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Task level Planning and Implementation of Robotic Assembly Under Machine Vision Guidance

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ABSTRACT

Robotics offers a flexible automation technology for turning assembly systems into efficient and flexible manufacturing systems. The traditional method of manually generating the task level plan for robotic assembly is very tedious and time consuming. It will be beneficial if the task level planning can be automated. The current paper presents our ongoing research work on developing a knowledge based system to automate the generation of task level plan for robotic assembly. The implementation of the above task level plan has been shown by using a vision assisted robotic assembly system involving a Yaskawa Motoman industrial robot manipulator.

1. Introduction

The application of flexible and programmable assembly equipment is on the rise [1]. Until recently, industrial assembly had been performed either by fixed automation or manually. Fixed automation is appropriate for mass production, while manual assembly is slower but more flexible. The purpose of flexible automation is to provide an alternative to these two methods. Robotics offers a flexible automation technology for turning assembly systems into efficient and flexible manufacturing systems. In today's era of rapidly changing customer requirements, the design of products may have to undergo frequent changes. The robots have to be accordingly reprogrammed to respond to the product design changes. Before programming the robot motions, a task level plan is usually first drawn up from the assembly sequence. The traditional method of manually generating the task level plan from the assembly sequence is very tedious and time consuming. Although, this task is usually performed by experts, any inadvertent mistake can be very costly and results in loss of productivity. Hence, it will be beneficial if the task level planning is automated. Ramos [2] presented an intelligent robotic assembly system, incorporating an interface with computer vision and an efficient task planning methodology based on a cooperative agent based approach and the execution of the planned task by a robot manipulator. The various agents are MODELS (representing the models of objects), VISION, world descriptor that converts numerical data given by VISION in symbolic relationships and constraints, task level planner, task executor which is responsible for the execution and monitoring of the tasks. Rocha et al [3] developed a comprehensive method to compute the number of plans needed for an assembly or processing task. Osuna et al [4] developed an intelligent task planning system that was built upon a collaborative web-based environment to integrate the product and assembly system design processes.

The integration of object-oriented and machine learning techniques had been used for intelligent task planning. Cambon et al [5] developed a planner, aSyMov. They considered symbolic and geometric constraints at each step of the planning process. An effective link between the representations used by a symbolic task planner and the representations used by a realistic motion and manipulation planning library had been shown. Cho et al [6] proposed the implementation methods of robotic task planning and execution based on the description logicknowledge base. Their implementation used a description logic knowledge base which had been extended to include the description of task's goal and behaviors. They investigated knowledge representation scheme and conceived of a simple algorithm. Their approach had the advantage to make the knowledge base to be simple and close to the original robot knowledge base without irrelevant extension or translation. Thomas and Wahl [7] presented a complete process chain starting from the initial specification of assembly tasks via assembly sequence planning to task planning and execution. Their system demonstrated how to generate robot programs automatically from CAD data. Backhaus [8] introduced and discussed a concept to simplify the application of task-oriented programming for assembly systems. The system in the output provided the device specific code based on the input as description of assembly systems and device descriptions (namely robot, gripper, conveyor belt, etc.). Recently, Alatartsev et al. [9] surveyed several papers and presented their findings detailing robotic task sequencing problem considering collision-free path planning, production scheduling, multi-robot task planning, task-level planning, combination of task-level planning and path planning, online control-based planning, and manipulation planning.

Once, the task level plan for the required assembly is generated, a robot manipulator guided by a machine vision

system can be deployed to automatically assemble the constituent parts. A few investigations in this regard are discussed below. Dagli and Vellanki [10] discussed the use of artificial neural networks in automating assembly systems. The system was demonstrated through a surface mount assembly of power supply board. Pena-Cabera [11] proposed a new methodology for fast object recognition and POSE estimation for assembly components in manufacturing cells. Accurate recognition of assembly components was successfully carried out by using a Fuzzy ARTMAP neural network model. Golnabi [12] described the role and importance of the machine vision systems in industrial applications. They discussed system design methodology and a generic machine vision model. The justification for utilizing machine vision had been considered on the basis of economic and logistic considerations. Zhang et al. [13] introduced a vision-guided alignment method that aimed at closing the gap between a manual assembly and a fully automatic assembly, where parts with less tolerance were considered. The vision-guided alignment system utilized a camera space manipulation control process and relied on the CAD model of the components with a local calibration method to achieve the high accuracy alignment for the final assembly. Kobari et al. [14] presented an error resilient vision based motion control method for parts assembly. They considered those assembly parts which get deformed during assembly. In the method, force applied for the work is generated by visual information from a camera reading the deformation of the parts. Chen [15] reviewed papers on vision system working in combination with force-control integrated assembly and demonstrated a system using a high accuracy assembly process. The combination of vision and force control enables industrial robots to perform high accuracy assembly in a semi-structured environment. The vision system was not calibrated carefully as it provided only rough position data of parts. In addition to vision, a local searching method based on force-torque control was developed to deal with errors.

The current paper presents our ongoing research work at IIT Kharagpur on developing a knowledge based system to automate the generation of task level plan for robotic assembly. Further the implementation of the above task level plan has been shown by using a vision assisted robotic assembly system comprising of a Yaskawa Motoman industrial robot manipulator, an overhead camera, the National Instrument(NI)'s Lab view graphical programming environment, and NI's Vision Assistant utility for image processing. The planning system generates all the tasks that a robot manipulator has to perform from a given assembly sequence. These tasks are then performed by the robot through regular inputs from machine vision system, which mainly is used to detect the object position and its attributes. The task planning is comprehensive ensuring appropriate motion sequences and states. The comprehensive nature and regular vision inputs make the system less prone to errors. The implementation of the proposed system is demonstrated by performing a mechanical assembly.

2. Proposed methodology of task level planning and vision assisted robotic assembly

2.1 Knowledge-based system for generation of task level assembly plan

A knowledge based system has been developed to generate the task level plan for robotic assembly, given a feasible and optimal assembly sequence, which in turn is generated based on the methodology outlined in [16]. The above knowledge based system has been implemented using the expert system shell, CLIPS (C Language Integrated Production System). Fig. 1 shows the architecture of the developed knowledge based system. The database comprises of detailed information about the assembly components such as, component number, its name, type (i.e. functional part or fastener), part count, components with which it has contact, assembly direction, any special assembly requirement, etc., which are to be provided by the user. This is shown in the Fig. 2 (a). A set of



Fig. 1. Architecture of the developed knowledge-based system

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Fig.2 (a) Templates for entering the assembly information in databases (b) A rule for generating task level plan (c) Assembly information facts stored in the database

production rules have been developed for generating the task level plan to efficiently program a robotic assembly system. The rules are stored in the knowledge base of the expert system. An extract from the knowledge base rules and database facts in CLIPS format are shown in the Fig. 2 (b) and 2 (c) respectively.

2.2 Vision assisted robotic assembly

After the task level plan is generated using the knowledge based system, it has been implemented by a vision assisted robotic assembly system, that comprises of an industrial robot manipulator (Make: Yaskawa Motoman) equipped with a two finger gripper, an overhead camera (Logitech c 920, 5MP), the NI Lab VIEW graphical programming environment, a robot control interface (Digimetrix), and the NI Vision Assistant utility for image processing.



Fig. 3. Flowchart of operations performed by machine vision system



Fig. 4. Flowchart of the strategy for robotic assembly

2.2.1 Recognition of parts, and estimation of position and orientation by machine vision

To carry out assembly using the robot, it is necessary to first of all recognize all the parts involved and determine their initial locations and orientations. The vision system is used to further determine the target hole (cavity) locations and orientations on the base part, where each part has to be inserted for assembly. The Vision Assistant Utility of LabVIEW has been used to accomplish these tasks. At first, an overhead camera is used to acquire the image of the parts placed inside the robot work envelope. The camera is calibrated using the LabVIEW calibration module, which maps the pixels of the image to real world coordinates of the robot. Then a thresholding scheme works on the 3 channels of the color image acquired to generate a binary image with the parts separated from the background. Erosion and dilation morphological operations are then performed on the binary image to remove clutter (isolated particles) and make the boundary of the parts regular. These operations enhance identifying features of assembly parts. Then the assembly parts are recognized by performing pattern matching through multi-level pyramid decomposition. The pattern matching operation requires the user to input a binary image of the concerned parts. This process not only identifies the parts but also estimates angle of the parts, the X, Y positions of the parts in terms of image pixels and robot coordinates. The flowchart of the above operations performed in Vision Assistant utility of LabVIEW is given in Fig. 3. Coordinate transformation needs to be done to get al 1 the required data in real world coordinates from the image coordinate system.

2.2.2 Strategy for Robotic assembly under machine vision guidance

Once the assembly parts are recognized and their positions and orientations are determined by machine vision system, decisions regarding motion of the robot manipulator are implemented in accordance with the assembly task level plan generated earlier. The task level plan lists sequentially the tasks that need to be performed in order to pick up the parts one by one from their initial positions and orientations, and assemble them into the respective positions and orientations of the holes (cavities) in the base part. The task level plan also contains details of the motion sequences of the robot manipulator for handling each part in a proper order as shown in Fig. 4, starting from moving the robot to a safe height above the recognized part before picking it and ending with actuating the opening of the griper fingers to release the recognized part on the base part before moving up to a safe height. After these sequences, the manipulator needs to move away to clear the field of view of the camera and await instructions for handling the next part. For this, machine vision system is employed repeatedly as explained earlier. Each of the above motion sequences have been implemented by developing a sub VI in LabVIEW, which is shown in Fig. 4.



obtain coordinates of base(1) by vision

obtain coordinates of rectanglular_part(2) by vision MOVE robot in joint mode above rectanglular_part(2) MOVE robot in linear mode to component rectanglular_part(2) close gripper obtain coordinates of assembly fixture MOVE robot in joint mode above fixture

(b)

Fig. 5. (a) An eight component assembly (b) Extract of the Task level plan for the eight component assembly



(a)

obtain coordinates of motor_base(1) by vision MOVE robot in joint mode above motor_base(1) open gripper MOVE robot in linear mode to motor base(1) close gripper obtain coordinates of assembly fixture unclamp assembyly fixture check if fixture is empty MOVE robot in joint mode above fixture MOVE robot in linear mode to fixture open gripper MOVE robot in linear mode above fixture clamp assembly fixture obtain coordinates of motor(3) by vision _____ _____ MOVE robot in joint mode to safe point **REPEAT** steps of block 1 times

MOVE robot in joint mode above fixture

(b)

Fig. 6. (a) A twelve component Motor drive assembly (b) Extract of the Task level plan for the motor drive assembly



Fig. 7. Initial, intermediate, final states of the task environment showing the robot's movement for performing assembly



Fig. 8. Output from the vision assistant

Table 1

summary of information of estimated initial positions

S1.	Assembly	Real World Co-		Angle	Score	No. of	Destination co-
No	part	ordinates (mm)		in deg.	(Out of	Matches	ordinated on
		Х	Y		1000)		fixture assembly
							(X,Y, in mm)
1.	Rectangular	282.64	452.67	9.533	871.93	1	(276.063,
	part						348.72)
2.	Cylinder	355.10	367.45	246.16	817.36	1	(279.712,
	with cross						287.834)
3.	Smaller	452.57	257.07	2.219	904.92	2	(224.348,
	Rectangular						288.274)
	parts	210.09	285.27	1.199	999.99		(202.201,
							287.262)
4.	Cylinder	412.43	458.07	28.377	794.97	1	(203.238,
	with tick						355.29)
5.	Square part	512.63	421.00	133.05	733.25	1	(278.692,
							347.677)
6.	Cylinder	444.78	347.71	8.403	837.16	1	(212.671,
	with star						286.126)

3. Results and discussion

Two examples are given to demonstrate the results of the develop knowledge based system for generation of the task level plans. The first example is an eight component assembly shown in Fig. 5 (a). Fig.5 (b) shows the corresponding task level plan generated automatically by the knowledge based system. The second example is a twelve component motor drive assembly shown in Fig. 6 (a). The Fig. 6 (b) shows the corresponding task level plan generated automatically by the knowledge based system.

The first example is used to further demonstrate the results of the developed vision assisted robotic assembly system. Fig. 7(a), (b) and (c) show the initial, intermediate, and final states of the task environment, respectively indicating the positions of the base part as well as other parts and the robot's movement for performing the assembly. All the above parts were initially scattered randomly in the task environment of the robot but placed within the field of view of the overhead camera as shown by the initial state of the task environment in Fig. 7(a). Table 1 summarizes the information about the estimated initial positions of all assembly parts including the holes (cavities) on the base part that were extracted using the Vision Assistant utility of LabVIEW. Fig. 8 presents an extract of the output from the Vision Assistant for one of the assembly parts, showing the estimated initial X, Y positions, angle, score, etc. Finally Fig. 7(c) shows the final state of the task environment after successful completion of the assembly by the robot.

4. Conclusion

In this paper, a task level planning system for mechanical assembly has been developed and its implementation has been shown using a vision guided Yaskawa Motoman industrial robot manipulator. To accomplish task level planning, a knowledge based system has been developed and implemented using the Expert System shell CLIPS, which is capable of automatically generating all the assembly tasks that need to be performed by the robot. Further a strategy for robotic assembly under machine vision guidance has been developed, in which the vision system is used to guide the robot in performing mechanical assembly operations in a task environment where the parts are initially scattered randomly. The system is found to be successfully working with minimal human intervention. Future scope of the paper could be use of multiple cameras and other sensors.

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