Paper ID #18596

Development of Automatic Reconfigurable Robotic Arms using Vision-based Control

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1 Abstract

The traditional industrial robotic systems are designed for mass production, in which each robot needs to be calibrated and programmed for a specific task. These systems are expensive, only effective in specific applications, and vulnerable to any changes in the working environment or the task. However, mass customization has become the new frontier in product manufacturing and marketing. In order to satisfy the changes in market needs, especially for small and medium enterprises (SMEs), it is desirable to have low-cost industrial robotic systems that can be automatically reconfigured for different applications. As a supplement to traditional robotic courses, students should be educated about how to design a robust, flexible, reconfigurable and redeployable industrial robotic system. However, these contents are missing from most of current engineering curriculum due to the lack of appropriate educational robotic platforms.

The research presented here uses an assembly line robotic arm as a prototype to prove the feasibility of automatic reconfiguration. The system first uses cameras to detect and recognize objects in the assembly line and then automatically chooses the best manipulator for the assembly task. Next, the system predicts the end-effector's error using cameras in a markerless approach. The error is compensated in the last step, in which the system automatically generates the control commands for the robotic arm using visual results as feedback. Using this robotic system as an educational platform, the students will be able to learn about several important aspects of flexible/reconfigurable manufacturing systems (e.g. robustness, flexibility, reconfigurability, redeployability, etc.) through one low-cost and easy-to-use experimental setup.

Key words: Industrial Robotics, Robotic Arms, Vision-based Control, Reconfigurability.

2 Background

Traditional industrial robotics applications rely on the high repeatability of robots for repetitive tasks, which is preferred when the environment, the workpieces involved, and the details of the tasks remain unchanged. To start each specific operation, the robots need to be calibrated and programmed separately. To address potential changes in the environment, the workpieces involved or the details of the operation, the robots may need to be recalibrated and the programs may need to be changed. These factors all add up to significant upfront cost and preparation time. In addition, industrial robots are expensive and their effectiveness is application-specific. Overall, the acquisition cost of a robot can vary between $25,000 and $700,000, excluding initial integration costs and ongoing maintenance.

The traditional industrial robots are suitable for mass production. However, mass customization is the new frontier in the field of product manufacturing and marketing [1]. Custom-made products with a low cost are the specialty of mass customization. An industrial robotic system, especially a low cost one, with the capability of automatic reconfigurability has great potential in this market. Taking industrial assembly lines as an example, fixed sequences of operations are very efficient when the production is set to the maximum throughput [2]. Due to the rigidity and centralization of their control structures, the traditional industrial robotic systems are not designed to exhibit responsiveness, flexibility, robustness and reconfigurability [3]. This centralized hierarchical organization could potentially lead to a situation where the whole system could be shut down by a single failure at one point of the system hierarchy [4].

3 The Missing Component in Current Robotics Education

Reconfigurability and flexibility are two key aspects when designing an industrial robotic system. A new trend of research which focuses on Reconfigurable Process Planning [5], enables local reconfiguration of assembly plans, while minimizing the extent of change/reconfiguration on the shop floor and the costs associated with making changes to existing facilities, tooling, labor training and quality concerns. Reconfigurable Manufacturing Systems (RMSs) provide customized flexibility on demand in a short time, while Flexible Manufacturing Systems (FMSs) provide general flexibility designed for the anticipated variations [6]. Flexibility represents the ability of a system to change and assume different positions or states in response to changing requirements with little penalty in time, effort, cost, or performance. The concepts of reconfigurability and flexibility have attracted extensive interest in the academic and industrial communities. However, many open questions remain and several fundamental and practical challenges represent fertile areas of research, which include but are not limited to [7,8,9]:

- Hardware and software enabling technologies
- Design of machines, systems, and controls for flexibility, changeability and reconfiguration and integration with current systems and software
- Smooth and optimal system transition and changeover

The complexity of programming remains one of the major challenges that prevent automation using industrial robots for SMEs [10]. Significant research efforts have been focused on improving the programming methods for industrial robots, such as online programming, offline programming, programming using Augmented Reality and integrating with powerful 3D CAD software, computer vision, sensor technology, etc. Visual servoing has been adopted as a supplementary technique for automated online programming. For example, a hybrid position/force/vision control platform can be used to control the robot motion to follow a marked path using various sensor date as feedbacks [11]. Other examples include using 3D machine vision and stereo vision [12,13]. Most of the research outcomes are not commercially available because they are limited to specific setups and are yet to be applied to general applications.

RMS is a manufacturing system with customized flexibility and FMS is a manufacturing system with general flexibility [6]. In most undergraduate curricula, the concepts of RMS and FMS are not distinguished and they are usually taught as part of Computer Integrated Manufacturing courses [14,15]. FMS is an automated production work cell which typically processes multiple automated stations and is capable of performing variable routing among stations. Automation is usually chosen as the main focus of teaching FMS. A major barrier in teaching automation and FMS is the lack of state-of-the-art equipment that would provide students with the opportunity to develop skills that prepare them for entering the workforce [16]. Many students are not exposed to FMS because of the high cost of instructional equipment.

Two main components need to be paid attention to while teaching manufacturing system reconfiguration/flexibility, namely the physical (hardware) and logical (software) manufacturing system re-configuration methods. The physical category includes adding/removing the modules of layout, adding/removing machines, substituting machine elements, using material handling devices, etc. The logical category includes re-routing, re-scheduling, re-planning, re-programming, etc.

4 Reconfigurable Robotic Educational Platform

4.1 System Overview

The main goal of the work presented here is to prove the feasibility of designing a robust, flexible and reconfigurable educational robotic arm with a vision-based feedback control system. The system is believed to have great potential in teaching students the basics of FMS/RMS and the transformation of industrial robots from mass production to SMEs. The prototype platform will be constructed using a low-cost and open-source Hekateros robotic arm (which has a built-in 2D camera near the manipulator) and a fixed high resolution camera (see Figure 1). The minimal requirements of hardware necessary for implementing this system in undergraduate robotics courses (if the equipment presented in this paper is not available) could be as simple as any open-source robotic arm with a manipulator, a computer, a camera and a 3D scanner if necessary.

Figure 1: Hekateros Robotic Arm by RoadNarrows Robotics

Flexibility and reconfigurability require any robotic system to be used in different scenarios without the traditional processes of hardware modification, manual re-programming of the robot commands, calibration and test runs. The Hekateros robotic arm is compatible with various manipulators for different application scenarios. It would be desirable for this automatic robot system to "understand" the specific application needs and select the most suitable manipulator by itself. Refer to Figure 2 for an overview of the presented robotic automation system.

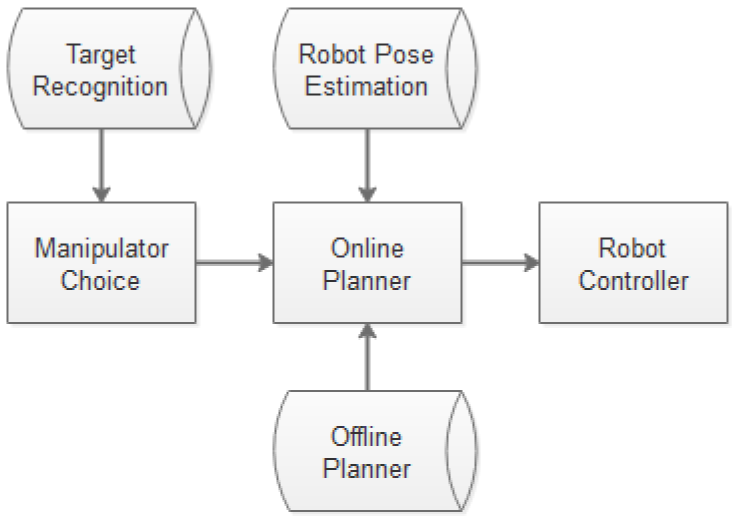

Figure 2: Overview of the Vision-based Robotic Automation System

First, the robotic system analyzes the current application scenario and selects the most suitable manipulator. Second, the offline planner automatically generates the initial control commands for the task at hand. Meanwhile, the camera mounted on the manipulator measures the relative distance between the target and the manipulator in real time and the fixed camera estimates the poses of the robotic arm. By comparing the estimates with the real-time pose feedback from the robot controller, the vision system calculates the robot's end-effector errors, which are then fed back to the online planner in real time. In the last step, the online planner automatically generates a new set of robot commands. Instead of analyzing the total errors as reported by other researchers' efforts, this system is able to determine what contributes to errors (e.g. controller, sensors, actuators, etc.). Given the details of each error source, the robot commands generated by online programming can be better optimized.

4.2 Anticipated Student Learning Outcomes

The main objective of this research is to develop a low-cost educational platform for teaching the fundamental concepts and applications of robotics and automation in FMS. The system should enable the students to participate in hands-on exercises in an innovative laboratory setup, and expose the students to the state-of-the-art methodologies in FMS.

The robotic arm platform could be used in teaching the following subjects that are essential to flexible/reconfigurable manufacturing systems:

- machine elements replacement for hardware configuration
- Material handling devices for flexible manufacturing
- Manufacturing system re-programming
- Manufacturing system planning automation

5 Prototype Implementation

5.1 Tasks and Challenges of the Instructors

To teach automatic reconfigurable/flexible manufacturing concepts using a low cost robotic arm and vision-based feedback control system, the following topics should be covered by the instructors during the lecture. Furthermore, they could also be used as separate laboratory assignments for the students:

- Choose suitable manipulator for the current task
- Automatically generate offline plan
- Estimate pose of robotic arm, predict and compensate errors of the robot's end-effector
- Update online plan

The above-mentioned tasks may also represent challenges for some instructors, who need to get familiar with the following topics: 2D/3D image processing, kinematics and kinetics of robotic systems, feedback control systems, and robot programming and automation. The details of the prototype system implementation are explained in Sections 5.2 to 5.6.

5.2 Choose Suitable Manipulator

One of the main objectives of this paper is to teach the concepts of flexibility and reconfigurability of industrial robotic systems. In order to automatically reconfigure the same robotic system for different application scenarios, it is desirable that the robotic system is capable of selecting the best tool (i.e. manipulator) for the task at hand by itself. This portion of the course project starts with an analysis of the vision data captured by the cameras. The main challenge lies in choosing suitable computer vision algorithms to perform object classification, recognition and localization [17,18,19,20]. After recognizing the workpieces, the system automatically chooses the most suitable manipulator (the process of changing the manipulator still has to be conducted manually), and the hybrid online and offline automation is adjusted to different application scenarios accordingly.

The Hekateros robotic arm has a well-defined, standardized, open-source end-effector interface located at the end of its continuously rotatable wrist. Due to open architecture of this robotic arm, there are many application-specific end-effectors made available by third-party manufacturers.

End-effectors are the devices at the end of a robotic arm that allow it to interact with its environment and without which the robotic arm alone could not accomplish any useful task. In the prototype assembly line robotic arm presented here, robot grippers are usually chosen as the end-effectors. Two important factors must be taken into consideration when choosing a suitable gripper: the process (the requirements of the task at hand, cycle time, precision requirements, environmental conditions, etc.) and the part (size, shape, weight, surface type, etc.) [21]. The exercise presented here requires knowledge about the process information beforehand, a correlation between available robot gripper and different parts, and information about the parts. The latter can be accomplished automatically using a fixed camera and image processing techniques (object recognition, classification and tracking). Some useful and easy-to-implement open-source tools include OpenCV [22], Pixy [23], Raspberry Pi [24], etc.

5.3 3D Object Grasp Synthesis Algorithms

The interaction between industrial robots and objects (i.e. generating 3D object grasps) is a very important subject in teaching robotic automation. Over the past decades, several algorithms for synthesizing robotic grasps for achieving stability, force-closure, task compatibility and other properties have been developed [25]. Two categories of grasp algorithms are commonly used, namely analytical and empirical approaches. The former ones are based on geometric, kinematic and dynamic formulations of grasp synthesis problems while the latter ones mimic the human grasping strategies. In the industrial robotic application presented here, the analytical approach was applied.

Most previous analyses were limited to polyhedral objects such as boxes. However, commonly seen objects in assembly lines (e.g. cylindrical objects) are not necessarily polyhedral and can rarely be modeled with a limited number of faces. In this case, general approaches that place no restrictions on the object models and in which the objects are modeled with 3D point clouds or triangular mesh become desirable [26,27]. The strategy behind this category of grasp synthesis using analytical approaches is illustrated in Figure 3:

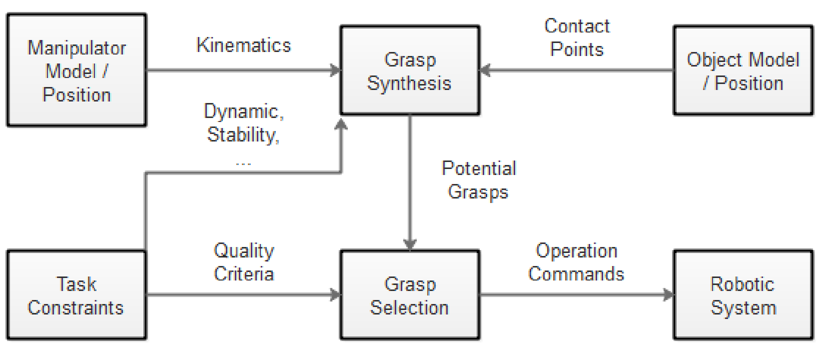

Figure 3: Strategy for Grasp Selection

5.4 Generate Offline Planner

For any industrial robot, there are two basic entities that need to be programmed, namely positioning data and procedures. There are a number of ways to program a robot's positions, including positioning commands, teach pendant, lead-by-the-nose, etc. In the platform presented here, a combination of online and offline programming approaches is used. First, offline programming is used to define the task and sequence of operations and then, online programming that uses data from the visual sensors as feedback is used to predict and compensate the relative position error (refer to Section 5.6). One feasible approach for implementing offline planners is to use visual programming interfaces (e.g. Grasshopper plug-ins for Rhinoceros [28]) to automatically generate the initial robot commands (which represent a list of sequential instructions for each motor and the robot manipulator).

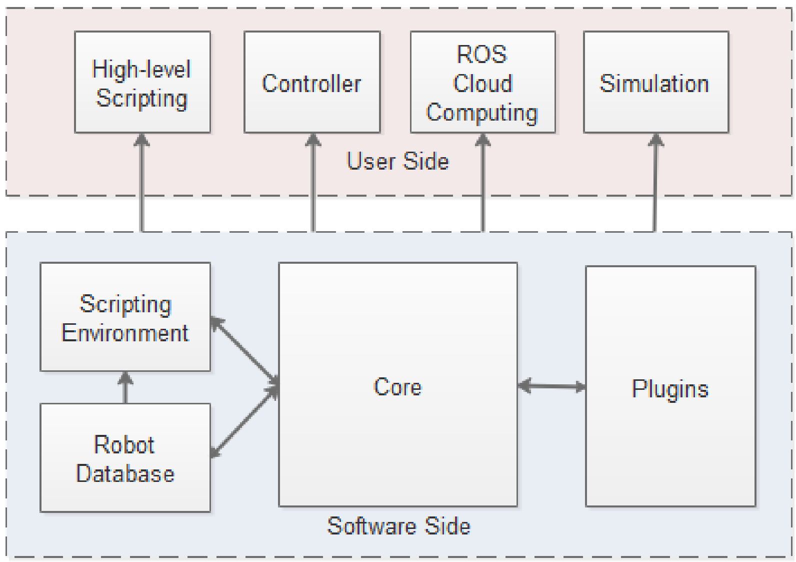

Figure 4: OpenRAVE for offline programming

Open Robotics Automation Virtual Environment (OpenRAVE) [29] is another open-source tool suitable for offline programming in this application. OpenRAVE provides an environment for testing, developing and deploying motion planning algorithms in real-world robotics applications. In order to use OpenRAVE as offline programming tool to generate the initial robot commands, several tasks (refer to Figure 4) need to be accomplished either by the instructor or by the student (could be used as project assignment), which include:

- Build and compile plugins, or select an available plugin for the tasks
- Select a scripting environment (OpenRAVE is compatible with Python and Octave/MATLAB)
- Build robot database, provide to OpenRAVE the information of the kinematic, quasi-static, dynamic, and geometric analyses of the robot and the task

5.5 Estimation, Prediction and Compensation

This part of the exercise is to estimate the pose of the robotic arm using cameras. To fulfill the potential of using this robotic arm on a mobile platform (which enables more applications, a robot system must be able to establish the accurate 6-DOF transformation between the robot's base and the environment's reference frame. The localization accuracy must be at the centimeter level [30], which could not be easily achieved using state-of-the-art Visual SLAM type techniques [31]. A more convenient and accurate solution for this is using marker-based pose estimation [32], which limits the robot's potential for being adopted in other applications (thus preventing the realization of the value of flexible manufacturing systems). In order to detect and track the pose of the robotic arm, the depth information needs to be retrieved from the images captured by the camera. The depth information could be estimated through a single monocular image, stereo images, or video [33,34]. However, implementing these approaches tends to be difficult, which could potentially hamper the taskes for the instructor and the students. An easier method of recognizing and tracking robotic arms is to use a low-cost 3D scanner (e.g. the Microsoft Kinect, if possible), which produces accurate joint estimation [35,36].

Accuracy and repeatability are important factors to consider when programing industrial robotic applications. Accuracy is the measure of the difference between the actual position of the end-effector and the pre-programmed input position. Using the end-effector error as feedback, a compensated command trajectory can be programmed. Compared to traditional offline programming methods, this approach keeps the original kinematic model of the robot and improves the accuracy along the particular trajectory of interest. The main focus is the prediction and compensation of the relative position error along the robot's end-effector paths. One interesting approach is to construct error prediction models by training an Artificial Neural Network based on the visual measurement, then train a second neural network that yields joint coordinates to minimize position error as proposed in [37].

5.6 Online Planning Automation

In the final part of the course project, the commands generated by the offline planner are modified if the robot's real-time pose feedback conflicts either with the pose information generated by the pose estimator or with the real-time measurements from the camera mounted on the manipulator.

There are three major disadvantages associated with using only the offline programming approach in flexible manufacturing applications. The first disadvantage arises when the virtual model differs from the real world. Instead of altering the virtual model, the combined online and offline programming approach presented here treats the potential differences as changes in the environment and adjusts the robot commands accordingly. Second, although it reduces the downtime of the robot, the time spent in developing the simulation might be longer overall. Moreover, users sometimes end up spending time resolving simulator-related issues instead of solving production challenges. The second and third disadvantages could be eliminated by choosing a robust and open-source software such as the above mentioned OpenRAVE.

6 Conclusions and Discussion

In this paper, the state of the art of traditional industrial robotic system used in mass production is briefly reviewed. Since the market is gradually transforming from the mass production to mass customization, flexible/reconfigurable manufacturing systems are believed to have great potential in the future. However, designing an industrial robotic system that could prepare the students for the flexible manufacturing market is missing in a lot of undergraduate curricula. In the research presented here, an assembly line robotic arm is used as a prototype to prove the feasibility of automatic reconfiguration. The system uses vison-based feedback control to achieve a combination of offline and online programming. This low-cost setup of an FMS educational platform has the potential of achieving various objectives, which include teaching the fundamental concepts and applications of robotics and automation in FMS, enabling students to participate in hands-on innovative laboratory exercises, and exposing students to the innovative methodologies in FMS.

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