	Meaning	Detector	Env. model node responsible
:Loc-exist	Identify and locate objects	Object-finder	World
:Found-moving	A moving **target** (hand) is found inside **base** (world)	Motion-detector	World
:Disappeared	**target** (hand) went outside of **base** (world)	Hand-tracker	HandLoc, World
:Large-motion	**base** (hand) is moving fast	Hand-tracker	HandLoc
:Small-motion	**base** (hand) is moving slowly	Hand-tracker	HandLoc
:Near	**base** (hand) is near some **target** (blocks)	Visual-search	HandLoc, Loc
:Far	**base** (hand) is far from **target** (specified blocks)	Hand-tracker	HandLoc, Loc
:Join	**base** touches **target** (specified blocks)	Hand/object tracker	HandLoc, Loc
:Split	**base** separates from **target** (specified blocks)	Hand/object tracker	HandLoc, Loc

TABLE IV
QUALITATIVE MOTION FEATURE VALUES AND THEIR THRESHOLDS (V_L = LOWER THRESHOLD FOR SPEED, V_H = HIGHER THRESHOLD FOR SPEED, A_D THRESHOLD ANGLE FOR DOWNWARD, A_U = THRESHOLD ANGLE FOR UPWARD)

Value	Speed	Direction
:Staying	$v < V_L$	—
:Moving-up	$V_L < v < V_H$	$A_U < a$
:Moving-down	$V_L < v < V_H$	$a < A_D$
:Moving-laterally	$V_L < v < V_H$	$A_D < a < A_U$
:Moving-Fast	$V_H < v$	—

not used since we do not have reliable means to visually track the fingers in real time.

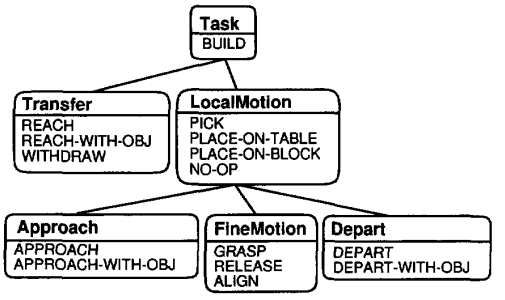


Fig. 9. Assembly motion classes (boxes with bold labels) and associated operations.

B. The Action Model

The "Action model" is a collection of nodes (henceforth, ACT-nodes) that represent temporal structure of assembly actions.

1) Classification of Assembly Actions: We classify assembly operations by following two stages: First, define "assembly motions" that characterize certain temporal extents based on temporally continuous features such as movement and relative positions. Second, for each "assembly motion," define a set of "assembly operations" that characterize the effect of the motion based on changes or invariants in the environment during the given temporal extent. The assembly motion classes and assembly operations defined in our system is shown in Fig. 9.

Currently, assembly motions are characterized by the qualitative motion features (Table IV) of the hand and the relative location of the hand with regard to the target objects. As shown in Fig. 9, we have a class hierarchy defined by inclusion relations between the temporal extents of assembly motions.

The "Task" is an abstract class that covers a whole temporal extent of one task. There are two types of basic assembly motions: 1) "Transfer"—A large movement of the hand in free space, and 2) "LocalMotion"—A slow, upward/downward hand movement near specific target objects. "LocalMotion" is further resolved into three types of assembly motions: 1) "Approach," in which the fingers and the grasped object move toward the target objects, 2) "Depart" is the reverse motion to Approach, and 3) "FineMotion," the duration between "Approach" and "Depart," e.g., grasping/releasing, or the held object moving in contact with the target objects.

An assembly motion is classified into several operations depending on the change or the invariant during the temporal extent, as shown in Table V.

In our current system, a "Task" is always classified as a generic "BUILD" operation. It is used to bind the entire action model and to record the initial and the final task states.—

"Transfer" is classified into three types of operations: "REACH" (move an empty hand to a block), "REACH-WITH-OBJ" (move a grasped block elsewhere), and "WITHDRAW" (retract the hand after an operation).

"LocalMotion" is classified as "PICK" (pick up a block from the table), "PLACE-ON-TABLE" (put a block down on the table), "PLACE-ON-BLOCK" (put a block on (an) other blocks (s)), or "NO-OP" (did neither PICK nor PLACE).

Our current system handles only one meaningful operation for "FineMotion." It is "ALIGN" (move a block in contact with another to align their side faces).

2) Structure of Action Model Nodes: (ACT-nodes): Prototypical nodes (class nodes) of the action model provide hand-coded knowledge used for action recognition. They are implemented as EUSLISP object classes corresponding to assembly motion classes. They are instantiated during recognition process to represent actual actions.

An example instantiated ACT-node is shown in Table VI. Each ACT-node has pointers to related ENV-nodes: `base` always contains the subject of the current motion (e.g., the hand or the grasped object), `target` contains the target of

TABLE V
CLASSIFICATION OF ASSEMBLY OPERATIONS [EACH MOTION IS CLASSIFIED USING THE FEATURE VALUES TO ONE OF THE CORRESPONDING OPERATIONS. HOLD = TRUE IFF THE HAND IS HOLDING A BLOCK. SILDIFF = TEMPORAL DIFFERENCE OF SILHOUETTE BASED SUBIMAGE SNAPSHOTS. COPLDET = TEMPORAL DIFFERENCE OF TRUTH VALUES (TRUE = 1, FALSE = 0) MEANING WHETHER COPLANAR EDGE JUNCTIONS WERE FOUND.]

Motion class	Feature type(s)	Feature value	Operation type
Task	None		BUILD
Transfer	(SegEvent, Hold)	(:Near,:False)	REACH
		(:Near,:True)	REACH-WITH-OBJ
		Other	WITHDRAW
LocalMotion	SilDiff	:decreased	PICK
		:increased	PLACE-ON-TABLE
		:increased	PLACE-ON-BLOCK
		:no-change	NO-OP
Approach	Hold	False	APPROACH
		True	APPROACH-WITH-OBJ
Depart	Hold	False	DEPART
		True	DEPART-WITH-OBJ
FineMotion	CoplDet	:Positive	ALIGN
		Other	NO-OP

the operation (e.g., the object to be picked up, or the object on which the current grasped object is to be placed), `special` contains relevant objects that are neither `base` nor `target`, typically, a grasped object.

The `parent/subnode` pointers represent temporal embedding of coarse and fine actions.

In order to record the result of recognition, following slots are used: The `initial/final-event` slots for recording the segmentation events, the `initial/final-state` slots for snapshot copies of the corresponding ENV-nodes at the beginning and the end points of an action, the `operation` slot stores an identified operation type, and the `history` records a temporally ordered list of previous sub-actions (e.g., history of `subnode` contents).

As a collection of methods, each class node describes a mapping from change/invariants to corresponding operation types, previously given in Table V.

A class node also has a table that maps incoming events to their *interpretations*. An *interpretation* is a list of one "action transition specification" and any number of "attention redirections."

An action transition specification consists of 1) a transition direction, 2) the next action class, and 3) related ENV-nodes for the next action. A transition direction instructs the toplevel recognition process to manipulate the links and nodes of the action model. The direction may be either ":next", ":down" or ":up"—":next" instructs to terminate recognizing current action and generate a new ACT-node within the same hierarchical level, ":down" instructs to generate a subnode (if there is already one, terminate it an replace by the new node) for an embedded finer actions while retaining the current node, and ":up" instructs to terminate recognizing the current action, and truncate the subnode link of the parent node. Here, the "current node" denotes the one that received the original event. Transition specifications used in our current system is shown in Table VII.

TABLE VI
EXAMPLE OF AN INSTANTIATED ACT-NODE: LOCALMOTION2 (ALL THE SLOTS ARE FILLED JUST FOR EXPLANATORY PURPOSE. THIS DOES NOT CORRESPOND TO ANY MOMENTARY STATE DURING RECOGNITION.)

slot	Content
type	LocalMotion
name	LocalMotion2
parent	Task1
base	HandLoc1
target	Loc2
special	Loc1
subnode	Depart2
history	(Approach2, FineMotion2)
initial-event	:Near (time t_1)
final-event	:Far (time t_2)
initial-state	copy of (HandLoc1, Loc2, Loc1) at t_1
final-state	copy of (HandLoc1, Loc2, Loc1) at t_2
operation	PLACE-ON-BLOCK

The "attention redirections" are described later in this section.

3) The Attention Stack: The "Attention stack" is a key component for relating the action model and the environment model dynamically under the context of action recognition. It realizes a limited activation of the models for efficiency and hierarchical concurrent processing for robustness. Only the model nodes selected from the attention stack become active. These nodes are also processed concurrently. The stack has several levels corresponding to the hierarchy of assembly motion types.

Each level of the stack can hold one or more "attention nodes" (henceforth, ATTN-nodes). They represent the current expected events, links to corresponding ACT/ENV-nodes (denoted by thin arrows in Fig. 7), and temporary memory for detected events with feature values.

An ATTN-node has two methods:

1) ":Detect" generates a message containing an expected event name and a list of pointers to the related ENV-nodes. Then it sends the message to the connected ENV-node. Upon receipt of a response from the ENV-node, the ATTN-node records the result.
2) ":Analyze" sends the recorded event type and the feature value to the connected ACT-node. The response from the ACT-node is returned to the issuer of the ":Analyze" message (e.g., the top-level process).

Each ACT-node has a maping from incoming events to necessary "attention redirections," as shown in Table VIII. An "attention redirection" is a list of a stack operation, a new event name, a new `base` node and new `target` nodes. The stack operation may be either; ":add"—create a new ATTN-node and add it to the current level of the stack (if there is already another node with the same event name, replace it by the new one), ":reset"—pop all the nodes on the stack down to the current level and place a new node there, or ":delete"—delete the specified ATTN-node.

Beside the explicit attention redirections, when an action transition has occurred, an automatic attention redirection

TABLE VII
MAPPING FROM EVENTS TO NEXT ACTIONS AND ENV-NODES (COLDBOOT MEANS THE INITIAL STARTUP OF THE SYSTEM. THE EVENT :LOC-EXIST SEGMENTS ONLY A PERCEPTUAL ACTION. POINTERS IN base AND target ARE RETAINED UNLESS EXPLICITLY MODIFIED)

motion type	event	transition	next motion	new base	new target
ColdBoot	:True	—	Task	World	—
Task	:Loc-exist	—	—	base	Loc's found.
	:Found-moving	:down	Transfer	target (= Hand)	—
	:Disappeared	:up	—	—	—
Transfer	:Near	:next	LocalMotion	base (= Hand)	Loc's found. (= objects near)
LocalMotion	:True	:down	Approach	base	target
				special	target
	:Far	:next	Transfer	base	—
Approach	:Join	:next	FineMotion	base	target
Depart	:Join	:next	FineMotion	base	target
FineMotion	:Split	:next	Depart	base	target

TABLE VIII
MAPPING FROM INCOMING EVENTS TO ATTENTION REDIRECTIONS; STACK OPERATION (OP), NEXT EVENT, NEW base, AND NEW target. (CODED IN ACT-NODES. ":INIT" DENOTES THE INITIAL ATTENTION SPECIFICATIONS FOR EACH ACT-NODE. POINTERS IN base AND target ARE RETAINED UNLESS EXPLICITLY MODIFIED. AUTOMATIC REDIRECTIONS DURING ACTION SEGMENTATIONS ARE NOT LISTED IN THIS TABLE.)

motion	event	op	next event	base	target
Task (base = World)	:Init	:add	:Loc-exist	World	—
	:Loc-exist	:reset	:Found-moving	base	HandLoc
	:Found-moving	:add	:Disappeared	base	target
Transfer (base = HandLoc)	:Init	:add	:Small-motion	base	—
	:Staying	:add	:Near	base	—
	:Moving-down	:add	:Near	base	—
LocalMotion	:Init	:add	:Large-motion	base	—
(base = HandLoc)	:Init	:add	:Far	base	target
	:Init	:add	:True	base	—
	:True	:delete	—	base	—
Approach	:Init	:add	:Join	base	target
Depart	:Init	:add	:Join	base	target
FineMotion	:Init	:add	:Split	base	target

is simultaneously done by the toplevel process: A ":reset" operation is issued for the stack level corresponding to the new action, placing a new ATTN-node created according to the ":Init" attention redirection of the new ACT-node.

V. RECOGNITION OF ACTION SEQUENCES

The role of the action recognizer is to observe the continuous performance of a task and generate a symbolic description of the sequence of operations. In order to do this, the recognizer must first detect those points in time when one action ends and the next action begins. Secondly, the recognizer must identify each temporal period as one of the known operations. Such processing is called *temporal segmentation* and *action identification*. We do not want to store the entire image sequence and then spend hours analyzing it off-line. Therefore, the processing must be reliably done on-line and in real time.

A. The Detect-Analyze Loop

The main part of the top level algorithm for action recognition is a detect-analyze loop described below. The detect loop and the analyze loop are executed alternately to simulate parallel processing. Example behavior of the action recognizer during an action transition from a Transfer to LocalMotion will also be explained using Fig. 10.

1) Detect: Scan the attention stack from bottom to top, sending a ":detect" message to each ATTN-node. Repeat this step until at least one of the nodes receives an event.

Example: Let us focus on the two ATTN-node labeled "NR" and "FM" in Fig. 10 (up).

The "NR" node has a link to "HandLoc1." When "NR" receives a ":detect" message, it sends a ":Near" message to "HandLoc1." Then "HandLoc1" sends itself a ":visual-search" message. This invokes a visual-search procedure described in Section III-E, using the hand-tracker and a sil-finder. The target object "Loc2" is found, and a message containing "(:Near HandLoc1 Loc2)" is returned to the "NR" node and stored there for later processing in the analyze phase. The "FM" node converts a ":detect" message into a ":Found-moving" message and directs it to the "World1" node. Then the "World1" node sends a ":found" message to the associated motion-detector. If the motion-detector has found some movement, its 3-D position is returned. Then the "World1" node sends a ":stimulate" message with the detected position to the "HandLoc1" node in order to check if it coincides with the current position of the hand (updated by the hand-tracker). If there is a big

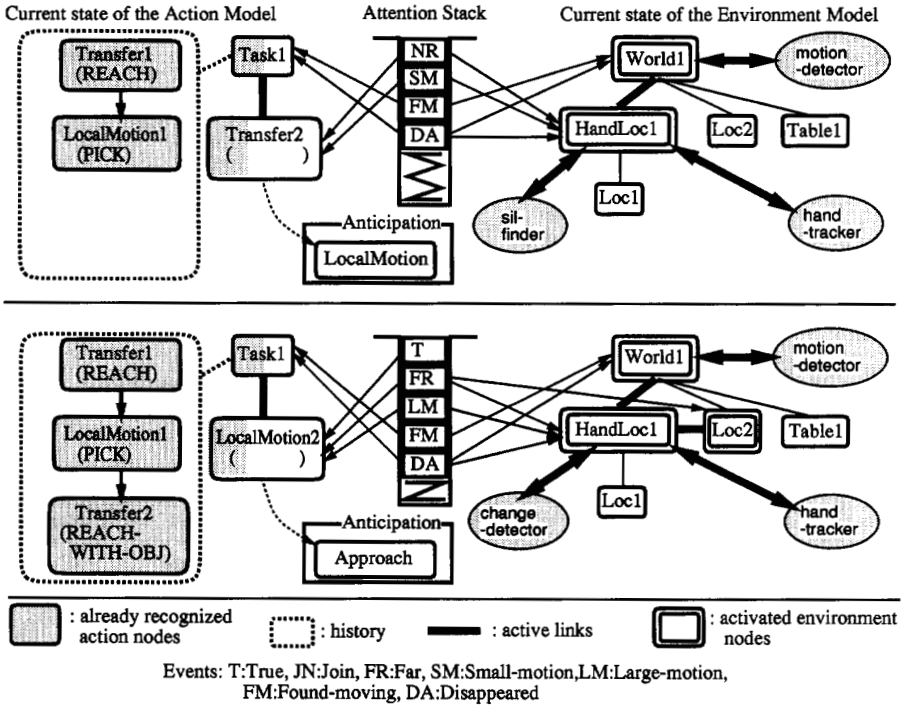


Fig. 10. Examples states of the action recognizer. Before (up) and after (down) a transition from "Transfer" to "LocalMotion."

difference[12] between the positions, which means that the hand-tracker is capturing a false target, the hand-tracker is repositioned, and the "World1" node returns a list of an event label ":Found-moving" and a pointer to the "HandLoc1" node. Otherwise, if no movement was found or the positions are close, "nil" is returned. The result is stored in the ATTN-node "FM."

2) Analyze: Scan the stack from bottom to top for an ATTN-node with a detected event, and if it is found, send it an ":analyze" message. This returns zero or one action transition specification and any number of attention redirections. Execute them.

When the event signals an action segmentation (transition), the following steps are taken: 1) Take a visual snapshot of the region represented by the connected ENV-node. 2) Differentiate the specific features in the initial and the final snapshots to identify the current operation. 3) Save the current ACT-node with the copied ENV-nodes into memory. 4) Instantiate a new ACT-node and generate new ATTN-nodes. 5) Associate ENV-nodes with the new ACT-node. The ENV-nodes are passed from the previous ACT-node or from the result of attention control, such as visual search.

Let us consider the following two cases for the example of Fig. 10.

Case 1: Only ":Near" was detected. This is the case in Fig. 10 (down). The result of "analyze" will be one action transition specification "(:next LocalMotion `base` Loc2)" (Table VII). This instructs to invoke the above action segmentation procedure. The current assembly motion "Transfer2" is classified according to the Table V as "REACH-WITH-OBJ" and stored into the `history` of "Task1." A new node, "LocalMotion2," is generated by instantiating a class node "LocalMotion." It is connected as a new subnode to the "Task1." Also "HandLoc1" is connected to its `base` and "Loc2" is connected to its `target`. Then an automatic attention redirection takes place—By a ":reset" command, the nodes "NR" and "SM" are popped away. And the initial attention of "LocalMotion" ("LM," "FR," and "T"; see Table VIII) are pushed onto the stack. A change-detector is allocated and an initial snapshot is taken.

Case 2: ":Found-moving" was detected. This case is not shown in Fig. 10. In this case, regardless of whether ":Near" was detected or not, the result of "analyze" will be one action transition specification "(:down Transfer `target` nil)" (Table VII) and one attention redirection "(:add :Disappeared `base target`)" (Table VIII). The action transition means to generate a new subnode of "Task1." So, the "Transfer2" is terminated, its `operation` identified as "WITHDRAW" (Table V), and stored in the `history` of "Task1." A new ACT-node, "Transfer3," is generated with a pointer to the HandLoc in its `base` slot, and connected to the `subnode` of "Task1." By an automatic redirection, the ATTN-nodes "NR," "SM," and "FM" are popped from the stack. Then the initial attention of "Transfer3," "SM" (Table VIII), is pushed onto the stack. Finally, the explicit redirection is executed: the "DA" is replaced by a new one ("DA").

B. Recognition Flow of Pick and Place Sequence

A typical recognition process for a "PLACE" operation is shown in Fig. 11. The top horizontal arrow ("Scene")

[12] The 3-D distance currently set as 120 mm.

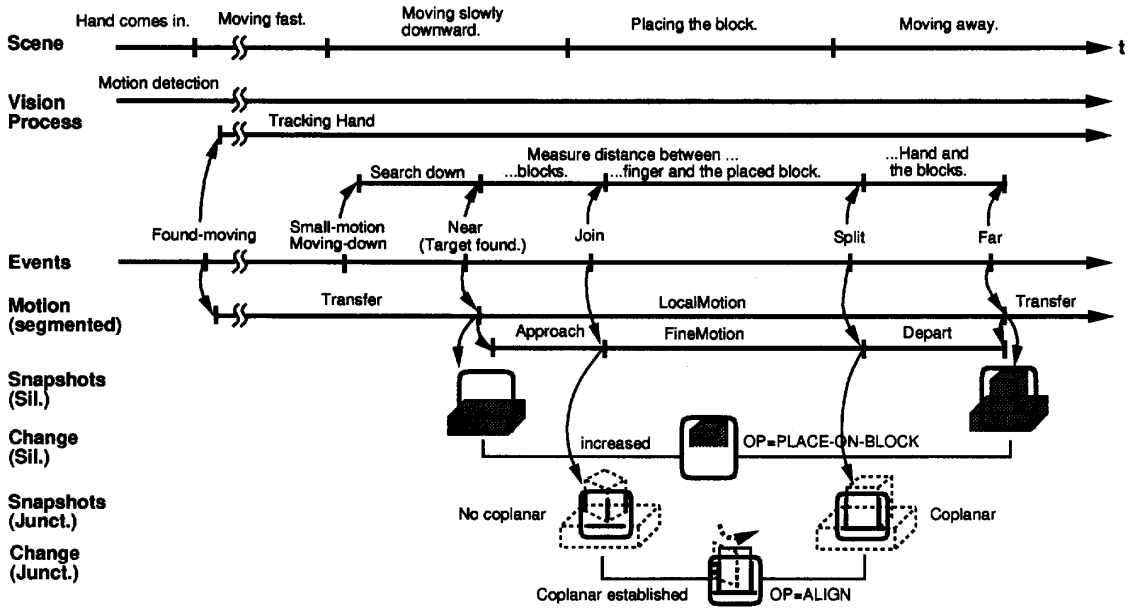


Fig. 11. Recognition flow of PLACE operation.

shows the time axis with scene descriptions. The "Vision Process" lines represent continuous vision processes executed in parallel. The marks on the "Events" line show the time when various events are raised. Thin arrows connect the events and corresponding effects. Intervals on the "Motion" lines denote segmented assembly motions. Two types of "Snapshots" at the segmentation points and their "Changes" are given. The "(Sil.)" snapshots are gray scale silhouettes. The "(junct.)" snapshots are the connectivity of local edges near the target faces of objects.

1) Recognition of Transfer Motion: First, a motion detector is invoked. When a large movement is detected, the event ":Found-moving" is raised, signaling the start of a "Transfer" motion. At the same time, the hand-tracker is invoked to track and extract motion features.

For explanatory purposes, we assume that one PICK operation is completed and another Transfer motion is started in the breaks marked by waves in Fig. 11.

2) Initial Point of LocalMotion: When the hand starts to move slowly downwards, the event ":Moving-down" (:Small-motion), is raised. This event invokes a visual search procedure. When the target object is found, the event ":Near" is raised. This signals the end of the "Transfer" motion and the start of "LocalMotion." Based on the prior recognition of a PICK, the ENV-node "HandLoc" records that the hand is holding an object. So, the attention of the change-detector is directed to the expected PLACE position.

3) Final Point of LocalMotion: The hand starts to move again. Once it gets far enough away from the target objects, the event ":Far" is established. This event signals the end of the "LocalMotion" and the start of next "Transfer." The change-detector extracts another snapshot and then finds that the area of the silhouette has increased. This results in the identification of the operation as a "PLACE-ON-BLOCK."

4) Updating the Environment Model: The environment model is updated to reflect the new state of the environment. The "holding" relation between the hand and the placed object is deleted. An "on" relation between the placed object and the target object is added. The target position of the operation is estimated by measuring the center of area from the differentiated stereo images.[13] Based on the knowledge that the operation was a "PLACE-ON-BLOCK" and the dimensions of objects in the model, the vertical position of the placed object is recomputed and stored.

Copies of ENV-nodes corresponding to the hand and the objects are made, and are stored in the `final-state` slot of the current action model node.

5) Recognition of FineMotion: A finer level of recognition proceeds in parallel with the "LocalMotion." The relative position of the held object and the target object is continuously monitored by vision. When they touch each other, the event ":Join" is established, which signals the start of "FineMotion." A coplanar-detector is invoked and gives a result "No Coplanar," because faces of the objects are not aligned at the beginning of the "FineMotion."

When the fingers release the placed object,[14] the event ":Split" is established, signaling the end of "FineMotion." This time, the coplanar-detector finds the "Coplanar" state. Differentiating the initial and the final states, the "FineMotion" is identified as an "ALIGN" operation. The coplanar relation defines the relative orientation of the objects, which is then recorded in the environment model.

[13] This method sometimes suffers measurements errors due to occlusion.

[14] Our current system does not track the fingers precisely. Therefore, the detection of ":Split" is based on comparing the positions of the hand and the target location. As a result, the event ":Split" is unreliable. But this does not affect recognition severely, because the termination of the FineMotion is forced by the upper level events, ":Far" or ":Found-moving."

```
(reach01 pick01 reach-with-obj01 place-on-table01
 reach02 pick02 reach-with-obj02 place-on-block01
 reach03 no01
 reach04 pick03 reach-with-obj03 place-on-block02
 reach05 pick04 reach-with-obj04 place-on-block03
 withdraw01 withdraw02)
```

Fig. 12. Recognized action sequence.

The hierarchical parallelism contributes to robustness. Even when the hand suddenly moves off during a FineMotion, the system quickly catches up with the gross motion. The attention stack extends at important points and winds up elsewhere, thus dynamically controlling the depth of the recognition process.

VI. Dependency Analysis of Task Structure

The action recognition process presented in the previous section outputs symbolic descriptions of action sequences. Information about the ordering and the dependency within a task can be attained by analyzing the observed action sequences. This knowledge is useful when the need arises to reorder or modify the sequence. This will greatly contribute to increasing the reusability of the result.

A. Representation of the Task Plan

1) Input: Sample output from the action recognition procedure is shown in Fig. 12. In this task, a structure with an inverted arch balanced on a center pillar is built. The intermediate states at the start and end points of each action (IS, FS) are remembered as partial snapshot copies of the environment model.

2) Output: An example of a higher level task description generated from the sample action sequence is illustrated in Fig. 13. A hierarchical task plan is represented in terms of state change operators (round boxes), subtask links (solid straight lines), and dependency links (arcs for non-ordered sequences and arrows for ordered). The hierarchical levels of the plan are divided into upper and lower parts at the *object state level* (OSL), where the state of only one object is changed per unit operation. Fig. 13 shows only the upper part.

3) Operators: The classes of general operators are given *a priori*. We define only one class, "ACHIEVE" of OSL operators. An ACHIEVE manipulates one object and establishes relations with other objects(s). Operators at the lower levels are labeled as FETCH, PUT, or FAKE (meaningless operation). Upper level operators are called PACHIEVE (ACHIEVE while keeping special relations), or BUILD (put together several blocks). In Fig. 13, operator classes are indicated by initial letters (A(chieve), P(achieve), B(uild)).

A summary of the contents of PACHEVE01 generated by our system is shown in Fig. 14. The operator description consists of three major components: 1) Focused Objects: `base` (manipulated objects), `target` (objects concerning new relations established by the operator), `special` (objects associated with the `base` by relations maintained by the operator). 2) State Changes: SC^+ (newly established relations), SC^- (removed relations), `SI` (unchanged relations), `SP` (specifically maintained relations). Each slot contains a list of support relations among objects described in terms of symbolic descriptor and relative coordinates. 3) Subprocedure (`plot`): A procedure for achieving the state change of this operator. Described in terms of a partially ordered set of lower level operators.

In Fig. 13, focused objects slots are denoted as "`b:`," "`t:`," "`s:`." For the topmost operator BUILD03, the graphics of the state changes, SC^- and SC^+, are displayed. They are generated from the environment model. For other operators, only SC^+ is shown as schematic displays. Arrows denote the ordering of procedures and arcs denote the parallelism.

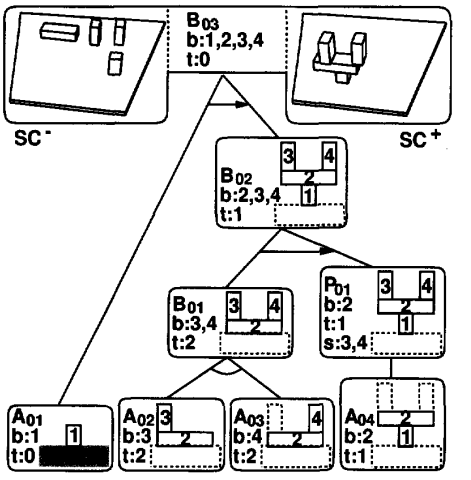


Fig. 13. Generated task plan.

slots	contents
class	PACHIEVE
name	PACHIEVE01
type	instance
base	(planar-brick2)
target	(short-brick1)
special	(medium-brick3 medium-brick4)
SC^+	(planar-brick2 on short-brick1 :at #f(-16.0 1.8 37.7) :wrt short-brick1))
SC^-	(planar-brick2 on table0 :at #f(121.0 284.3 12.7) :wrt table0)
SP	(medium-brick3 on planar-brick2 :at #f(-16.5 15.3 42.7) :wrt planar-brick2) (medium-brick4 on planar-brick2 :at #f(34.3 -42.4 42.7) :wrt planar-brick2)
SI	(medium-brick3 on planar-brick2 :at #f(-16.5 15.3 42.7) :wrt planar-brick2) (medium-brick4 on planar-brick2 :at #f(34.3 -42.4 42.7) :wrt planar-brick2) (short-brick1 on table0 :at #f(-20.7 126.6 25.0) :wrt table0)
plot	($action achieve04)
next	nil

Fig. 14. Generated PACHIEVE operator.

B. Gathering State Changes and Determining Focused Objects

The plan analysis process described in Section VI-C proceeds in a bottom up manner by organizing mutually dependent input operators into a partial procedure, and then relating it to a newly generated upper level operator. In the course of this analysis, the contents of the upper level operator are calculated from those of the constituent lower operators.

1) Gathering State Changes: First, state change descriptions for each input operator that initially has only the intermediate state descriptions is calculated as follows:

$$\mathtt{SC}^+ = \mathtt{FS} - \mathtt{IS}, \mathtt{SC}^- = \mathtt{IS} - \mathtt{FS}, \mathtt{SI} = \mathtt{IS} \cap \mathtt{FS}$$

Next, the state change for an upper level operator OP_i is calculated from lower level operators $\{\mathrm{OP}_j\}$ in the `plot` (subprocedure) slot of the OP_i:

$$\mathtt{SC}_i^{+\prime} = \bigcup_j \mathtt{SC}_j^+$$

$$\mathtt{SC}_i^{-\prime} = \bigcup_j \mathtt{SC}_j^-$$

$$\mathtt{SI}_i' = \bigcup_j \mathtt{SI}_j$$

$$\mathtt{SC}_i^+ = \mathtt{SC}_i^{+\prime} - \mathtt{SC}_i^{-\prime}$$

$$\mathtt{SC}_i^- = \mathtt{SC}_i^{-\prime} - \mathtt{SC}_i^{+\prime}$$

$$\mathtt{SI}_i = \mathtt{SI}_i' - \mathtt{SC}_i^{+\prime} - \mathtt{SC}_i^{-\prime} + (\mathtt{SC}_i^{+\prime} \cap \mathtt{SC}_i^{-\prime})$$

2) Determining Focused Objects: The contents of the `base` and the `target` slots of the upper level operator are obtained by screening the objects that appear in the newly generated state change description: Let obj^+ and obj^- denote the sets of objects appearing in $\mathtt{SC}^+$ and $\mathtt{SC}^-$, respectively.

$$\mathtt{base} = \mathrm{obj}^+ \cap \mathrm{obj}^-, \mathtt{target} = \mathrm{obj}^+ - \mathtt{base}$$

3) Extracting Protected Conditions: A set of relations SP that must be held (protected) during the application of an ACHIEVE operator, and the related set of objects (labeled `special`) is obtained as follows:

$$\mathtt{SP} = \mathtt{SI} \cap \{\mathrm{rel}(x, y) \mid (x \in \mathtt{base} \bigvee y \in \mathtt{base})\},$$

$$\mathtt{special} = \{x \mid \exists \mathrm{rel}(x, y) \in \mathtt{SP}\} - \mathtt{base}$$

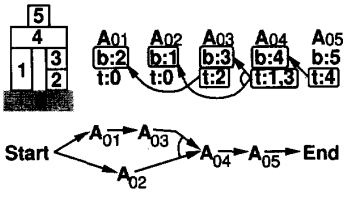
Fig. 13 shows how the state changes and the focused objects (illustrated with solid lines) are gathered as the plan analysis process builds up the hierarchical plan.

C. Generating a Hierarchical Plan by Task Procedure Analysis

1) Step 1—Analyzing Fixed-Order Procedures: In the assembly plan below the OSL, fixed patterns of the partial operator sequences appear repeatedly. Thus, we can provide to the system a set of templates for the partial sequences. The templates are described by the regular expressions shown in Fig. 15. Identification of a partial procedure and relating it to an upper-level operator is carried out by matching the sequence with the templates by an ATN (Augmented Transition Network) interpreter [28]. At the end of this step, the whole input sequence is organized into a set of ACHIEVE operators.

ACHIEVE:	FETCH,FAKE*,PUT
FETCH:	REACH,PICK,WITHDRAW*
PUT:	REACH-WITH-OBJ, {PLACE-ON-BLOCK|PLACE-ON-TABLE}, WITHDRAW*
FAKE:	{REACH|REACH-WITH-OBJ},NO,WITHDRAW*

Fig. 15. Templates for fixed-order procedures. Upper-level operators in the left column expanded into partial sequences of lower-level operators in the right column. "*" denotes repeating more than zero times. $\{a|b\}$ denotes selecting either "a" or "b."



($sequence
($parallel ($sequence A_{01} A_{03}) A_{02})
A_{04} A_{05})

Fig. 16. Extraction of a partially ordered mutually dependent procedure by searching for a B-T transitive closure.

2) Step 2-Analyzing Dependencies: Dependency among operators above the OSL are analyzed by tracking the coincidence of focused objects.

An operator OP_i moves the objects included in its base slot. When an operator OP_j establishes some new relations at an arbitrary time in the future, the set of objects contained in the `base` and the `target` slot of the OP_j serves as a support or a domain of those relations. At this time, the objects in the `base` of OP_j are moved but those in the `target` are not.

Thus, we can state that if `base` $(\mathrm{OP}_i) \cap$ `target` $(\mathrm{OP}_j) \neq \phi$ then the validity of the OP_j depends on that of OP_i. We call this type of dependency "B-T relation" (`base-target` relation).

Let us see an illustrative example: An object A is placed (OP_1) at a certain point in time and then after several other objects has been moved, an object B is placed on $A(\mathrm{OP}_2)$. In this procedure, the OP_2 depends on the OP_1 and therefore the ordering of the two operators cannot be changed.

By extracting a transitive closure of B-T relations, a partial procedure connected by the dependency can be identified. Fig. 16 illustrates an application of this method. The example task is to build the structure shown in the upper left corner. The task is accomplished by the sequence of ACHIEVE operators displayed on the right hand side. The middle row of Fig. 16 is the transitive closure extracted by searching backward from the maximum ACHIEVE05. This graph means that a partially ordered procedure in which the two parallel subprocedures A_{01}, A_{03} and A_{02} are executed in an arbitrary order followed by the sequential subprocedure A_{04}, A_{05}. This sequence is internally represented using grammatical notations as shown in the bottom row of Fig. 16.

Similarly, a B-S relation defined by `base` $(\mathrm{OP}_i) \cap$ `special` $(\mathrm{OP}_j) \neq \phi$ indicates a type of dependency where the object placed by the OP_i is carried by the OP_j (PACHIEVE).

Also, a C-T relation defined by

$$\texttt{base}(\mathrm{OP}_i) \cap \texttt{special}(\mathrm{OP}_j) \neq \phi$$

indicates the parallelism of OP_i and OP_j. This is where more than two objects are assembled on one common object.

Starting from the ACHIEVE sequence generated by Step 1, the plan analysis process searches for each type of transitive closure in the order of C-T, B-T, B-S, B-T. When a closure is found, an upper level operator is generated with its plot containing the closure, the focused objects and state changes (as described in Section VI-B). In the case of an assembly task in which a connected graph is built, the whole procedure is connected by dependency relations. Such a plan is integrated into one BUILD operator by the above described procedure.

The `plots` of the operators from the example task of Fig. 13 are shown in Fig. 17.

Our plan analysis method extracts high level task structures from observed operation sequences. Each operator in the input sequences describes only very simple changes in terms of relations between a hand and an object. By applying the plan analysis, a spatio-temporal range of description is automatically expanded. In the topmost BUILD operator, descriptions of focused objects, state changes, and procedures over the whole task are summarized in one place.

The method only requires a small amount of *a priori* knowledge and a small amount of computational time.

VII. Instantiation of a Task Plan in a Different Environment

In contrast with the teaching data from the traditional teaching by guiding, the result of "Learning by Watching" has a symbolic structure. This means that the system can make partial modifications to the teaching result, thereby instantiating it in a different environment.

A. Matching the Task States between Teaching and Execution

In the current implementation, we assume that the initial positions of parts differ between teaching and execution, whereas the final position of the complete assembly structure is the same in the world coordinates fixed on the worktables. Also, we assume that the parts used for the final assembly have exactly the same shapes between teaching and execution. There can be irrelevant objects not used in the final structure both in teaching and execution.

It follows from the above first assumption that, in world coordinates, the goal positions of the PICK operations must be modified according to the given initial state, but PLACE operations need not be modified. Transformation from the world coordinates to the arm coordinates is always necessary.

The goal positions of the PICK operations are determined by matching the initial positions of every object between the teaching and execution environments.

The initial state matching is done follows:

1) Initialize the environment model by copying the recorded initial state of the teaching phase.
2) Refer to the task-level plan generated by the plan analyzer and get a list of objects (ENV-node name and shape name) used for the final assembly. Irrelevant objects in the teaching environment are ignored in this step.
3) Using vision (an object-finder), create a temporary environment model for the current workspace state.
4) Do a two-stage match from the temporary model through the list of objects to the environment model, using shapes as keys. This step removes irrelevant objects even if they were present in the execution phase.
5) For each matched object in the environment model, replace the position/orientation data with the current state measurement. If there are more than one objects with the same shape, the matching is done in a first come first serve manner. As a special treatment, the HandLoc data is left unspecified, and the Table is instantiated using the calibration data.

```
build03:    ($sequence ($action achieve01) ($action build02))
achieve01:  ($sequence ($action fetch01) ($action put01))
build02:    ($sequence ($action build01) ($action pachieve01))
build01:    ($parallel ($action achieve03) ($action achieve02))
pachieve01: ($action achieve04)
achieve03:  ($sequence ($action fetch03) ($action put03))
achieve02:  ($sequence ($action fetch02) ($action put02))
achieve04:  ($sequence ($action fetch04) ($action put04))
```

Fig. 17. Contents of `plot` slots of generated operators for the example task.

Then the plan (recorded action model) is executed by the following procedure:

1) Take the final record of the action model from the teaching phase. Call it a *plan*.
2) Trace the temporal evolution of the *plan*: First, create a new Task node in an empty action model and link the World node in the environment model to its `initial-state`. Then, starting from the oldest node in the history list of the Task node, get one ACT-node by another from the *plan* in a depth-first manner. For each such node, do the following:
   a) If the node is a REACH or a PICK operation, replace its goal position (`target` node in the `final-state` slot for a REACH, and `target` in the `initial-state` slot for a PICK) with the current ENV-node with the same name.
   b) For any type of operation, generate manipulator commands and execute them.
   c) Update the ENV-node so that it reflects the difference between the `final-state` and the `initial-state` of the current operation. Correspondence between a node in the current environment model and a node in the `initial/final-state` is done on the name basis.

This procedure keeps the environment model to reflect the expected task state at the end of each operation during the execution phase. This will be useful for task execution monitoring and failure detection.

B. Generating Manipulator Commands

Every operation in the task plan is translated into manipulator commands using the macro expansion rules shown

TABLE IX
EXPANSION OF PICK AND PLACE ACTIONS TO ROBOT COMMANDS

action	expansion
TRANSFER(pos1,pos2)	amove(pos1)
	amove(pos2)
PICK(pos1)	open-hand
	go-pickpos(pos1)
	close-hand
	go-maxheight
PLACE(pos1)	go-placepos(pos1)
	open-hand
	go-maxheight

subcommand	expansion
go-pickpos(pos1)	z ← hand-pos_z
	amove(pos1_x,pos1_y,z)
	amove(pos1)
go-placepos(pos1)	z ← hand-pos_z
	amove(pos1_x,pos1_y,z)
	amove(pos1)

in Table IX. The positional parameters calculated in world coordinates are converted into arm coordinates.

For simplicity, the arm trajectory is generated in a point to point mode. The approach/depart points for pick and place operations are set at a constant distance above the worktable.

VIII. EXPERIMENTAL RESULTS

We have run our system for simple assembly tasks in order to test the described algorithms. The background and the surface of the workspace were painted black and the blocks were painted white. We assume that complete occlusion does not occur between the blocks.

In the example task presented here, the human instructor placed four upright rectangular blocks as "legs," then placed a rectangular plate on top of them to construct a "table." The coplanar-detector was not used in this example.

The initial and the final states in both teaching and execution phases are shown in Fig. 18. The graphics were generated from snapshot copies of the environment model during an experiment. It can be seen that between the teaching and execution, the initial states are different and the final states are equivalent.

The human instructor performed the task once from the beginning to the end without pausing. The system automatically segmented and identified assembly operations in real time.

Fig. 19 shows snapshots of the monitor display during task recognition. Along the bottom lines of the snapshots are messages from the system stating the results of recognition.

The elapsed time for the task recognition was 3 min 50 s, excluding recognition of the initial state. An assembly procedure consisting of 21 operations was recognized. The whole sequence is given in Fig. 20 and detailed descriptions of the final PLACE operation is given in Fig. 21. In the figures, "Loc" nodes are indicated by their names (e.g., brick187, plate189).

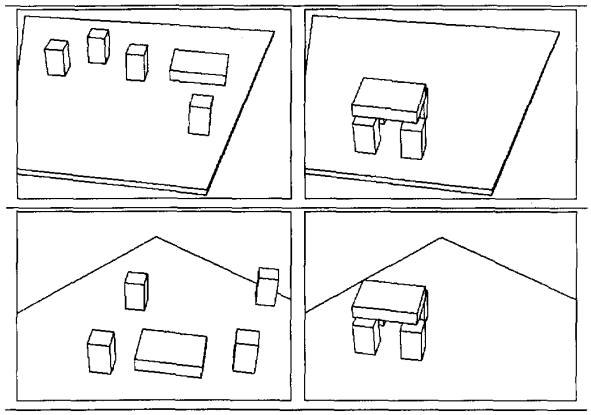


Fig. 18. Task "Build Table." Initial and final states in teaching (above)and execution (below).

A high-level task structure was extracted by applying the plan analysis process to the recognized action sequence. Fig. 22 summarizes the topmost two levels of the hierarchical task plan generated by the process. Each generated operator has state change descriptions, but are not shown here. The root operator, BUILD5197, states that building the table requires five blocks to be put together, which is accomplished by a BUILD5164 operator and an ACHIEVE4824 operator in this order. The BUILD5164 describes a parallel subprocedure for placing the four "legs" by four ACHIEVE operators, which can be executed in any order. The ACHIEVE4824 describes placing the top plate on the four legs. The whole plan is grounded at the level of visually recognized operators (REACH, PICK, PLACE, WITHDRAW). The total number of upper-level operators generated during the plan analysis, which constitute the final plan, was 17. The elapsed time for this analysis step was less than 10 s on a 10 MIPS workstation.

In another workspace, same set of blocks are placed at arbitrary positions. The system recognized the initial state by vision. The assembly procedure was reinstantiated for the given initial state. Forty-five manipulator commands were generated from the instantiated plan and were executed to carry out the task. The equivalent "table" structure was successfully constructed. A part of the command sequence is given in Fig. 24. Graphic displays of some of the intermediate states generated during the task execution is shown in Fig. 23.

Other tasks recognized successfully by the system include; 1) a pick and a place with an ALIGN operation, 2) building a tower, 3) building an arch, 4) building an inverted arch balanced on a center pillar.

IX. LIMITATIONS AND FUTURE DEVELOPMENT

The presented implementation has many limitations as discussed in this section. There are two reasons for this.

First, in order to achieve near real time performance with a considerably complex system[15] using a rather limited computational resource, we were forced to choose simple algorithm, especially for vision processing.

[15] 20 K lines in object oriented Lisp, plus 10 K lines in C.

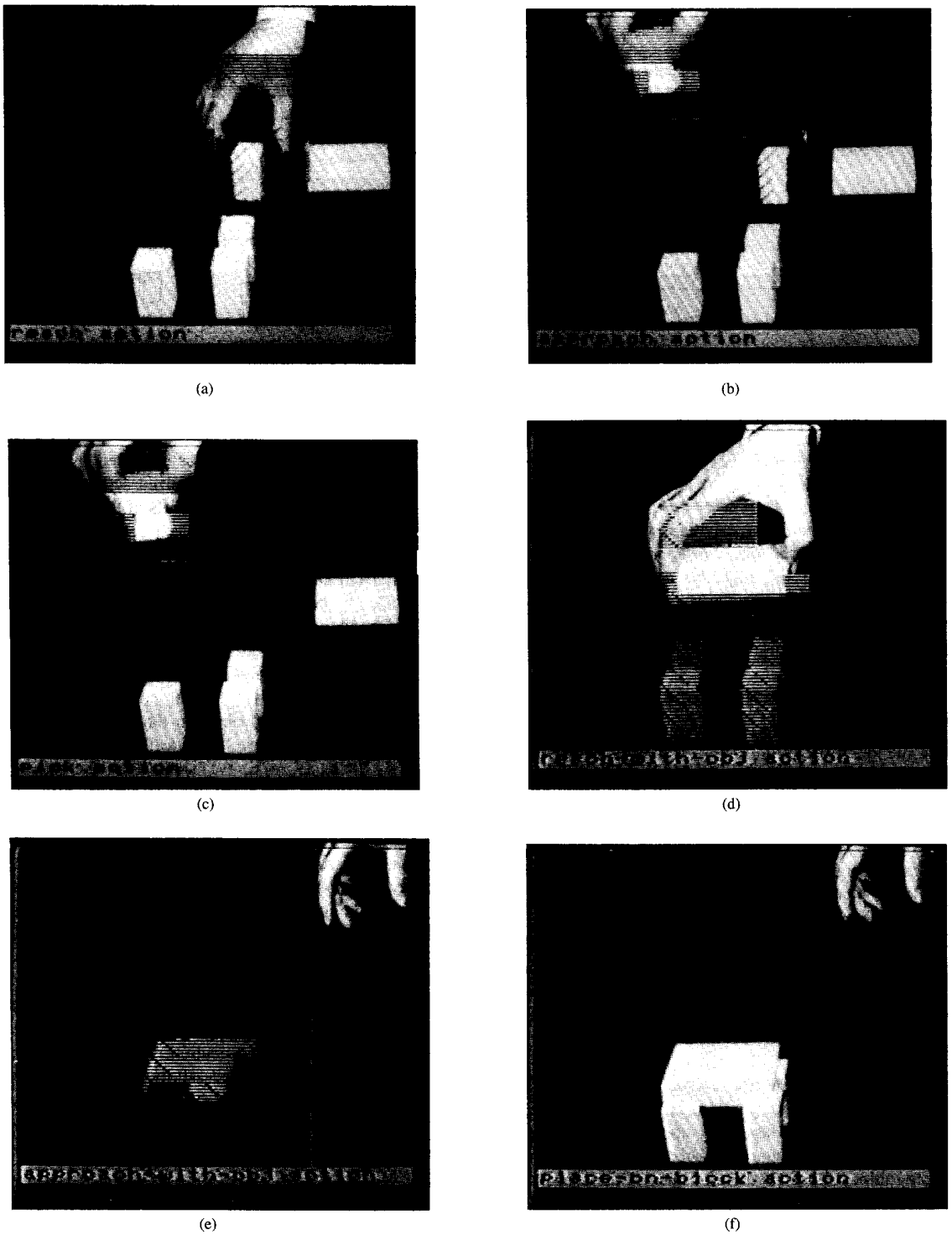


Fig. 19. Two action recognitions involved in recognizing the task "BuildTable:" (a), (d) Target region defined. (b), (e) Differentiation. (c) Classified "PICK." (f) Classified "PLACE-ON-BLOCK."

Second, our main purpose in building the current system was to verify the action recognition algorithm and to demonstrate at least one working example of "Learning by Watching" and "Teaching by Showing." Hence we did not put much emphasis on completeness or generality of the overall system.

A. Vision Processing

1) Object Center Measurement: Some VFD's (object-finder, sil-finder, change-detector) measure an object position (geometrical center) using center of mass of a binarized area. Reasonable results are obtained only when the both cameras are at non-special viewpoints. For an irregularly shaped object, there is no guarantee that the measurement is useful.

This problem is essential to any snapshot view of an arbitrary object. So, a solution will require use of shape knowledge obtained either from temporal observation or by matching to a shape database.

2) Occlusions: Since the VFD's use binary image features, they are easily affected by occlusions.

The change-detector is most severely affected. Although it can detect qualitative events unless there is a complete occlusion, the reported position (i.e., in a PLACE operation) sometimes has a significant error when the placed object is partially occluded, or when the object partially occludes other previously visible objects. Our current system corrects the vertical position of the placed object using knowledge about the sizes of the support objects. But there is no justification for an offline adjustment of the horizontal position or orientation. Quickly fitting a geometrical model to local edges after change detection may be useful.

3) Motion Segmentation: Our motion-detector is robust and reliable for the current task environment. But it will break quickly when we try to generalize the system. Especially, it will be useless for a moving observer or for a workspace with multiple and/or complex moving objects. An alternative will be to use optical flow [29] for motion segmentation.[16] It will enable the system to detect independent motion from a moving observer, segment and classify moving objects more precisely and reliably, and extract movement feature such as 3-D rotation directly.

4) Object Identification: The model-based shape recognition is so computation intensive that we use it only at initial state recognition. It is the edge-based topological matching phase that uses up most of the computation time, because it is combinatorial. Once a correspondence between the object and a model is established, the fitting process converges quickly. So, our conclusion is that the matching phase does not meet our real time requirement, whereas the fitting phase will be useful in measuring an orientation of an object at snapshot times.

The current system relies on binarized silhouettes and motion segmentation to detect/identify an object. It is clear that we need a more powerful real time object detection/identification algorithm. If it is realized, we can relax the black and white constraint, reduce the effect of occlusions, deal with multiple independently moving objects and achieve on-line registration/correction of objects in the environment model.

One possibility will be to use a combination of multiple 2-D features (e.g., color, primitive shape, texture, etc.) to efficiently index an object in a predefined database.

[16] These computation intensive algorithms are becoming feasible thanks to the recent hardware development.

```
(reach pick reach-with-obj place-on-table
 reach pick reach-with-obj place-on-table
 reach pick reach-with-obj place-on-table
 reach pick reach-with-obj place-on-table
 reach pick reach-with-obj place-on-block withdraw)
```

Fig. 20. Recognized operation sequence for "Build Table."

```
motion: localmotion305 operation: (place-on-block)
  |base: hand183
  |target: (brick190 brick186 brick187 brick188)
  |special: plate189
  |initial-event: :near |final-event: :found-moving
  |initial-state:
   hand183 pos: #f(-41.9 129.9 137.4) with relation:
     (holding plate189)
   plate189 pos: #f(0.0 0.0 0.0) with relation:
     (held-by hand183)
   brick190 pos: #f(-24.9 178.9 25.0) with relation:
     (on table182 :at #f(-24.9 178.9 25.0) :wrt table182)
   brick186 pos: #f(12.5 126.9 25.0) with relation:
     (on table182 :at #f(12.5 126.9 25.0) :wrt table182)
   brick187 pos: #f(-73.1 137.3 25.0) with relation:
     (on table182 :at #f(-73.1 137.3 25.0) :wrt table182)
   brick188 pos: #f(-42.9 85.7 25.0) with relation:
     (on table182 :at #f(-42.9 85.7 25.0) :wrt table182)
  |final-state:
   hand183 pos: #f(167.5 153.2 125.2)
   plate189 pos: #f(-25.1 151.0 59.8) with relation:
     (on-multiple (brick190 brick186 brick187 brick188)
      :at #f(-25.1 151.0 59.8))
   brick190 pos: #f(-24.9 178.9 25.0) with relation:
     (co-support plate189 :at #f(.1 27.9 -34.8)
      :wrt plate189)
     (on table182 :at #f(-24.9 178.9 25.0) :wrt table182)
   brick186 pos: #f(12.5 126.9 25.0) with relation:
     (co-support plate189 :at #f(37.6 -24.1 -34.8)
      :wrt plate189)
     (on table182 :at #f(12.5 126.9 25.0) :wrt table182)
   brick187 pos: #f(-73.1 137.3 25.0) with relation:
     (co-support plate189 :at #f(-48.0 -13.7 -34.8)
      :wrt plate189)
     (on table182 :at #f(-73.1 137.3 25.0) :wrt table182)
   brick188 pos: #f(-42.9 85.7 25.0) with relation:
     (co-support plate189 :at #f(-17.9 -65.3 -34.8)
      :wrt plate189)
     (on table182 :at #f(-42.9 85.7 25.0) :wrt table182)
```

Fig. 21. Recognized final "PLACE" operation in task "Build Table." Placing the top plate.

5) Tracking: The hand-tracker does not fail even when the hand touches many objects in turn. However, it usually fails in a particular situation—when the hand touches an archlike shape of similar size. This is reasonable because they both look similar. Even in such cases, the motion-detector finds the hand and the hand-tracker recaptures it. This combination is quite powerful for our current task environment. One problem is that although it rarely fails as a whole, either one of the windows often loses or oscillates. Therefore, the reported hand position is not always stable.

It is also clear that this tracker does not function in a realistic environment since each window basically tracks binary image features. As an alternative, gray-level correlation is a pow-

```
;;; Top level (Expansion level 0)
($action build5197
  :base (plate189 brick186 brick188 brick187 brick190)
  :target (table182)
  :special nil
  :next-action nil
  :plot ($sequence ($action build5164) ($action achieve4824)))
;;; Expansion level 1
($action build5164
  :base (brick190 brick187 brick188 brick186)
  :target (table182)
  :special nil
  :next-action (achieve4824)
  :plot ($parallel ($action achieve4748) ($action achieve4679)
   ($action achieve4610) ($action achieve4541)))
($action achieve4824
  :base (plate189)
  :target (brick188 brick187 brick186 brick190)
  :special nil
  :next-action nil
  :plot ($sequence ($action fetch4773) ($action put4812)))
```

Fig. 22. Topmost two levels of generated task plan.

erful and simple method.[17] We cannot simply use one large correlation window to track a hand, since it has a concave, variable shape with changing backgrounds. But using them in place of current binary trackers will greatly improve the overall robustness and reliability.

In addition, we could use a Zero Disparity Filter [30], a method to extract only such image features with zero stereo disparity. In combination with active control of stereo vergence, it has a strong depth selectivity. Therefore it will be a powerful tool for tracking in complex environments.

6) Visual Search: Currently the visual search discards the visually detected target unless it is confirmed by the environment model. This treatment is justified by the assumption that the environment model is correctly initialized and updated by the action recognition results to keep up with the task states. This assumption makes the system fragile against a recognition failure, since a failure will affect successive visual searches. Ideally, if we had a real time object recognition algorithm, we could use it to visually confirm the existence of an object, and register it to the environment model online. We can even omit the initial state recognition in a teaching phase.

Another problem is that the search direction is currently fixed to downward. When the hand approaches a block from its lateral side, the block is not found by the visual search. More generally, the search direction should be determined using the velocity and pose of the hand.

B. Task Variety

1) Operation Types: Although we have implemented recognition of an ALIGN operation, the current system does not recognize nor execute general rotations of an object.

One trivial improvement is to apply the model fitting during change detection to measure the object pose, and apply a motion planning, possibly including grasping/regrasping, during execution.

Since we are only interested in meaningful operations, recognition of arbitrary motion of a grasped object during a Transfer motion may not be necessary (one exception is obstacle avoidance). Also, a relative pose is more important than an absolute one in an assembly operation. Thus, a local relation detector (e.g., parallel, diagonal, etc.) as a generalization of the coplanar detector may be useful.

Insertion, pulling out, and (un)screwing are also not recognized/executed but are very important in assembly tasks. Recognition of this class of operations requires detecting/relating two or more parallel fine motions (rotation, translation, swinging, etc.) and associate them with some qualitative changes (e.g., parts are fixed or came loose, increase/decrease of visible portion, etc.). And the execution will require manipulation skills (see Section IX-C). In other words, not only visual cues but also force and other sensing modality should be introduced into the action model.

The current recognizer forces to classify an observed action as one of known actions. This leads to a recognition error when a novel action is encountered. If we can compute a certainty of each candidate action, we will be able to detect a novel action. Then the new action can be registered to the models by storing an observed motion and change. A crucial problem here will be how to generate necessary attention control rules automatically.

2) Object Shapes: The presented system allows only convex prismatic objects due to 1) silhouette based position measurement, 2) lack of a general grasp planner, 3) restricted operation types (because concave shapes introduce new operation types such as insertions), and 4) limitations of inference skills about object relations (currently, only simple support relations). We have already discussed about Item 1 and 3. Implementing existing methods for grasp planning will significantly improve on Item 2. Item 4 requires geometric reasoning about contact-based motion constraints. There are

[17] These computation intensive algorithms are becoming feasible thanks to the recent hardware development.

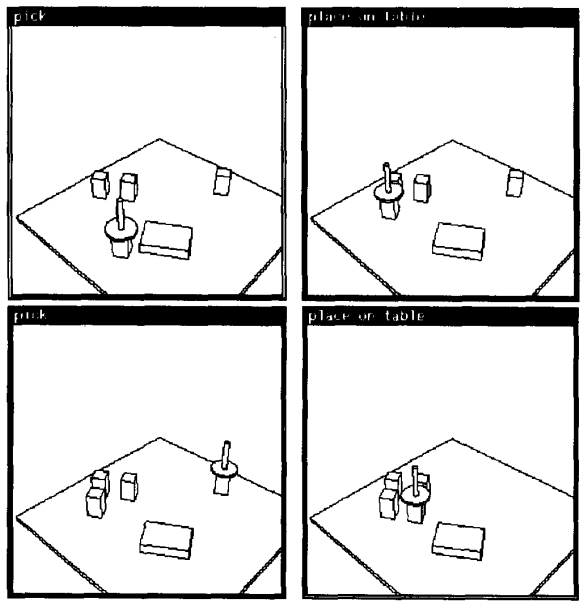


Fig. 23. Intermediate states generated during execution.

```
<<Fetch>>
  GOAL-POSITION #f(-40.1 -31.0 9.8)
  ARM GOAL POSITION #f(210.5 261.2 150.3)
 <reach>
  amove #f(210.5 261.2 55.0)
 <pick>
  open-hand
  amove #f(210.5 261.2 150.3)
  close-hand
  amove #f(210.5 261.2 55.0)
<<Put>>
  GOAL-POSITION #f(-25.1 151.0 59.8)
  ARM GOAL POSITION #f(301.1 102.6 100.3)
 <reach-with-obj>
  amove #f(301.1 102.6 55.0)
 <place-on-block>
  amove #f(301.1 102.6 100.3)
  open-hand
  amove #f(301.1 102.6 55.0)
```

Fig. 24. A part of generated motion sequence for "Build Table." Placing the top plate.

successful implementation for simple cases [15], but solving a complex general cases in reasonable time (hopefully, real time) is still an open problem.

3) Disassembly: Our system does not recognize disassembly sequences. This is due in part to the weakness of the object-finder, i.e., it cannot recognize two objects in contact as separate objects. Also, due to lack of real time object detection/identification algorithm, our attention control method depends too much on the environment model. As a consequence the system cannot handle the cases where an initially coalescent shape breaks apart. The core part of the action recognizer has an ability to recognize disassembly sequences. However, the plan analyzer handles only strict assembly sequences, and requires an improvement.

4) Learning and Memory: The learning performed by our system is one-time. The system does not accumulate past experiences. If it does, it can build a domain knowledge of its own. As discussed in Section IX-C, such knowledge can be used to assist the action recognition and the task execution. One possibility would be detecting failures and/or generating local path plans based on similar past experiences using Case-Based Reasoning [31]. In order to realize this, an appropriate action memory structure must be explored.

C. Treatment of Errors and Failures

1) Positional Errors: Proper treatment of positional errors is crucial for successful assembly tasks. The presented framework contains three major source of errors: visual measurement, hand-eye calibration, and manipulator motion.

As described earlier, our system automatically corrects vertical goal positions of PLACE operations in teaching phase using geometrical data. Since we assume exactly the same shapes for execution, vertical positional errors are small. Similarly, the gripper openings can be accurately computed from orientation and shape for the simple objects used in the experiment.

The horizontal positions directly reflect considerable errors in visual measurement. They are not large enough to break simple support relations in our example tasks. But it will be critical when we extend the system to handle fine operations such as insertions.

The camera and the world (fixed on a worktable) coordinates are calibrated for both teaching and execution workspace. The hand and the world coordinates are also calibrated for the execution phase.

Despite all the above techniques and efforts, there are still vertical positional errors up to several mm. We did not treat this error properly. And let the inherent compliance in our super-low-geared 6 DOF parallel manipulator (wrist) absorb the residual errors. Thus, our current implementation of task executor cannot handle precise operations.

A proper treatment of errors will require automatic generation of sensor feedback code. A promising direction will be to integrate "manipulation skills" [32] with our action model, because the two concepts have some similarlity. A manipulation skill is a combination of hybrid position/velocity/force control and sensing strategies to detect (contact) state transitions, which provide systematic strategies to robustly achieve various contact states. For example, a PLACE-ON-TABLE operation may contain a command such as a "move-to-contact, vertex-to-edge, edge-to-face."

In addition, visual feedback will also be necessary for fine motions. Our coplanar detector will be used for visually detecting a state transition (termination condition) in ALIGN operations.

2) Failure Detection and Recovery: We have to consider two types of failures in our framework 1) Recognition failures, and 2) Execution failures.

The recognition failures should be handled by the plan analyzer. Currently it only removes redundant operations (by the ATN method), and irrelevant objects.

Dealing with mis-recognized and unrecognized operations requires some domain knowledge and inference. For a limited domain, we can apply techniques developed in classical planning research [33]. First, we must define generic knowledge of every assembly operations such as its precondition, effect, etc. and domain rules for inferring about side effect, etc. Then, we simulate the execution from the beginning of the plan by applying the operators and the rules. When we hit a contradiction, we invoke a local repair techniques. The range of repair is determined by tracing casual links from the problematic point. Then apply a local re-planning to the range, such as variable modification, insertion/deletion of appropriate operators, abstraction to some upper level while cutting the lower nodes and then re-instantiating new operators downward, etc.

In order to minimize the effect of a recognition failure, it should be corrected on-line, as quickly as possible. Therefore, the above processing should be done in real time.

Since our framework integrates seeing, understanding, and doing, failure recovery can be handled at any phase. We think that, as opposed to the above knowledge-intensive method, it is more appropriate to handle failures at execution time, as failure recovery actions.

Failure recovery is one of the hardest problems in robotics and we do not have any concrete solution yet. Our proposal is that we can use the action recognizer for execution monitoring. We have already presented a method to trace an "expected" plan and environmental state transitions in the execution phase in Section VII, and showed its results in Section VIII.

A straightforward method will be to just apply the action recognizer to recognize the robot actions, and compare each operation name with the currently executed operation name. If they are different there is a failure.

This method will become more powerful when we succeed in building a more powerful recognizer. Our current recognizer cannot recognize unexpected (and hence undefined) actions, such as dropping a block, toppling over a pile, etc.

Once a failure is detected, the local repair technique can be used to recover.

In contrast with the traditional knowledge-intensive approach, this method does not require simulating the whole task, nor inferring about numerous possibilities of side effects of each operation. This is because they are automatically computed by the physical real world during task execution, and the system only has to observe the outcome.

X. Summary and Conclusion

Based on the consideration of previous methods of robot programming, a novel task instruction method, namely "teaching by showing," was presented. With this method, a human instructor only needs to perform a task while a robot extracts reusable task description automatically by watching the performance without disturbing it. In this method, the robot has special functionality called "learning by watching," which consists of real time visual recognition of human action sequences and symbolic plan analysis. Functional units and working algorithms for this functionality are presented. The overall system is model based and integrated at the symbolic level. Effectiveness of the method is supported by experimental results with various block assembly tasks.

The raw input to the system is continuous flow of image data. In order to strictly maintain the undisturbing nature of the system's performance, we assume that the human instructor provides no explicit signals at the end of each assembly operation, such as pushing a button or withdrawing the hand out of the system's sight. Therefore, the recognizer has to watch the continuous motion of the human hand or the objects and detect implicit signs of temporal segmentation.

Temporal segmentation is defined by switching the target of operations. It is detected by an active visual search invoked by qualitative motion changes. A segmented assembly motion is classified into one of a number of possible operations by the qualitative change of a simple feature. This change pinpoints a certain operation type because of active selection features and the control of regions of interest based on the ongoing task context [34].

This recognition technique is quick and reliable, as opposed to classical quantitative techniques. For example, let us consider how to detect a coplanar relation between side faces of two blocks moved in face contact (Fig. 11). A classical technique might first measure precise positions and orientations of a pair of objects and then try to calculate a transformation matrix between them to detect a coplanar relation. This method wastes most of the computation because intermediate results are thrown away in the final step. Moreover, whereas final result is a binary valued information, intermediate arithmetic must be carried out with high precision to insure reliable detection. In contrast, our system tries to find a special class of edge junctions that directly indicates a coplanar state provided that current context is FineMotion.

The recognized action sequences are passed onto an additional off-line process to extract high level structures such as goal hierarchy and dependency among operations. This information will be of great help when reordering or local fix of the plan is required. The proposed method works in a bottom up manner efficiently and requires little domain knowledge.

An AI planner to generate a plan for a task from scratch, similar to that shown in Fig. 13, could be built [35]. But it requires large amounts of sophisticated domain specific knowledge, a complete description of the workspace state and a high computational load. In contrast, our system quickly extracts a high level task plan from an observed action sequence using little knowledge.

The usefulness of the recognition result was shown by reinstantiating it to a different initial state to accomplish an equivalent assembly task. A symbolic representation of the task plan enables matching initial states between teaching and execution.

As discussed in Section IX, our current system is not complete nor general. Therefore, development of a practical system will demand improvements on many points. We have made suggestions on possible approaches to such improvements.

A future version of the system might eventually break the silence after all the efforts of action recognition, plan analysis, and execution practicing, and ask a question about the instructor's ambiguous intention, in natural language.

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