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A Generalised Multi-Attribute Task Sequencing Approach for Robotics Optical Inspection Systems

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Abstract - **Robot programming usually consists of four steps: (1) task planning; (2) task sequencing; (3) path planning and (4) motion planning. Task (2) and (3-4) are strongly coupled. For example, the optimal robot path, which is function of the robot kinematics, relies on the pre-defined schedule of tasks, whose sequencing is computed based on the assumption that the travelling "cost" from one task to the next is only driven by the Euclidean distance in Cartesian space. Current methods tends to decouple the problem and sequentially compute the task sequencing in the T-space, and then compute the robot path by solving the inverse kinematics in the C-space. However, those approaches suffer the capability to reach a global optimum. This paper aims at developing a novel approach which integrates some of the key computational requirements of the path planning in the early stage of the task sequencing. Multi-attribute objectives are introduced to take into account: robot pose and reachability, data quality, obstacles avoidance, overall cycle time. The paper introduces a novel multi-attribute approach to find the optimized task sequencing via candidate poses solving inverse kinematics in the T-space. This is based on the core idea to combine T-space and C-space. The proposed solution has been tested on a vision-based inspection robot system with application to automotive body assembly systems. Results could however impact a wider area, from navigation systems, game and graph theory, to autonomous driving systems.**

Keywords - Robotic task sequencing, TSPN, Robot vision system, Multi-attribute Optimization

I. INTRODUCTION AND MOTIVATION

Industrial robots play a key role for industrial automation and process consistency [1]. In today best practice robot programs are developed off-line using CAD/CAM simulation suits, such as Delmia, RobCAD, etc., to compute collision free robot trajectory [2]. Though those practices are still a premium solution to model and simulate production systems, they are unable to find the optimal solution subject to multiple attributes. In case of robotics vision-based inspection system an optical inspection system is installed at the end of a robot arm to exploit the robots' high flexibility to re-position and re-orient the inspection system to different poses, to take several pictures and generate high dense 3D cloud of points, with the purpose of surface inspection and process monitoring of part and sub-assembly [3] - see Fig. 1 for full-scale simulated vision-based inspection system. The generation of the optimal robot plan is dependent upon several attributes, such as: camera technological parameters (field of view, depth of field, optimal working distance, etc.); robot technological parameters; obstacles in the robot workspace; color and surface finish of the part being measured.

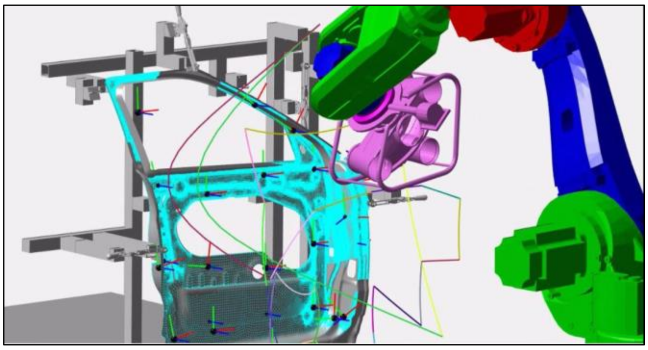

Fig. 1. Example of task sequencing and path planning of optical inspection system installed at the end of a robot arm.

All those attributes affect the overall robot path and trajectory [4], which impact the cycle time but also the quality of the collected data. "Data quality" is related to both: (1) amount of surface data points collected from a given pose of the robot; (2) accuracy and repeatability of the measurement process. Since optical-driven inspection systems make use of 2D images to reconstruct 3D cloud of points, the data quality is therefore affected by the resolution of the image and its saturation. Image resolution is typically given by the optical parameters of the sensor (i.e., focal length and chip size); however, the saturation is strongly dependent on the amount of light which reflects back from the surface being scanned and measured. It has been proved [5] that the specular reflected light tends to over-expose the image which leads to typical “white spots” in the images. White spots prevent the segmentation and the detection of features in the image with leads to incomplete data and low data quality. On the contrary, scattered reflections help to keep the image saturation to a minimum. Surface reflection is function upon material type and surface finish, but also driven by the relative position and orientation of the optical inspection system to the surface. Position and orientation can be controlled by the robotic arm. Fig. 2 shows a 3D cloud of points reconstructed from a stair-case aluminum specimen and measured from the different orientation of the optical inspection system (from 0 to 50 degrees).

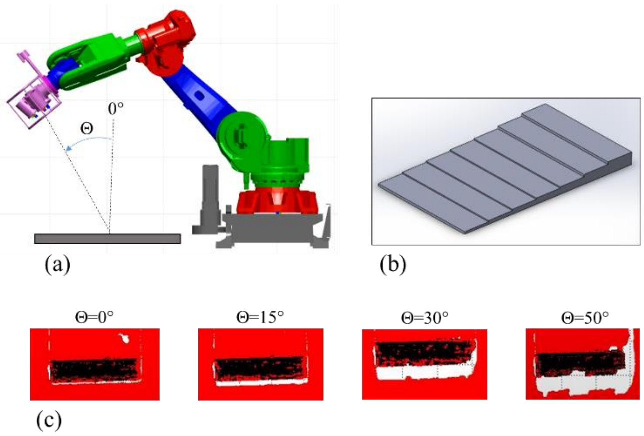

Fig. 2. Effect of orientation on data quality; (a) specimen used for the experiment; (b) collected cloud of points. White areas correspond to missing data because of over-saturated images.

In this context, multi-attributes can be generally discussed as follow [6]:

A1 - *path length*: it is the length of the path described by the optical inspection system while moving through tasks. We aim to minimize the total length;

A2 - *pose quality*: pose of the optical inspection system which leads to given quality of the collected data. Data quality is aimed to be maximized;

A3 - *pose reachability*: pose of the optical inspection system is directly related to the accessibility of given tasks. For instance, it may happen that a tasks though feasible in terms of collision and pose, could not be reachable by the robot; that is, no solution to the inverse kinematics. We aim to maximize the reachability;

A4 – *collision*: robot movement must be collision free.

Robot programming is usually decomposed in four sub-problems/steps [2],[7]:

Step[1] *task planning* – robot tasks are described through (hyper)volume (Task region (TR)) in a pre-defined coordinate system. That volume corresponds to the envelop of the all Tool Centre Point (TCP) poses (position (x_{EE}, y_{EE}, z_{EE}) and orientation (α, β, γ)). TCP is the representative point of the end-effector (EE), which corresponds to the optical inspection system (see also Fig. 3.a);

Step[2] *task sequencing* - sequence of tasks is generated according to pre-defined attributes. Optimal sequence is usually computed based on TCP’s positions; and, it is solved in Cartesian space, also called T-space;

Step[3] *path planning* - path is generated according to task sequence and attributes. The route which leads from one robot configuration to another is named path. A path is the locus of TCP points when it moves throughout configurations, for given sequence of tasks [8]. Path planning allows to compute robot configuration for each TCP pose and the sequence of configurations that moves the robot among configurations. The computation is performed into the configuration space of the robot, also called C-space; and,

Step[4] *motion planning* - robot movements are generated to follow the path.

Those steps are strictly coupled as robot trajectory is strongly affected by Step[2] and Step[3]. There are few approaches that allow to generate automatic robot programming. However, none of them use a complete integration of task sequencing and path planning. Classical approaches consider a simplified formulation: task sequencing and path planning problem are completely or partially decoupled [9]. As no robot information is involved in task sequencing, no attributes can be directly computed in T-space (neither A1 as it involves the information about the robot configurations). As consequence, no feasible solutions are guaranteed in T-space. Therefore, these single-attribute methods require multiple iterations between task and path to converge to a (near)optimal solution which can be far from the optimal one.

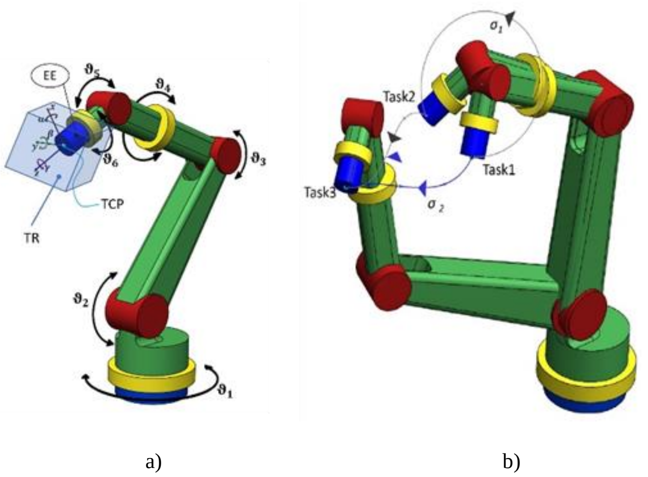

Fig. 3. a) Task region as envelope of the TCP poses. b) Path solutions based on different task sequences: $\sigma_1 \rightarrow S = \{Task1, Task2, Task3\}$; $\sigma_2 \rightarrow S = \{Task1, Task3, Task2\}$

For example, looking at Fig. 3.b, let σ_1 be the path related to the sequence $S_1 = \{Task1, Task2, Task3\}$. Assuming a single-attribute optimization driven by A1, σ_1 is far from the optimal one, because of excessive rotation of the robot wrist. After taking into account robot information as related to configurations and joint operating ranges, the optimal sequence and path could be $S_2 = \{Task1, Task3, Task2\}$ and σ_2, respectively. σ_2 is better than σ_1 in terms of A1 but gives no guarantee that σ_2 is still optimal when considering simultaneously multi-attribute (A1 to A4).

The key challenge is therefore defined as follow: to generate a feasible optimal task sequence directly assessing attributes in T-space. A novel effort in the task sequencing problem formulation is then required to provide a synergic integration of multi-attribute. Task sequencing is modelled as Travelling Salesman Problem with Neighbourhoods (TSPN) [10], where a “neighbourhood” corresponds to a robot task. Existing task sequencing solutions only focus on single-attribute problems. Recent study [9] has tried to use a decomposition approach to reduce the problem to simple ones that can be solved sequentially or in parallel applying heuristics methods to get solution in reasonable time.

This paper focuses on robotic task sequencing and aims to solve task sequencing problem considering multi-attribute scenarios. It develops a novel method to find both optimal TCPs' pose and optimal TCPs' sequence based on multi-attribute solution. The method uses a novel approach which uses pre-computed feasible robot poses based on analytical formulation of Euclidian weighted functions. The proposed solution has been tested with a vision-based inspection robot used for in-line dimensional inspection and control with

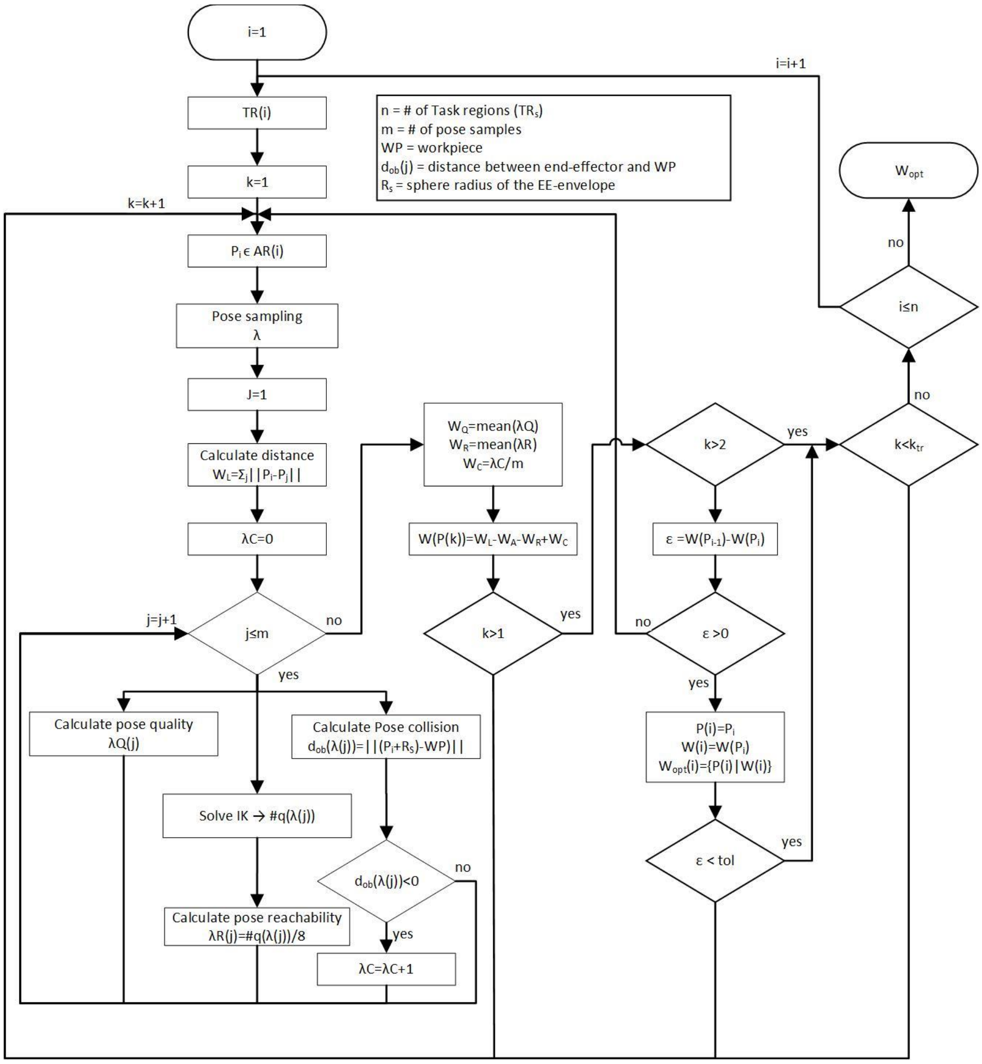

Fig. 4. Flowchat of the proposed method

application to automotive body assembly systems [11]. The proposed approach allows to take into account the feasibility of the robot configurations from the very early stage of the optimization workflow. This leads to the following two benefits: (i) more accurate and faster convergence to optimum; and, (ii) reduction of costly forward and feedback iterations between task sequencing and path planning.

The rest of the paper is arranged as follows: Section 2 presents the problem formulation; Section 3 summarizes the proposed approach; lastly, industrial case study and conclusions are depicted in Sections 4 and 5, respectively.

II. Problem Formulation

Industrial robots perform a cycle of actions to carry out a task. Given a task, T, there exist a region, TR_i, where robot can reach a pose, λ_i, to perform the task. The aim is to find the optimal sequence, $\boldsymbol{S}$, of poses by optimizing cycle-length, as well as selection of the optimal pose $\boldsymbol{\lambda}$ for each task. Therefore, one can formally write:

$$\forall\, T_i \;\exists\, \boldsymbol{\lambda}_i \in TR_i \;:\boldsymbol{S} \Rightarrow L_{min} \qquad i \in [1, n] \tag{1}$$

A pose is defined in T-space by its position $P = (x, y, z)$ and orientation $\Theta = (\alpha, \beta, \gamma)$; whereas, in C-space through configuration $Cs = (\vartheta_1, \dots, \vartheta_m)$ where m is the number of joints. Although in C-space it is possible to define a complete TCP pose as well as robot configuration, it is difficult to define an optimal task sequence. Therefore, it is more convenient to model the robot task sequencing problem in the T-space. The proposed approach formalizes the task sequencing problem in T-space bringing attributes from C-space. Within T-space, robotic task sequencing can be modelled as TSPN [10],[12], where each neighborhood (region TR represents robot task and any inner points represent the TCP point).

III. Proposed Approach

The proposed approach is based on integration of multiple attributes to find a near-optimal task sequence. Four attributes are fused in a TCP point. They are computed for each generated pose within TR. Formally we can write:

- *A.* *path length,* W_L
- *B.* *pose quality,* W_Q*;*
- *C.* *pose reachability,* W_R*;*
- *D.* *collision,* W_C*.*

Path length is affected only by position P ($W_L = f(P)$) and, therefore, it is directly computed in T-space. Pose quality, reachability and collision attributes are affected by both TCP position and orientation; therefore, they are computed in C-space, thus requiring solution of the inverse kinematics (IK).

In this way, although there is no information on path planning, we can generate an optimal sequence which corresponds to the best feasible sequence as follow:

$$\begin{gathered} argmin(W) \\ W_P = f(P, \Theta) = W_L - W_A - W_R + W_C \end{gathered} \tag{2}$$

where W_P represents the total weight of the point P in T-space. Due to multi-space attributes, the present approach concurrently combines multi-space data. It fuses TCP and robot data in TCP position making a multi-level point. Solutions are generated for static robot (stopped in a poses) and no motion attributes are still tackled. The Proposed method flowchart is depicted in Fig. 4. Let sequence $\boldsymbol{S} = \{P_i\}$, $i = 1, \dots, n$ be the sequence of via-points, $\boldsymbol{P}_i$, to be optimized within regions which are locus of feasible points. Given a set of tasks T, the proposed approach is composed by two main steps: (I) via-pose optimization, as in (2); (II) task sequencing optimization. For each TCP position $\boldsymbol{P}_i$, a pose sampling generates a set of λ. IK solver runs on the discretized set of TCP poses λj. W_P can be computed for each pose λ mapping the whole TR. Then, sequence optimization finds the best sequence starting from the minimum W_P point of each region. A classical TSP solver was used to construct the optimal sequence. In particular, we have implemented a robust TSP based on Genetic Algorithm (GA). GA has been triggered by initial random population. Tournament selection method has been used to initiate the 2-point cross-over, followed by flip-swap-slide mutation. Fixed number of iterations has then been adopted as termination criterion. The developed algorithm simultaneously optimizes pose-to-pose distances (T-space), pose accuracy (C-space), collision (C-space) and reachability (C-space); finally, in T-space, a task sequencing $\boldsymbol{S}$ is generated through via-point $\boldsymbol{P}_i$, $\forall i = 1, \dots, n$.

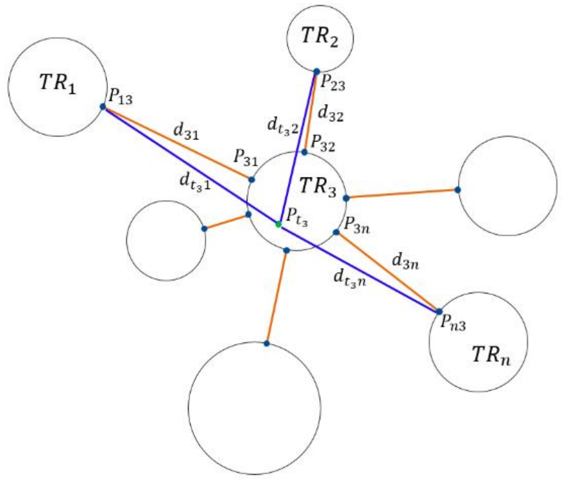

Fig. 5. Pose length optimization – schematic representation

A. Path length weight (W_L)

Euclidean distance is assumed as key metric to compute the length of the sequence. Given two generic points in $\mathbb{R}^3$, there is a straight-line which is the shortest route between them. Therefore, given two task regions TR_i and TR_j, there are two points $P_{ij} \in TR_i$ and $P_{ji} \in TR_j$ that are extremity of the shortest straight-line which connects the two regions. The extremity point P_{ij} is named target points, usually located on the regions' boundaries, P_{ij} represent the best via-point to move from TR_i to TR_j. Considering a set of n regions (Fig. 5) and taking into account the i^{th} region, there are $n - 1$ target points related to the other regions. It can be defined a point P_{t_i}, inside TR_i, which is the optimized via-point to get each target point. Therefore, given a set of n tasks, the pose length W_L is computed as follow:

$$W_L = \sum_{\substack{j=1 \\ j \neq i}}^{n} \left\| P_{t_i} - P_{ji} \right\|^2 \qquad \begin{gathered} with\colon i, j \in [1, n] \\ n \text{ no. of TR} \\ \boldsymbol{P}_{t_i} = (x_i, y_i, z_i) \\ \boldsymbol{P}_{ji} = (x_j, y_j, z_j) \end{gathered} \tag{3}$$

B. Pose Quality weight (W_A)

Pose quality, W_A, aims to evaluate the quality of task execution. It is calculated as average of all sampled pose accuracy indices λAs for each position P_i.

$$W_A = mean(\lambda As) \tag{4}$$

C. Pose Reachability weight (W_R)

Reachability weight aims to evaluate the feasibility degree of the poses. It is affected by relative work-piece placement within robot workspace and inverse kinematics. Solving inverse kinematics for a pose, pose reachability λR is calculated as number of solutions by admissible solutions.

$$\lambda R = \frac{no.\ of\ solutions}{no. of\ admissible\ solutions} \tag{5}$$

W_R is calculated as average of all sampled pose reachability indices λRs. Higher value means better reachability; therefore, it has to be maximized.

$$W_R = mean(\lambda Rs) \tag{6}$$

D. Collision Weight (W_C)

Collision index aims to evaluate the collision tendency of a pose. By assuming d_{ob} as the minimum distance between EE-envelope and workpiece, if $d_{ob} \leq 0$ collision exist, count collision, not count. For each pose λ, pose collision index λC is 1 if collision exist, otherwise 0.

$$\lambda C = \begin{cases} 1 & collision\ true \\ 0 & collision\ false \end{cases} \tag{7}$$

CoI is calculated as average of all collision indices λCs of the sampled pose.

$$W_C = \lambda Cs/m \tag{8}$$

Collision checking algorithm is based on proximity query package (PQP) library available at [13].

IV. INDUSTRIAL CASE STUDY

The proposed methodology has been validated with a vision-based inspection system, used for in-line dimensional inspection and control for automotive assembly systems. The robotics vision comprises of: 6(+1) axis ABB industrial robot, Hexagon WLS400A optical scanner (white light scanner measuring system equipped with three 4.0 megapixel digital cameras. It has a field of view equal to 500 x 500 mm, 230 mm as depth of field and an optimal working distance of 780 mm). The attributes are characterized as follow:

- Pose quality – for evaluating capture quality we have used the coverage index (CI) which is defined as ratio between valuate area covered by point cloud and nominal area of the geometry.

$$CI = \frac{Valuate\ Area}{Nominal\ Area} \tag{9}$$

  CI is calculated respect incident angle ϕ (Fig. 7) using a mapping function of WLS400A (Fig. 8) developed at WMG (University of Warwick).
  Discretizing turn angle γ in m angle samples. For a given camera position, we calculate λAs as average of CI_γ that is calculated as average of CI_{P_c} between the camera and the k sampled points in the FoV affected by a different incidence angle ϕ:

$$\lambda As = \frac{\sum_i^m CI_{\gamma i}}{m} \qquad CI_{\gamma_i} = \frac{\sum_j^k CI_{P_{Cj}}}{k} \tag{10}$$

- Reachability index – ABB IRB 6620 is a 6 axes robot; therefore, it has 6 DoF. Such a robot admits up to 8 solutions; which are the number of admissible solutions.

$$\lambda R = \frac{no.\ of\ solutions}{8} \tag{11}$$

- Collision index – spherical volume (described by a sphere radius R_S) was assumed as EE-envelope (Fig. 6).

Fig. 9 shows the robot cell installed at University of Warwick, WMG, used for the validation tests. The digital model, twin of the WMG's cell, has been developed in Matlab. The proposed approach has been implemented in C++ and linked to MatLAB via MEX interface.

In order to assess the benefits of the proposed multi-attribute approach we have compared two task sequencing solutions:

(1) classical task sequencing solution, it corresponds to a sequence generated only by distance attribute;

(2) proposed multi-attribute solution, it computes all attributes (distance, accuracy, reachability and collision) acting simultaneously.

In the first case, as illustrated in Fig. 10, obtained via-poses present collisions with the workpiece. Therefore, further iterations are needed to generate a feasible solution and more computation time are required. In the second case, using all attributes, no more actions are needed; indeed, as show in Fig. 11, the generated solution is feasible because no collisions occur. Besides, obtained via-points are reachable and characterized by high capture quality.

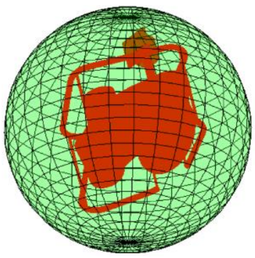

Fig. 6. EE-envelope

V. CONCLUSIONS

This paper proposes a new approach for solving robotics task sequencing which enables to check the feasibility of reachability, collision and pose accuracy for a metrology 3D scanner. The approach allows to find the near-optimal solution to perform a specific task. It is based on the idea to solve task sequencing by multi-attribute optimization.

The approach has been tested in the context of automotive body assembly systems for solving task sequencing of an inspection robots with optical camera system. However, results could impact a wider area, from navigation systems, game and graph theory, to autonomous systems.

Currently, the proposed method evaluates collisions between end-effector and workpiece. There are other collisions to take into account: end-effector and obstacles; robot and obstacles; end-effector and robot; robot and obstacles; robot and workpiece. An improvement of the collision attribute is required to increase the feasibility of the solution.

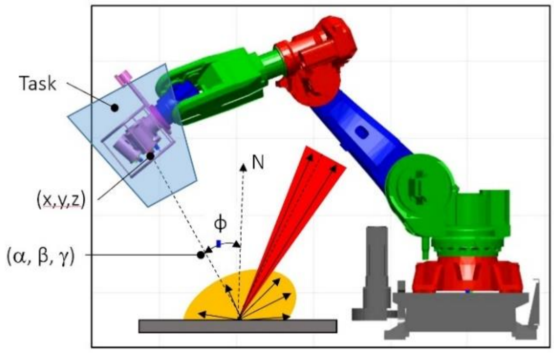

Fig. 7. Pose quality scheme for WLS400A.

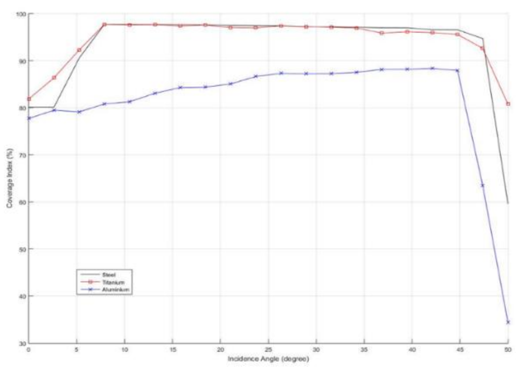

Fig. 8. CI map for WLS400A

Fig. 9. Robot cell installed at WMG

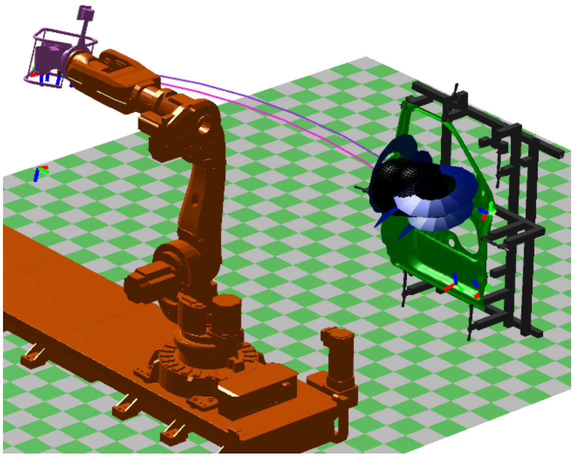

Fig. 10. Task sequencing solved only with distance attribute

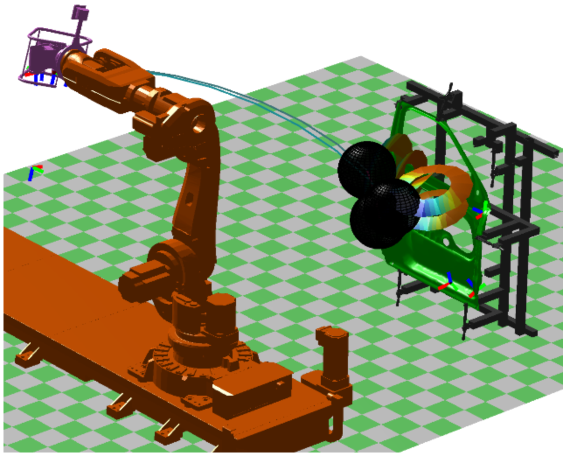

Fig. 11. Task sequencing solved with all attributes: distance, accuracy, reachability and collision

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