Machine Vision and Planning Applied on Assembly Line of Multiple Products

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***Abstract*—This article describes the use of Artificial Intelligence (IA) techniques applied in cells of a manufacturing system. Machine Vision was used to identify pieces and their positions of two different products to be assembled in the same productive line. This information is given as input for an IA planner embedded in the manufacturing system. Therefore, initial and final states are sent automatically to the planner capable to generate assembly plans for a robotic cell, in real time.**

***Index Terms*—Planning, Artificial Intelligence, Machine Vision, Manufacturing System.**

I. Introduction

An important area to apply research results on action planning in Artificial Intelligence and Computer vision is the manufacturing industry [1]. However, reports of actual applications are rare in literature [2], [3]. On one hand, most research has its origin in the departments of Computer Science, since they require extensive knowledge in logic and programming languages. On the other hand, there is the difficulty in conducting experiments in industry, which require interruptions in their production processes [4]. The automation laboratory of the undergraduate course in Automation and Control Engineering from UNESP Sorocaba hasa manufacturing system consists of several manufacturing stations and industrial robots [8] are interconnected by a conveyor belt. This structure has allowed the research, development and testing in an industrial environment indeed. This paper describes the implementation of machine vision integrated with a planner and this manufacturing system.

II. Methodology

This project was conducted in FESTO manufacturing system shown in Fig. 1. The system incorporates six manufacture cells: Material Input Cell, Processing Cell, Vision Cell, Robotic Assembly Cell, Storage Cell and Output Material Cell. Each cell consists of one or two manufacture stations, each one controlled by programmable logical controllers. The cells operate in an integrated way defining the flow of the material in the system with the help of the conveyor belt and a set of support (pallets) aiding the transport of raw material and products. For this project were used following cells: material input cell, vision cell and robotic assembly cell. Artificial intelligence techniques were applied to obtain a fully automated production system. Through a machine vision, the product to be assembled is recognized, automatically, by identifying the pieces and their positions at the pallet. This information is given for STRIP [6] planner embedded in the manufacturing system. Planners are investigated and raised by researchers in Artificial Intelligence. The planner generates the assembly plan and sends it to performers, a robot in this case. The expected result is the assembly in real time of different products in the same production line.

Fig. 1. Manufacturing system

III. Previous Work

The search for the excellence in the tripod cost-quality-flexibility opens new frontiers in the improvement of production methods, development and incorporation of new technologies of processing and easiness of systems reconfiguration. In this direction, planning systems can play a important role in the automation of the programming and configuration of manufacturing processes. In a manufacturing system, each product type requires a particular assembly program, which depends on the same initial configuration of their parts. Beyond these limitations, the programming of the production process occurs in a "offline" way. In previous work [5], the authors integrated the STRIPS planner [6] in a Robotic Assembly cell to generate action plans for an assembly process. The use of a planning system it makes possible "online" programming of assembling processes in a manufacturing system from 1) general tasks (actions) that the system is able to perform and

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2) a domain model. Thus, the product parts and the assembly tools can assume several configurations in real time. For each initial configuration, the planner finds an action sequence (plan) that when executed it allow the manufacturing system to obtain the final product. Therefore, this process is able to increase the flexibility degree of the system regarding its programming and configuration. The domain model used in this work can be seen in [5].

A user interface of the system allows the user to provide the identity and locality of the components in the pallet to the planner. Such information characterizes what is called, in planning research area, "initial state of the world" [7]. The component types (identity and quantity) determine the product to be assembled by the robot, characterizing what is called "final state". In the work described here, the user participation is replaced by the vision station, which recognizes the components automatically (Fig. 2), making the system fully automated. The next sections present the details of the vision subsystem and its integration with the planner.

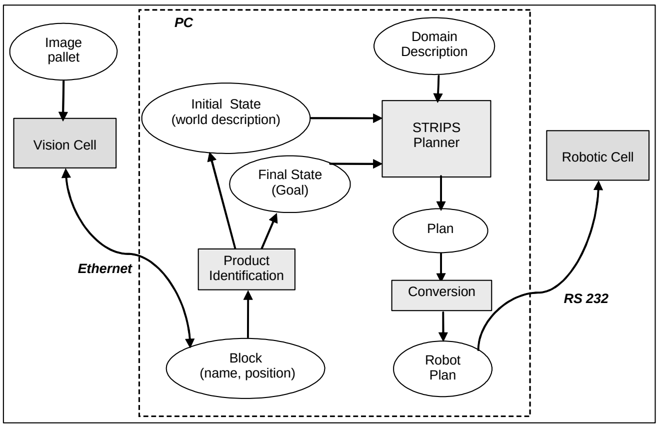


Fig. 2. Vision and planning system architecture

From the initial state representation (pallet configuration) and the final state (assembled product), the planner determines a plan of actions for the robot. After planning, the system returns the plan-solution file to assemble the corresponding product. Such file is converted into a numeric code and sent to the robotic station, by serial communication. The code represents the sequence of actions and associated parameters to be executed by the robot.

IV. Component Identification by Machine Vision

The products to be assembled are composed of cylindrical parts in red, black and chrome. The products differ in quantity and color of the parts that compose them. The pieces are placed in pallets with four positions and passing in front of the manufacturing stations through the conveyor belt. Fig. 3 shows two pallets with parts of two products: P1 and P2.

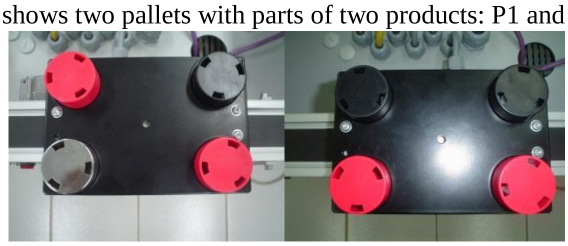
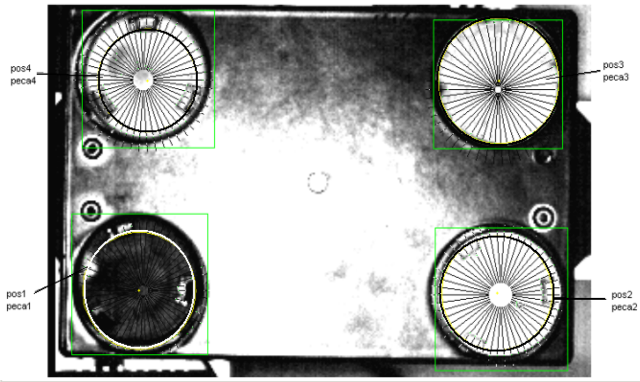


Fig. 3. Product components: P1 (left) and P2 (right)

The vision system consists of a vision sensor that generates images in gray scale with Ethernet communication capability. Due to the size of the pallet, wasuseda35mm lenspositionedatadistanceof1.20 meters from the conveyor belt, thus defining the working distance (WD) andanexposuretimeof6000µs. This allowed an adequate vision field to capture the complete picture of a pallet. Figure 4 shows an image generated by the system.

Recognition of parts is achieved by using software sensors (soft sensors). Soft sensors are variables configured in the image processing tools (algorithms) from the development environment of the manufacturer. In the application developed, two tools were selected for two-dimensional image processing: *Detection of Polygons* and *Analysis Brightness Intensity*. The first was used to detect the presence of pieces and the second to identify the piece color. The detection of polygons tool was configured to find circles with radius between 70 and 80 pixels, positions where the pieces are on the pallet. Fig. 4 shows the circles found by sensors pos1, pos2, pos3 pos4 on a tool monitoring screen.



Result Table: Product1

Overall Result PASS

SoftSensor	Result	Output Value
pos4	PASS	Radius = 73.14 Pixels
pos3	PASS	Radius = 75.81 Pixels
*pos1	PASS	Radius = 77.32 Pixels
pos2	PASS	Radius = 74.98 Pixels
peca4	PASS	Value =76.2 ClosestColor= v Color Difference=0.6
peca3	PASS	Value =89.3 ClosestColor= l Color Difference=0.2
peca2	PASS	Value =81.2 ClosestColor= c Color Difference=0.3
peca1	PASS	Value =17.1 ClosestColor= p Color Difference=1.7

Fig. 4. Analysis of a pallet imagem

The first column of figure 4 lists the sensors of the tools used in this work. The PASS value is displayed when the sensor detects values within the preset limits. Otherwise, it displays the FAIL value.

V. Communication of Vision Station and Planner

The data transmission from vision sensor to PC takes place via data link, a built-in tool capable of sending ASCII strings via Ethernet. Strings are created based on the para meters of the sensors and sent according to conditions. As shown in Figure 5, the STRING 1will be sent if all sensors have the PASS value, i.e., the positions and colors of the pieces were correctly identified. The strings text can be composed of messages typed by the programmer and/or parameter values of the sensors.

The STRING 1 consists of the Match Color Name parameter of each sensor responsible for identifying piece color or free position on the pallet. This parameter contains the code colour, defined as: v is red, p is black, c is chrome and 1 is free position. After the components of a product are arranged on a pallet, a assembly cycle starts with the shooting of an application that connects to the camera as a TCP/IP client and receives information sent by data link. To receive STRING 1 requires four read cycles. The information received is stored in the knowledge base the planner and represents the initial state.

The final product can be configured on the planner a priori. Table 1 shows the description of the initial and final state of a product and the result of planning: the generated plan. The symbol $\wedge$is a logical connective denoting conjunction of predicates. Thus, the final state is achieved when all the predicates are true.

TABLE I: INITIAL STATE, FINAL STATE, PLAN

Initial State	block(a0). block (b0). block (a1). block (c0). position(a0,po1). position(b0,po2). position(c0,po3). position(a1,po4).bfree(a0). bfree(b0). bfree(a1). bfree(c0). pos(po1). pos(po2). pos(po3). pos(po4). pos(aux). pfree(aux). not_holding.
Final State	position(a1,po4) $\wedge$ on(c0,a1) $\wedge$position(a0,po3) $\wedge$ on(b0,a0).
Plan	start. pickup(c0, po3). stack(c0, a1). pickup(a0, po1). putdown(a0, po3). pickup(b0, po2). stack(b0, a0).

By describing the initial state, the system deduces the configuration of the pallet: block a0 is on position 1, block b0 is on position 2, block c0 is on position 3 and the block a1 is on position 4 (Fig. 6). Similarly, the final state (the assembled product) after execution of the plan by the robot: c0 is on a1 and b0 is on a0 at pallet position 3.

The generated plan is submitted to post processing, converting the actions to numeric code and transmitted to robot. Each action of the plan is converted into a sequence of three to five numbers where the first number corresponds to the action to be executed and the following ones correspond to blocks positions and heights. Finally, a program in the robot receives and interprets such information.

Several tests were conducted with the domain model proposed, where the robot alternately assembled products P1 and P2 successfully. Delays were observed due to the serial communication between the robot and the computer (planner). However, this is a restriction easily minimized, since there are other communication channels that can be used.

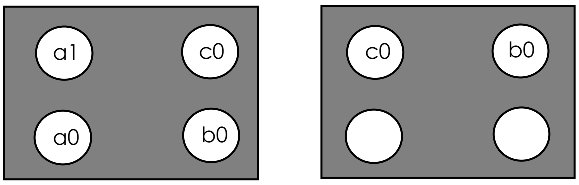


Fig. 6. Initial state and final state

VI. CONCLUSION

The application presented in this paper describes the use of AI techniques applied to cells in a manufacturing system. Machine vision was used to identify components for assembling two different products that cover the same production line. An industrial sensor vision was integrated in the system developed by the authors in previous work where STRIPS planner was used to generate assembly plans products for a robot cell. This work allowed achieving an excellent level of automation without human intervention. From the processing of the pallet image, the system is able to infer the product to be assembled and how to do it.

The vision sensor was found to be sensitive to small changes lighting conditions and it is intended, in future work, implement special lighting near the focused object (the pallet).

Tests performed on the system showed that the flexibility of an intelligent manufacturing system increases when components of different products can move through the production line in any position and robotic agents are able to identify, sort and assemble different products in the same production line.

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