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A VISION SYSTEM FOR ROBOTIC INSPECTION AND MANIPULATION*

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Sensor Driven Robotics

Advanced robotic systems should be able to perform a variety of tasks in complex, unstructured environments with increased level of autonomy. Robots provide the physical link between intelligence and action. Structurally, a robot can be considered as having three modules. These include, (1) *Mechanical assemblies*, such as robot arm, end effectors, and mobility platforms, (2) *Sensors*, for sensing the work environment of a robot, and (3) the *Perception, Planning and Control unit*, which is utilized for interpreting the sensory inputs and for planning and controlling the actions of the robot. Most of the robotic systems currently employed in the industry require a highly structured environment for the robot to operate [1,2]. This requirement can be relaxed if the robot is endowed with an array of external sensors to sense its environment. The sensor-driven operation is critical for making robots more versatile and flexible to use. Advanced robotic systems which are capable of utilizing sensor modalities such as vision, range, force, and touch can be employed in a variety of application domains. Of these, vision is recognized to be a very important sensory modality. It offers rich sensory data for accurate and detailed interpretation of the composition of a robot's work environment. Object recognition, determination of their locations in the 3–dimensional workspace, inspection of their status are all important tasks where vision derived information can be effectively utilized.

In this paper we describe efforts directed towards the design, development, and testing of a vision system that can be employed for performing a variety of inspection and manipulation tasks. Most of our presentation and findings should be of relevance to a broad class of industrial automation tasks. The specific operational environment which we considered in our development was that of nuclear power plants. The need for and importance of inspection systems to be employed in Nuclear Power Plants is well documented in a report prepared for the U. S. Nuclear Regulatory Commission by White *et. al* [3]. The authors concluded that robotic inspection capabilities will reduce both radiation exposure to personnel and plant operating costs. It is clear that for a comprehensive inspection and surveillance system a wide array of sensory systems will have to be employed. Some of the most important types of sensors include vision, radiation, vibration, sound, and temperature. In this paper we concentrate only on the vision sensor which in its simplest form is a black and white camera. Some of the major inspection tasks which can be accomplished by utilizing advanced vision capability in nuclear power plants are listed in Table 1. These inspection tasks need not be performed totally autonomously. Images acquired by stationarily mounted cameras or those mounted on robots can be interpreted by a human observer. In this paper we describe design of a system where the complete process beginning from image acquisition to final interpretation of the scenes can be accomplished automatically.

Model-Based Approach in Computer Vision

The main goal of a robot vision system is to provide an accurate interpretation of a scene utilizing images of the scene as the primary source of input. Such interpretation can be provided in a variety of forms and at different levels of abstraction. A useful form of interpretation may include an object location map where different types of physical objects appearing in the scene are independently recognized and accurate locations of these objects in the scene are determined. Also, of utility is the information regarding the status or condition of an object. Design of a computer vision system that can perform such object recognition and scene interpretation is a complex and challenging task. The main difficulty arises from the fact that images are 2-dimensional projections of the 3-dimensional real scene and innumerable combinations affecting the illumination source, scene and sensor parameters can result in the same observable value of the recorded image intensity.

In order to make the object recognition task computationally tractable model-based approach has been proposed [4]. The approach requires models associated with objects which are expected to appear in the scene. These models are recorded in the knowledge-base of the system. Various features from the input images are extracted using low-level, general purpose operators. These operators should be robust in extracting image features corresponding to the various physical attributes of the objects. Finally, matching is performed between the image derived features and the scene domain models to recognize the objects. This is accomplished by utilizing various decision making schemes in the matching module. Successful design and implementation of a vision system utilizing the model-based paradigm is affected by a number of factors. These include, ability to derive suitable object models, nature of image features extracted by the operators, computationally effective approach to handle the task of matching, schemes utilized for knowledge representation and effective control mechanisms for guiding the overall operation of the system.

It is usually easier to develop models for objects expected to appear in an industrial plant environment than those appearing in outdoor natural scenes encountered in remote sensing applications. A number of studies describe applications where model-based vision systems are utilized for analyzing outdoor scenes as well as indoor, industrial scenes [4-8]. In an industrial plant environment one can control illumination, viewing geometry and background types to design practical model-based vision systems satisfying operational requirements of accuracy, speed, and robustness. Readers interested in reviewing robot vision systems developed for a variety of specialized tasks may refer to references 5, 6, 7, and 8. Most of the commercially available vision system for industrial inspection utilize binary image processing to simplify analysis [8]. This, however, restricts the types of objects and scenes which can be successfully analyzed. Examination of gray scale images, on the other hand, is more complex but one can successfully handle complex scenes with multiple object types. The vision system we describe utilizes gray scale image inputs.

Design of a Model-Based Vision System

In this section we discuss the design of a vision system for performing a variety of inspection and manipulation tasks. The discussion begins with a description of the test-bed utilized in the development. The main focus of our research is on the development of an autonomous system that is capable of performing various inspection and manipulation tasks associated with a typical control panel. This panel is designed in consultation with experts from nuclear industry, using only "off-the-shelf" components. The tasks range from reading of various meters and displays to operating different types of switches and controls. Also, included are tasks associated with valve operation. Teleoperation or automatic operation of valves in nuclear power plants is recognized as one of the important desired capabilities of a robotic systems [3]. Our experimental set-up includes a test panel, a robot having multiple sensory capability, computers, and various manipulation tools. The test panel and the robot with various sensors mounted on the arm are shown in Figure 1. We are considering a situation that does not require a mobile platform for robot movement. The industrial robot consists of a Cincinnati Milacron $T^3 - 726$ robot with enhanced sensory mechanisms. The sensors mounted on the robot include vision, range, and proximity as non-contact devices and touch and force/torque as contact devices. The camera and range sensor point in the direction parallel to the fingers, while the proximity and touch sensors are mounted within the fingers. The force/torque sensor is mounted between the gripper and the face plate of the end effector for measurement of the forces acting on the gripper.

The prototype system currently being developed using the above set-up is required to perform the tasks listed in Table 2 in an autonomous mode. Typical autonomous robot operation will involve the following. The robot first identifies the exact geometrical position of the panel using a camera calibration program. Next it uses a computer vision system to develop an object location layout map for various devices appearing in the panel. The task to be performed by the robot is specified by a code displayed on a LCD meter. After decoding the command the robot performs requested inspection or manipulation task. The above flow of processing steps is illustrated in Figure 2.

Vision System Architecture

The primary factors considered in the design of the vision system are as follows:

- The system utilize all meaningful information that can be extracted from image inputs. Information from spectral, spatial, and relational domains is extracted and analyzed.
- The system should be robust. In order to ensure robustness only relative information about the object attributes in spectral and spatial domains are used.

- Object models stored in the system's knowledge base should be provided by the user of the system. In the knowledge acquisition mode, the user is asked questions regarding her expectations about object properties manifested in the three independent information domains. Information about objects and constituent subobjects is acquired. Whenever the scene is modified, another knowledge acquisition session can be undertaken to update the knowledge base. The exact representation of the spectral, spatial and relational domain information is shown in Figure 3.
- The system should be modular and easy to expand.
- The system should possess an explanation capability. This feature is quite useful and important for the user to understand the line-of-reasoning followed in the system in making an object recognition decision.

Robustness and ease in expandability to accomodate changes in the task environment are two key features guiding the development of the vision system. The system is compartmentalized in two basic groups of procedures. The first group consists of general purpose procedures for knowledge acquisition, image acquisition, image segmentation, matching, and camera calibration. The second group consists of special purpose procedures mainly designed for determining status of individual objects.

The main functions supported by the first compartment of the system are:

(a) to allow a user to input object attributes in spectral, spatial and relational domains, and to encode this information in the system knowledge base,

(b) to acquire gray scale images of different resolutions,

(c) to perform segmentation of input images,

(d) to extract spectral, spatial and relational domain features from the acquired gray scale images,

(e) to perform matching of image derived features with object attributes to recognize various objects.

(f) to determine 3-dimensional locations of objects in the field of view of the camera using the camera calibration model [2]. This requires identification of 4 control points in the image for the camera calibration calculations. We utilize 4 lights mounted on the panel border as the control points. The robot acquires two images, one with lights turned on, another with lights off, the difference image is analyzed to detect these lights in the image plane. A transformation matrix which allows us to transform the image coordinates into 3-D world coordinates is calculated and stored.

The system is developed in such a fashion that the above functions are performed by procedures which are general purpose, that is, they rely on minimal knowledge about the scene and its constituent elements. For example, the sequence of procedures employed for recognizing and locating a meter in the panel will be basically similar to that of recognizing and locating a valve. The functional modules and sequence of processing steps for deriving object location map are presented in Figure 4. A robust region growing segmentation procedure is used to identify all distinct regions of uniform gray level intensity values. The segmented image is analyzed to extract spectral, spatial, and relational domain features of the detected blobs. The only spectral domain feature extracted is the mean gray level of a blob. The spatial features extracted from each of the blobs include: size, shape, perimeter, principal direction, coordinates of the smallest rectangle enclosing the blob, height, width, and elongation. Relational features can be derived from the coordinates of the smallest enclosing rectangles associated with the blobs. The matching module basically follows a bottom–up approach by first searching for the subobjects and then examining the appropriate relational constraints to see if an object can be formed by the detected subobjects. Initial search for a subobject is based upon matching of the spectral and spatial features of a blob with the corresponding properties specified in the knowledge base. As a simple example of the system attempting to find a *slider*, it will first identify all blobs which satisfy the spectral and spatial domain properties for the subobject *slot*, (as specified in Figure 3), similarly all blobs satisfying the constraints associated with the subobject *handle* are detected. In the next step, blobs associated with the subobject *slot* and *handle* are examined in pairs to verify if the specified relational domain constraints are satisfied or not. Search for objects without subobjects requires matching of only spectral and spatial constraints. Once all of the objects are recognized in the image then the transformation matrix calculated by the camera calibration module is used to specify the object locations in 3–D work space of the robot. The matching module utilizes relative spectral and spatial domain features instead of absolute values to ensure robustness. The relative features are derived using the attributes associated with the panel for normalization.

As opposed to the above described functions and procedures the second compartment of the system consists of procedures developed to address specialized requirements to deal with individual objects. The main function supported by procedures in this group is to determine the status of various objects which are recognized and located using the procedures from the first compartment. The objects appearing on the test panel and the type of status information associated with each one of them are listed in Table 3. Depending upon the type and nature of the object the camera mounted on the arm is moved to take close-up images which are analyzed to determine the status of the object. Detailed discussion of the routines developed for object status recognition is provided in reference 9.

Verification of the Vision System Performance

The performance of the vision system is tested using the test-bed described earlier. The system's capability to perform the tasks listed in Table 2 has been verified. Results of the various steps utilized by the vision system are presented in Figures 5 and 6. In Figure 5a, input gray scale images acquired by the robot after determining the panel position are shown. Results of the segmentation are presented in Figure 5b. These results were processed to determine the types of objects and their 3-D locations using the matching module. Results of the object recognition module are shown in Figure 5c. Results of the selected object status recognition modules are shown in Figure 6. Figure 6a shows a gray scale image of an analog meter. A status recognizer program which employs edge detection and Hough transform routines was used to determine the needle position as displayed in Figure 6b. A gray scale image of another type of an analog meter mounted on the panel is shown in Figure 6c. This image is analyzed in the manner similar to the one shown in part (a). The needle position was accurately determined as shown in Figure 6d. Figure 6e shows a gray scale image of a digital display meter. Edge detection and thinning routines were employed to get the results shown in Figure 6f. These results were later processed using Fourier shape descriptors to identify the 1.84 numeric code accurately. These results are derived in an on-line session where the time elapsed from the acquisition of the first image for panel position determination to the recognition of the status of various objects is less than 2 minutes on a general purpose VAX 11/785 computer. This system has been in operation for over a year in our laboratory. Over one hundred experiments involving varying illumination conditions and viewing geometry have been conducted to test the robustness and accuracy of the system. These results are most promising. In order to further test the vision system's performance, the vision system software was transported to another location, involving different robot, camera, and entirely different illumination conditions. The system has been performing successfully at these two locations. These tests lend support to the robust, accurate and reliable nature of the system performance.

Summary

Sensor-driven robotic system are required for performing tasks in complex, unstructured environments. In this paper we have described research efforts directed towards developing robotic systems with advanced sensory capabilities for operation in nuclear power plants. The only sensory modality considered in the paper is that of vision. A model-based vision system that can be used for various inspection and manipulation tasks is designed and developed. The system analyzes gray scale images of varying resolutions. It uses features from spectral, spatial and relational domains. The vision system uses general purpose procedures for recognizing various objects appearing in the scene and for determining their 3-D locations. Special purpose routines are employed to determine the status of various objects located. The system has been extensively tested at two different laboratories. Its performance has been accurate, robust, and reliable. Its performance has been quite robust. Further enhancements planned for the system include utilization of 3-D cues sensed by stereo or range sensors [10].

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Table 1. A list of inspection tasks required in a nuclear power plant where vision sensors can be utilized (From reference 3).

1.	Verification of position of valves and dampers.
2.	Measurement of oil and liquid levels in sight meters.
3.	Reading of instruments and gauges (pressure, temperature, flow).
4.	Detection and location of steam/water leaks.
5.	Verification of integrity, position, and leaktightness of pipe snubbers.
6.	Detection and determination of liquid and oil spillage.
7.	Detection of loosened parts and abnormalities in the operation of fans, pumps, blowers, etc.
8.	Verification of integrity of security locks.

Table 2. List of inspection and manipulation tasks to be performed autonomously by the robotic system.

1.	Locate the panel.
2.	Read command from binary light code.
3.	Read command from a 7-segment display.
4.	Identify, locate, and read analog meter.
5.	Identify, locate, and read digital meter.
6.	Monitor the status of meters and controls.
7.	Identify, locate, and turn valve.
8.	Identify, locate, and activate push button switch.
9.	Identify, locate, and operate an emergency knob.
10.	Identify, locate, and operate a slider control.
11.	Identify, locate, and manipulate the tool for valve turning.

Table 3. Objects appearing on the test panel and their status information.

OBJECT TYPE	STATUS
1. Light	On/Off
2. Analog Meter	Needle Position
3. Digital Meter	Numeric Code
4. Valve	Position of the Holes
5. Slider Control	Position of the Handle
6. Push Button Switch	On/Off
7. Toggle Switch	On/Off

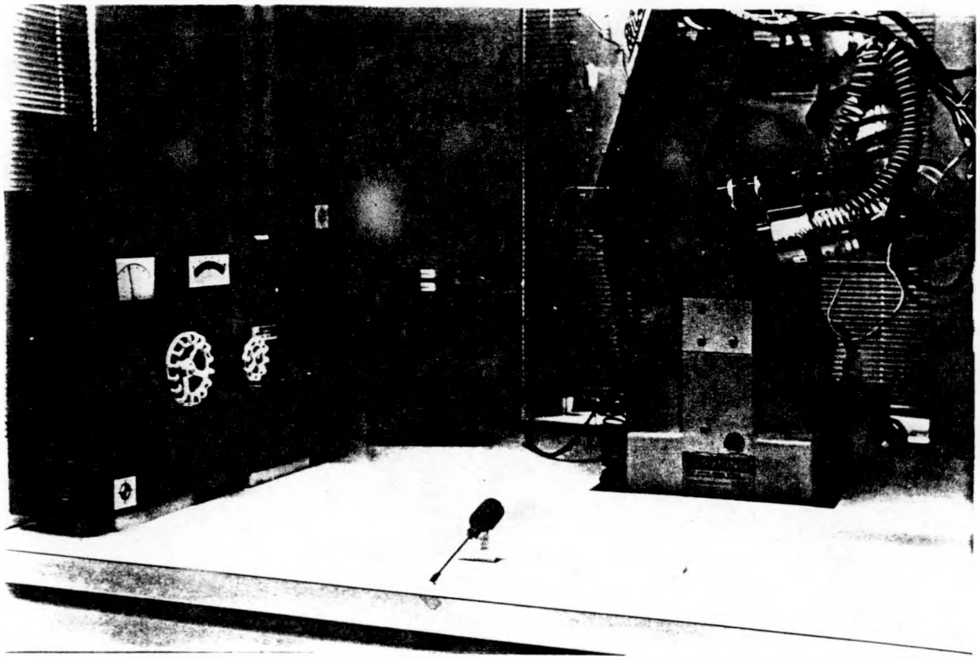


Figure 1: The test-panel and an industrial robot with vision, range, touch, force, and proximity sensory capabilities. The test panel includes variety of displays, meters, valves, controls, and switches.

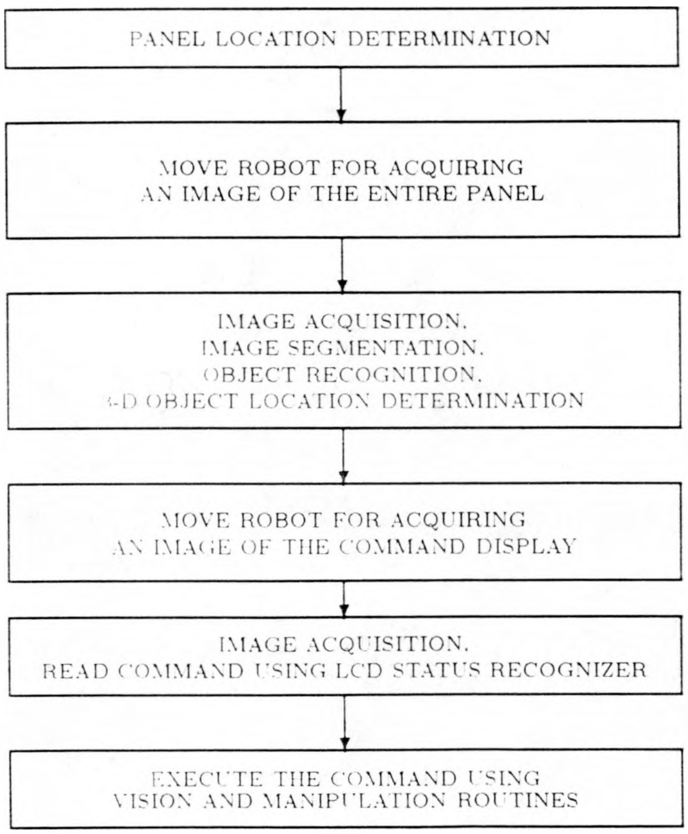


Figure 2: Flowchart showing the sequence of operations performed by the vision guided robotic system.

```
(id #=0), name:              panel,              number of subobjects=0
       Spectral property: the object's spectral property is undefined
(id #=1), name:              slider,             number of subobjects=2
       name of the subobject:                    slot
       name of the subobject:                  handle
       Spectral property: the object's spectral property is undefined
(id #=2), name:              slot,               number of subobjects=0
       Spectral property: the object is darker than background
(id #=3), name:              handle,             number of subobjects=0
       Spectral property: the object is brighter than background
(id #=4), name:          lcd_meter,              number of subobjects=0
       Spectral property: the object is darker than background
(id #=5), name:      analog_meter_1,             number of subobjects=2
       name of the subobject:             meter1_base
       name of the subobject:             meter1_face
       Spectral property: the object's spectral property is undefined
(id #=6), name:        meter1_base,              number of subobjects=0
       Spectral property: the object is darker than background
(id #=7), name:        meter1_face,              number of subobjects=0
       Spectral property: the object is brighter than background
(id #=8), name:         light_code,              number of subobjects=4
       name of the subobject:                  light
       Spectral property: the object's spectral property is undefined
(id #=9), name:              light,              number of subobjects=0
       Spectral property: the object is brighter than background
(id #=10), name:            valve_1,             number of subobjects=0
       Spectral property: the object is brighter than background
(id #=11), name:            valve_2,             number of subobjects=0
       Spectral property: the object is brighter than background
(id #=12), name:            E-knob,              number of subobjects=0
       Spectral property: the object is darker than background
(id #=13), name:     analog_meter_2,             number of subobjects=0
       Spectral property: the object is brighter than background
(id #=14), name:     analog_meter_3,             number of subobjects=2
       name of the subobject:             meter3_base
       name of the subobject:            meter3_plate
       Spectral property: the object's spectral property is undefined
(id #=15), name:       meter3_base,              number of subobjects=0
       Spectral property: the object is darker than background
(id #=16), name:      meter3_plate,              number of subobjects=0
       Spectral property: the object is brighter than background
```

(a)

```
(id #=0), name:              panel,              number of subobjects=0
       Spatial property:
              the object's min. size = 7000
              the object's max. size = 23000
              the object is rectangular-shaped
              the object's direction is undefined
              the object's W/H ratio = 50/100
(id #=1), name:             slider,              number of subobjects=2
       name of the subobject:                    slot
       name of the subobject:                  handle
       Spatial property:                     undefined
(id #=2), name:               slot,              number of subobjects=0
       Spatial property:
              the object's min. size = 15
              the object's max. size = 80
              the object is rectangular-shaped
              the object's direction is in 0 degrees
              the object's W/H ratio = undefined
(id #=3), name:             handle,              number of subobjects=0
       Spatial property:
              the object's min. size = 20
              the object's max. size = 55
              the object is rectangular-shaped
              the object's direction is in 90 degrees
              the object's W/H ratio = undefined
(id #=5), name:      analog_meter_1,             number of subobjects=2
       name of the subobject:             meter1_base
       name of the subobject:             meter1_face
       Spatial property: undefined
(id #=6), name:        meter1_base,              number of subobjects=0
       Spatial property:
              the object's min. size = 180
              the object's max. size = 400
              the object is U-shaped
              the object's direction is undefined
              the object's W/H ratio = undefined
(id #=7), name:        meter1_face,              number of subobjects=0
       Spatial property:
              the object's min. size = 400
              the object's max. size = 500
              the object is rectangular-shaped
              the object's direction is undefined
              the object's W/H ratio = undefined
(id #=10), name:           valve_1,              number of subobjects=0
       Spatial property:
              the object's min. size = 400
              the object's max. size = 900
              the object is circular-shaped
              the object's direction is undefined
              the object's W/H ratio = 100/100
```

(b)

```
(id #=0), name:              panel,              number of subobjects=0
(id #=1), name:             slider,              number of subobjects=2
          name of the subobject:                 slot
          name of the subobject:               handle
   Intra-relationship for slider: slot is RIGHT_OF handle
(id #=2), name:               slot,              number of subobjects=0
(id #=3), name:             handle,              number of subobjects=0
(id #=4), name:          lcd_meter,              number of subobjects=0
(id #=5), name:     analog_meter_1,              number of subobjects=2
          name of the subobject:          meter1_base
          name of the subobject:          meter1_face
   Intra-relationship for analog_meter_1: meter1_base is BELOW meter1_face
(id #=6), name:        meter1_base,              number of subobjects=0
(id #=7), name:        meter1_face,              number of subobjects=0
(id #=8), name:         light_code,              number of subobjects=4
          name of the subobject:                 light
   Intra-relationship for light_code:
                 light_1 is LEFT_OF  light_2
                 light_2 is LEFT_OF  light_3
                 light_3 is LEFT_OF  light_4
(id #=9), name:              light,              number of subobjects=0
(id #=10), name:           valve_1,               number of subobjects=0
(id #=11), name:           valve_2,               number of subobjects=0
(id #=12), name:            E-knob,              number of subobjects=0
(id #=13), name:    analog_meter_2,               number of subobjects=0
(id #=14), name:    analog_meter_3,               number of subobjects=2
          name of the subobject:          meter3_base
          name of the subobject:         meter3_plate
   Intra-relationship for analog_meter_3: meter3_base is BELOW meter3_plate
(id #=15), name:       meter3_base,               number of subobjects=0
(id #=16), name:      meter3_plate,               number of subobjects=0
```

(c)

Figure 3: Representation of the spectral, spatial, and relational domain knowledge of various objects expected to appear in the scene, shown in parts a, b, and c, respectively. (Note, that only a partial list of the spatial domain knowledge base is presented. Also, attributes listed are normalized.)

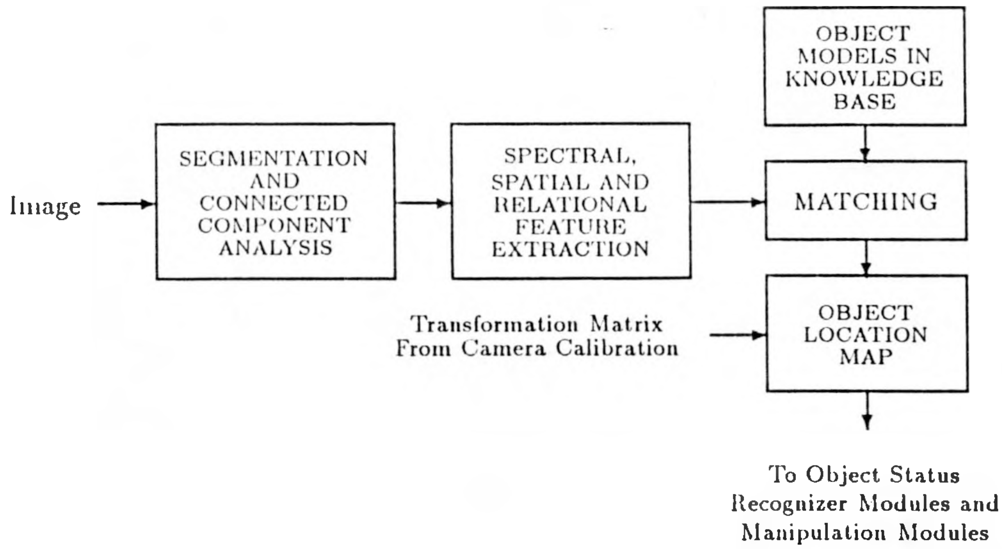
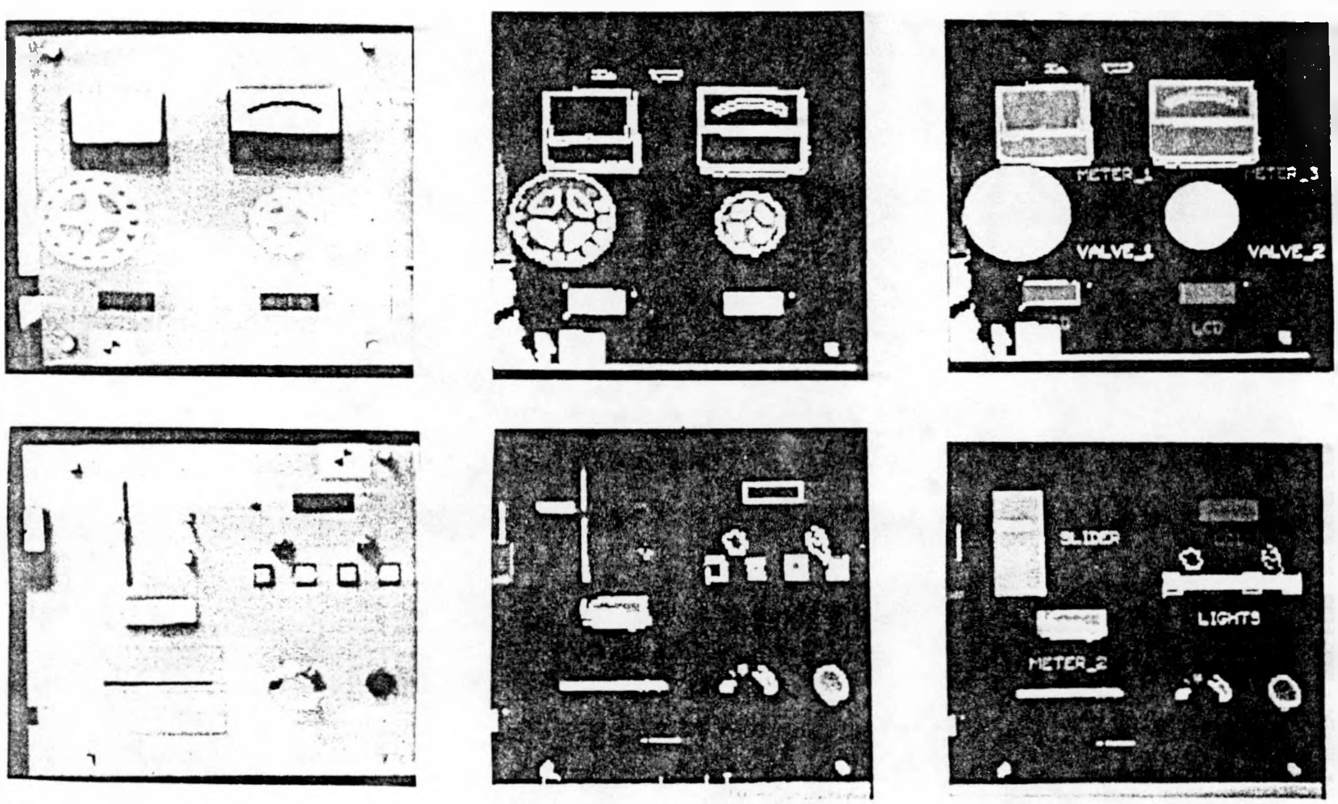


Figure 4: Functional modules used in the vision system to recognize objects and to determine their locations.



(a) (b) (c)

Figure 5: Recognition of the objects mounted on the control panel. Part (a) shows gray scale images of the test panel acquired by the camera mounted on the robot arm, part (b) shows segmentation results, part (c) shows the recognized objects.

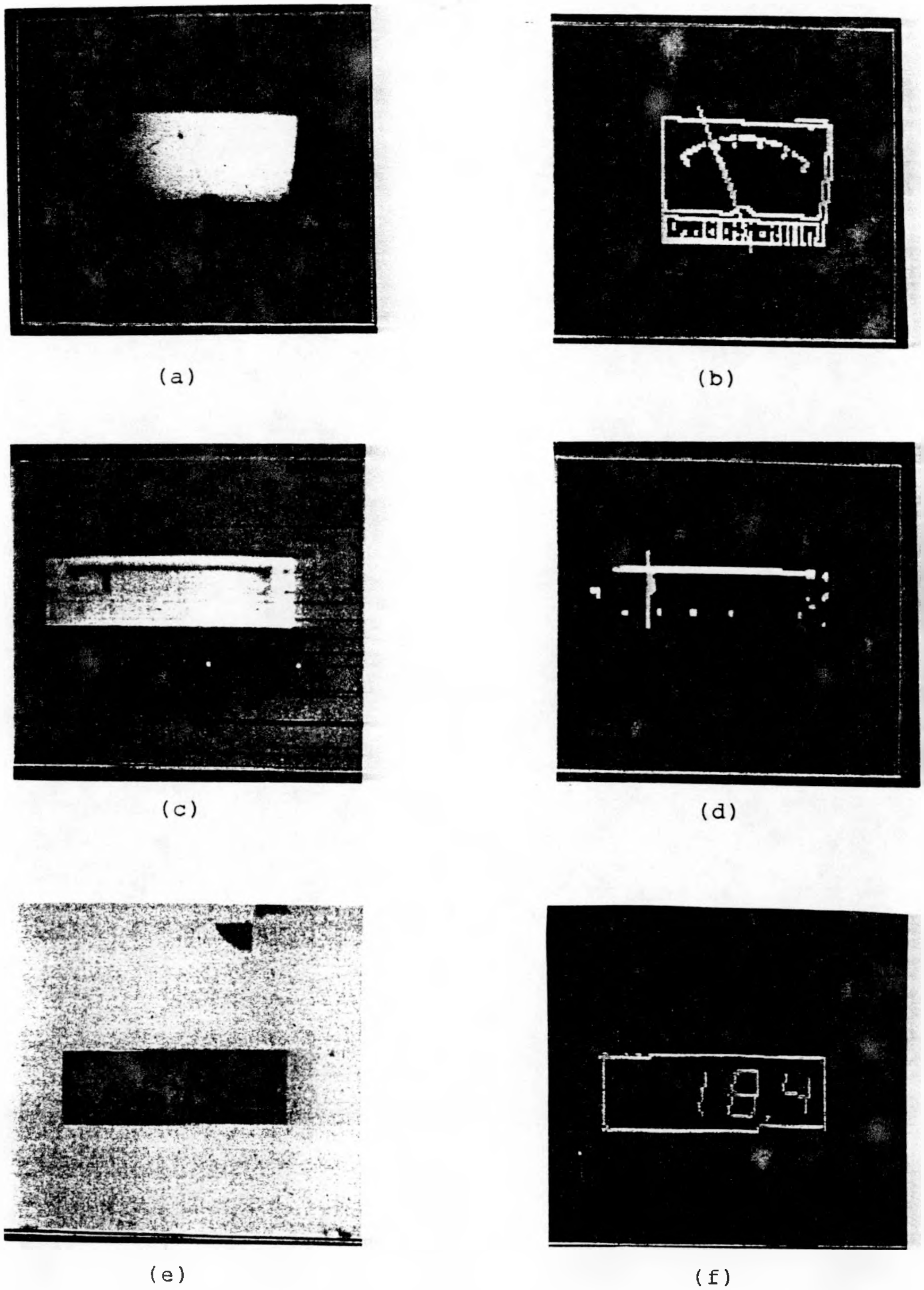


Figure 6: Automatic "reading" of the meters. Part (a) and (c) display gray scale images of analog meters, part (b) and (d) show results of needle position determination, part (e) shows a gray scale image of a LCD digital meter. part (f) displays the results of edge detection and thinning operations. These results are further analyzed using Fourier shape descriptors to read the code.