Automatic collision detection and avoidance in a peg-in-hole process with ToF sensor

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Abstract—**Industrial robot based production and assembly automation increases the throughput of a company but on the other hand enhances the need for robot intelligence in terms of decision making in collisions scenarios. A robot manipulator, working at the industrial facility, should be able to predict potential collisions and automatically prevent them with a safe detour around the obstacle/human. Industrial robots at the moment are able to detect collisions after a real contact with the obstacle but the existing proposals for avoiding collisions are either computationally expensive, need prior information about the obstacles or not very well adapted to the safety standards. This paper introduces an obstacle mapping based approach to localize the un-known, un-programmed obstacles and propose a safe detour to the robot without stopping the peg-in-hole assembly process in a static environment. A Time of Flight (ToF) sensor is used to capture the 3D information from the environment that is used to localize objects in the scene. The proposed quick and robust solution obtained currently for robot collision detection and avoidance is in static environment and will be adapted to dynamic obstacle avoidance in perspectives.**

Keywords—Collisions detection and avoidance, Industrial Robot; Path Planning; Peg-in-hole process; Time-of-flight sensor

I. INTRODUCTION

Modern industries especially the one in Europe are sentient to the importance of automation and process safety with high precision and flexibility keeping in mind the increasing salaries and unavailability of workers (skilled). Industrial process automation using robots enhances the throughput of the company and ultimately reduces the process dependencies on the workers. For instance, a peg-in-hole process can be automatized using Lightweight Kuka robot with force control strategy [1]. A peg inserted in a power train hole by this robot automatically will increase the process effectiveness. Usually the path planned to insert pegs in multiple hole is programmed into the controller of the robot.

In the case, if the powertrain is misplaced or any unknown obstacle is present in the planned pathway of the robot, it will not be taken into account by the robot manipulator. This may cause a potential risk of collision and must be avoided to ensure safe robot movement; otherwise damage may occur to the part machine or manipulator itself [2].

Currently Kuka LWR has forced control sensors attached and may stop after touching the obstacle and applying a safe controlled pre-specified force of few newton. But this may also be a problem for robot working in a fragile environment such as food packaging. Robots are usually used to continuously work and produce parts without any fatigue or stops during productions. A contact with obstacle and production stops is therefore highly undesirable for industries demanding a high-speed automation process [3, 4]. During this physical intentional contact exchange of forces between human and robot, which are, measure to predict human motion intentions [5]. These forces are limited after contact detection to harm human during collaboration. The contact issue becomes more serious when robots have to work in a human cooperative environment where more legal requirements [6] need to be taken into account. A repetitive contact with human is therefore annoying for the worker and should be in the limits of the standards available.

In order to avoid this unnecessary contact, many researchers [7, 8] have been working on different techniques e.g. gesture and voice command based contactless collaboration by a direct communication between a human and robot. But the difficulty in these techniques is that a human should provide proper command on time to the robot.

Many peoples have proposed methods to avoid collisions, for instance circular fields [9], and elastic strips [10] are the important collision avoidance strategies. An artificial potential field [11] algorithm is widely used in Robotics for collision detection and avoidance but the drawback of the method lies that the robot may get stuck in local minima.

While planning path for a robot, one should not only consider the positional continuity but also the dynamic aspects such as velocity and accelerations especially during assembly tasks [12]. These dynamic aspects are difficult to take into account in offline programming [13] and teach and replay methods. Authors [12] have highlighted several reasons why the CAD based offline methods has disadvantages for precise path planning:

- The design of industrial robots typically emphasizes better repeativity than accuracy.
- Difference between the real and virtual models of the working environment.
- Errors in calibration between actual hardware system and the software environment.

Different solutions were investigated [14] to adapt robot to the dynamic changing scene which is not programmed previously but a successful method which can take into account unknown obstacles and respond rapidly is still missing. The reason behind this is that a standard safe sensor technology is not in the market, and most of the existing methods needs robustness in terms of computation time to adapt itself to safe continuous path planning.

A depth information based collision avoidance algorithm [15] of the Human Robot Interaction scene is used for the first time. Intentional physical interaction between human and robot is enabled. The problem with method presented is that human robot tasks are activated using predefined gestures or voice commands. Machine vision techniques are also used to optimize the robot path during welding process [16, 17].

Using optical camera systems [18], surveillance zones can be defined, where the robot motion slows down in the collision area. 2D vision cameras are good for objects detection and identification but are sensitive to light and industrial environment. A Time-of-Flight (ToF) depth sensor on the other hand will give many advantages [19, 20] e.g. not affected by the intensity differences between images and provide immediate depth information of the environment. Many peoples are working to use Kinect camera sensors [21], which operate with infrared illumination of the scene and use triangulation to observe distances to the obstacles with reduced occlusion. The speed of the robot is adjusted while approaching obstacles. However, a correction of the path to detour around the obstacle is not provided yet.

An effective method is therefore devised, which provide rapid decision for robot path planning by taking into account the 3D information from the scene. An extra intelligence is required by these robots to detect potential risks of collisions and re-orient their self to the revised path plan of automatic collision detection and avoidance with a non-stop production.

The objective of method proposed can also be envisaged in a human-robot-collaborative environment. When a robot and human are working together in a shared production environment, human safety is the top most priority. A robot working with human should be intelligent enough to take decision about avoiding collisions with human or other unknown obstacles automatically. In order to avoid human injury, robot/machine damage, reduce idle time of the production/assembly by avoiding collisions with the obstacle/human this kind of intelligence in decision process is important.

II. Manipulator Automatic Path Planning System (MAPPS) approach

The Manipulator-robot Automatic Path Planning System (MAPPS) approach presented in this paper is a system for planning robot manipulator path in a partially unknown environment to avoid collisions with unknown, un-programmed obstacle. The major important steps during this path planning process includes the extraction of process information data, collision detection, collision avoidance with effective path planning as detailed in the flowchart in Fig. 1.

The flow chart shows that a robot manipulator has to insert a peg in a hole. A sensory vision system provides updated information about mapping of obstacles to the algorithm responsible for safe path generation. While using previous scene information from the scene a subtraction matrix is calculated, which provides the localized information about the new updates in the scene. A path generation process is then initiated and while using the new location of objects from the scene the trajectory points are verified for collisions. In the case of collisions, a secure row of secure points is generated above the obstacle to divert robot to a safe position where all his other robot joints has to follow. Arrival to the final goal point is verified each time and the secure verified trajectory points are stored in their corresponding solution matrix for further improvement and application on the robot.

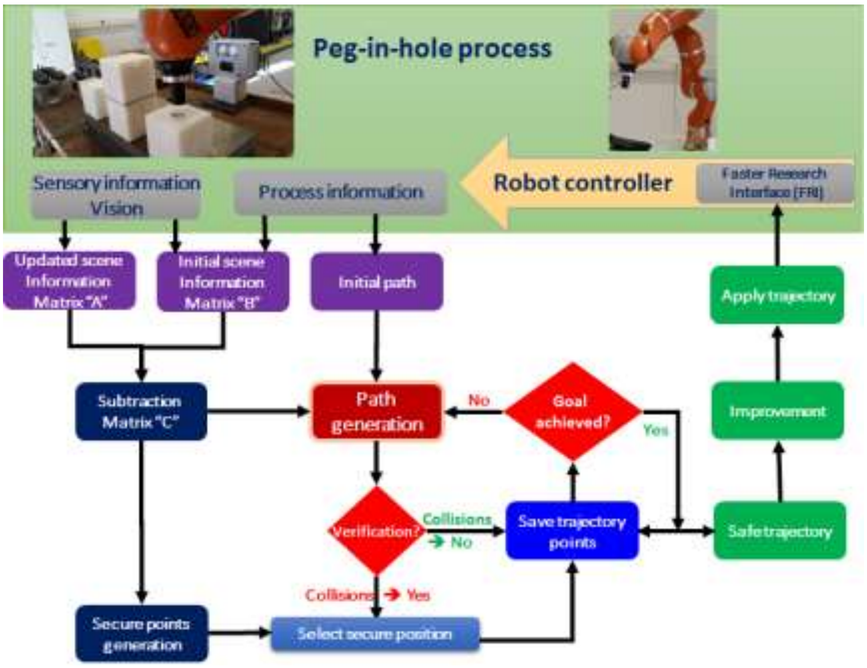

Fig. 1. Architecture flowchart Manipulator-robot Automatic Path Planning System (MAPPS)

A. Extraction of process information in Peg-in-hole process

In a peg-in-hole process in focus, a Kuka-DLR has to place a peg inside different holes (e.g. powertrain) and unknown, un-programmed object act as an obstacle as shown in Fig. 2. Initially a tip point of the peg is considered for path generation, whereas path in focus is a pre-programmed transversal path between three functional working points. Real information about the scene are collected by the 3D-MLI sensor [22] installed on the table. The object information data such as the localization of different object in the 3D assembly environment is collected as 3D point clouds and unknown, un-programmed objects are detected and localized using the previous and new information about the scenario on-hand.

Knowledge information about the process itself is already communicated to the controller of the robot and to the method/algorithm responsible for path planning. Knowledge information about several aspects of the process is important in order to take an intelligent/automatic decision during collisions. Some important knowledge information highlighted below is important to be known and accessible to the path planner e.g.

- Initial robot path
- Production points/stations
- Robot speed information
- Other machinery/accessories/equipment's information
- Robot limitations/working space limitations

All these process information are communicated to the path planner algorithm. Initial robot path is the most important to be verified for unknown obstacles. Production point information is necessary to distinguish between obstacle and assembly parts. Robot speed information is not important in the scenario considered in this paper because the obstacles in focus in only static obstacles but this information is very much important when dynamic scenarios need to be taken into account in future. The speed of robot will define the distance to the obstacle and rapidity of the decision/response action. The working boundary limitation information is also important to know in order to not command the robot to avoid collision while moving out of its limitations.

Fig. 2. Peg-in-hole process with dummy plastic objects using Kuka-DLR Robot

B. Collision detection

A single ToF 3D-MLI sensor installed monitors the peg-in-hole process environment where the robot is working. All the new changes to the environment will be pointed out and by detecting new unknown obstacles a potential collision will be detected if it fall along the initial programmed path of the robot. Initial status of the scene is detected and stored in a depth information Matrix A containing 3D coordinates (*XYZ)* information of known objects in the scene, where no obstacle is present as shown in Fig. 3 (a) (image taken from the ToF camera). The actual scene information are detected by a fresh 3D image from the scene. The actual information in the presence of an unknown static obstacle as shown in Fig. 3 (b), are stored as a new 3D image Matrix B with *XYZ* coordinates of each point cloud in the scene. A subtraction Matrix C provides the relevant information about new objects in the scene with their actual locations.

The already programmed path is then verified while using the information about unknown obstacles from the Matrix C. In the presence of obstacles, a potential collision is detected as shown in Fig. 3 (b). The approach proposed then diverts robot to another working point by effectively detouring the obstacles.

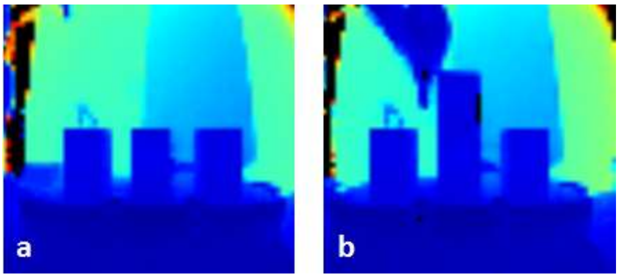

Fig. 3. Depth information matrices from the scene (3D-MLI sensor)

C. Collision Avoidance

In order to detour the obstacle when a potential collision is detected, the method proposed will provide intelligent decision to avoiding collisions. A diversion strategy is adapted to prevent the moment of robot to the risked workstation and a detour while keeping in mind the location of the obstacle. The obstacle present is therefore avoided by an intelligent decision by choosing a best diversion strategy above the obstacle to a secure position.

Secure points are generated, by detecting the height and depth of obstacle in the scene, and by defining a row of points above the obstacle in space. Once secure points are generated then the robot is shifted to a secure position by selecting one secure position using proposed intelligence to select a feasible direction.

1) Feasible direction selection: Selection of a feasible direction for collision avoidance is the most crutial part of the intelligence of the robot. The selected diversion position should abide by several criteria defined below:

- minimum distance criteria from the current point to secure point plus from the secure point to the final goal point,
- no collision between the current location and the selected secure point unless the secure point is discarded,
- does not stuck in a local minima,
- provide enough room for whole robot arm to pass
- minimize the number of axis of robot in movement and also keep in mind the robot accessibility limitations.

2) Trajectory onward verification and imporvement: After diverting the robot to a secure position the onward path is verified using the same procedure. In the case of collision detection, same procedure as above is adapted to generate a safe diversion for the robot to avoid collisions intelligently. The overall safe path produced is stored for reverification in the case of any change to the environment or improvement process. The safe trajectory obtained can be improved by removing the unnecessary trajectory points and finally the improved safe trajectory is send back to the Robot using Fast-Research-Interface (FRI).

III. Verification and Discussions

The planned path is verified for unknown obstacle lying on one of the workstation in the peg-in-hole process shown in Fig. 3. Once obstacle above the workstation is localized using 2.5D information from the ToF sensor, approach presented generates secure points above the obstacle and select the feasible position to divert robot to that location. Fig. 4 and Fig. 5 shows the results of safe trajectory generated using algorithm (programmed in C++) and re-applied to the robot using FRI. Fig. 4 (a) and Fig. 5 (a) gives the initial position on the workstation.

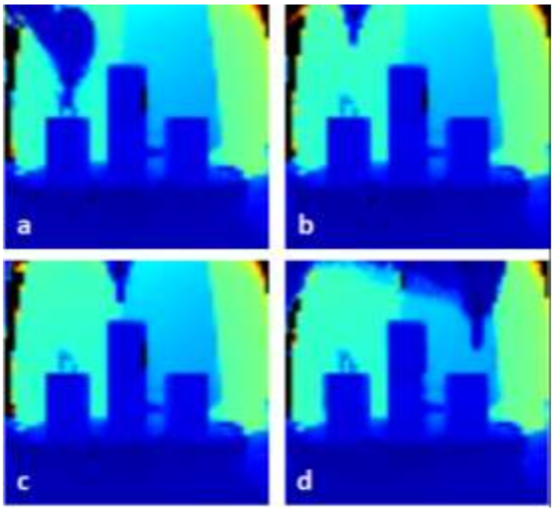

Fig. 4. Path planning results (from 3D-MLI sensor using MoDCAM)

In the case, if the obstacle present at the next station is not known prior then a collision might occur. While the manipulator is programmed to work at workstation 1 in Fig. 4 (a) & Fig. 5(a), an obstacle on next station 2 is predicted for collision and the MAPPS approach generate safe diversion above the obstacle to reach the station 3 as shown in Fig. 4 (b, c, d) & Fig. 5 (b, c, d). The path generated is for unknown static obstacle initially but the approach presented is also suitable for dynamic obstacle where the obstacle map needs to be updated in real-time. Communication with robot is possible every 2 milliseconds and the new path generated with scene updates takes only one second. In future, complex dynamic obstacle scenarios will be treated with more sophisticated image processing technique

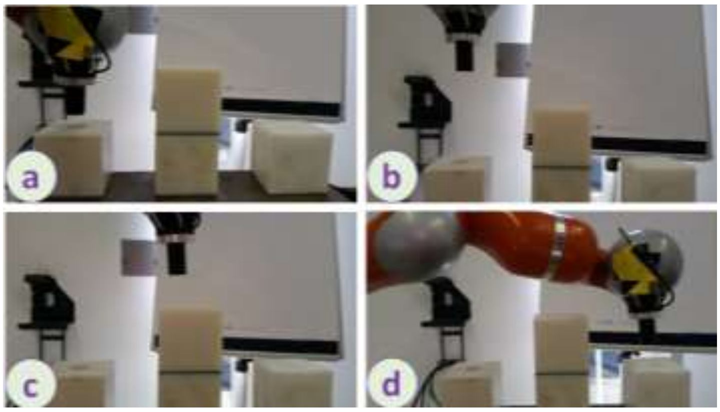

Fig. 5. Path planning application on real peg-in-hole process: a) Peg-in-hole scenario; b) Collision with an unknown, un-programmed obstacle; c) Path initial point; d) Manipulator retraction to secure position; e) Manipulator bypassing the obstacle; f) Reaching final position, while avoiding collisions between manipulator arm and unknown obstacle.

CONCLUSIONS

Automatic collision detection and avoidance using ToF camera sensor is explored in the context of peg-in-hole assembly process. An unknown, un-programmed obstacle present in the original programmed pathway of an industrial robot may cause collision problem. The proposed Time-of-Flight sensor assisted vision method takes information from the scene using 3D point clouds, detect the obstacle, locate its position and generate a safe path automatically for the robot to detour obstacles safely. The safe trajectory is commanded back to the KUKA-DLR lightweight robot using Fast Research Interface. This methodology gives intelligence to the industrial robots for automatically detecting any unwanted situation and programming its new trajectory with no-human intervention.

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