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Haptic Based Optimized Path Planning Approach to Virtual Maintenance Assembly / Disassembly (MAD)

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Abstract— **In virtual MAD environment the most significant phase is the A/D process (Assembly / Disassembly). The effectiveness of the maintenance scheme depends on the A/D sequence, number of gripper changes and the path used in an A/D procedure. However, in a constrained 3D environment simulating realistic models, path planning of the parts becomes more complex because of the factors like complex geometry computations, obstacles, orientation and initial/final position of the part. In this case the path planning of the parts becomes an important factor affecting the overall efficiency of the maintenance process. Therefore, to address this problem an intelligent assembly planner is developed with a combined approach based on potential field method and genetic optimization process for MAD path planning. Furthermore, haptic-assisted feature is implemented for user support for realistic 3D MAD path planning simulations.**

I. Introduction

Many virtual reality (VR) industrial simulations deal with assembly and maintenance process focusing on the whole product or some of its subsystems [1]. VR is becoming a popular engineering design tool because of its ability to provide intuitive interaction with computer-generated models and data. The immersive aspects of VR offer more intuitive methods to interact with 3D data than the conventional 2D mouse and keyboard [2]. Carrying out simulations for assembly activities within a virtual environment gives a person the ability to directly interact with 3D virtual models for assembly purposes. Raghavan et al. [3] illustrate an interactive tool for evaluating assembly sequences using augmented reality. Recently, Zhong et al. [4] presented a constraint-based methodology for intuitive and precise solid modeling in a VR environment. One of the important objectives can be cutting down the production cost or design errors. Operators can employ it to evaluate aspects of human-centric design for maintainability (accessibility, reachability, tool usability, part mount/dismount ability) [5]. But sometimes, in complex constrained environment, the user may be lost and may not be able to find the solution himself easily and might need some help.

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In VR when dealing with assembly simulations, CAD models are mapped to the physical environment possessing same behavior, architecture and simulating the real world maintenance process. The use of haptic interfaces in simulation to feel collision of 3D models in the environment allows the user to test those processes using CAD parts representation, and then, to detect design mistakes. With respect to well-established techniques based on the haptic feedback guidance, this approach offers a more direct, intuitive control over the interaction activity, thus speeding up the assembly process and its configuration controls, along with the opportunity to find out optimized assembly sequence from the assembly point of view. Furthermore, assemblers (mechanics, technicians) can be trained within a highly interactive, realistic virtual reality simulator, thus combining advantages of a safe training environment with the value of “learning by doing”[6].

In manufacturing and system’s development, path planning plays a vital role and therefore, has been widely studied for decades. A good number researches on path planning can be found in robotics [7], assembly maintainability [8], computer-animation [9] and computer-numerical control [10]. Many theoretical approaches to automatic path planning have been proposed. However, very few such approaches have been applied to industries. Many automatic path planners are only effective in some specific scenarios and may fail due to the difficulty in finding configurations or assembly sequence, which are critical for the resulting path [7]. Furthermore, to make the system efficient in terms of cost saving and beneficial; optimization is an important factor in assembly procedure. It is observed that in many assembly procedures cost can be saved by opting the optimal paths and even a minor change in assembly sequence of the whole process can effect in terms of cost producing beneficial results [11].

In this regard, our prior work has focused on 2D algorithm for path planning simulations and assembly framework [12, 13]. When extending from 2D to 3D the environment geometry becomes more complex resulting in an increased computation time for optimal solution. Furthermore, the planer may fail due to algorithm running out of time. Considering these issues a new approach is proposed for the extension of 3D optimal MAD planning. The 3D planner implements batch processing for optimization process returning solution in multiple levels. Each level optimal solution is used to further investigate the process. The planner utilized realistic 3D models and tries to find optimal path planning for all the parts involved in MAD process.

The proposed framework optimizes the assembly sequence, assembly path and automates whole process. Thus, optimizing the solution in multiple levels reduces the computation time and returns the optimal path by contributing to realistic MAD simulations using haptics interface

The paper is organized as follows. Sect. 2 gives the overview of the system architecture followed by sect. 3 that describes the approach used to develop the planner, with an overview of the planner algorithm and the levels involved in generating solution. Starting from the A/D preparation level, the path planning process, the gripper selection process, the sequence planning process and genetic optimization process are described. Finally implementation and results obtained from the developed MAD simulator with an example is detailed in sect. 4.

II. HAPTIC SIMULATOR FOR MAD

When humans have to perform an A/D simulation based on the direct manual interaction approach, a number of factors determine the usability of the system and, consequently, the reliability of the results. Aspects such as the sequence of the parts and the obstacles present in the environment have an effect on how much complex the user perceives the simulated environment can be, and may eventually affect the ability to reach the final assembly. Considering these facts, the simulator MAD is based on three pertinent aspects: The sequence of the parts, the grippers involved in the assembly process and obstacle free path planning.

The virtual maintenance system reported in this paper as shown in Fig. 1. Utilizes a pc based application and general-purpose hardware for interaction, making the system easy to use. The Graphical interface was designed in C++ to let the user interact with the virtual environment. 3D CAD files for A/D parts were developed with CATIA software package to be utilized by this environment. The Open Inventor API hiding many of the lower- level programming details required to develop, test, and debug VR applications provides the virtual environment facility.

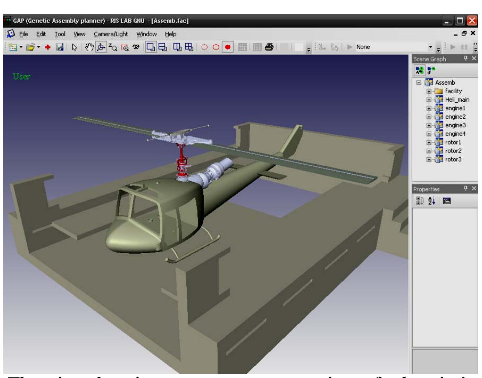

Fig. 1. The virtual maintenance system consists of a haptic interface, virtual environment, display engine, an optimal assembly algorithm.

Open-Haptics toolkit and device drivers from Sensable were used to drive the PHANTOM haptic device a three degree of freedom device that provides six inputs in form of force and torque coordinates and three outputs as force coordinates Sensable[14]. This haptic-assisted feature is particularly important for maintenance training applications as, in the reality, operators usually employ tools and parts to be maintained that have well-known mass and stiffness properties, and the VR system is expected to transmit them the same sensation. If these factors are neglected during the virtual training, such training could possibly be useless or could even affect negatively the experience.

III. ALGORITHM DESCRIPTION

The proposed system process MAD in three levels as shown in fig.2. Initially, the 3D CAD models are loaded with their initial and final position. The assembly procedure starts with assembling the parts in to their final position using multiple grippers. It's rather recognized that many gripper exchanges means that more time is needed to change from one gripper to another. Similarly, many direction or orientation changes require more effort to perform the maintenance tasks. Hence, MAD task may consume more than required time if not optimized. Therefore, one of the optimization objectives was to find the optimal assembly sequence that has the fewest gripper exchanges and less orientation changes. Pan et al. have shown that for both automated and manual assembly processes, the number of reorientations in an assembly sequence has a significant impact on assembly time [15]. To reduce the computation time the system was subdivided into parallel processing tasks called planners. Thus, in level one a sequence planner scheme was implemented to find all valid sequences to reach the end solution and the number of gripper changes involved in it. Each solution returned by the planner was stored as sequence population (SP) along with total gripper count.

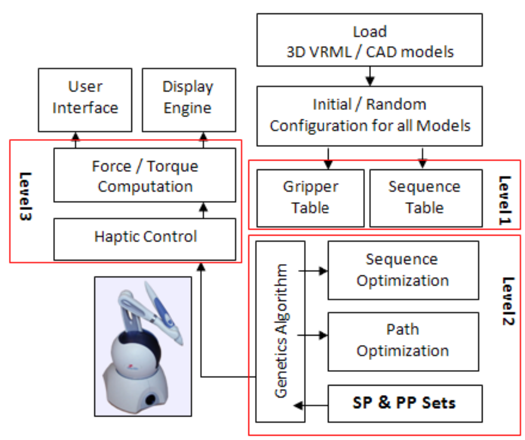

Fig. 2. Layout of interactive path planner using optimized results and haptic control features.

Then, in second level path planning algorithm is implemented that finds out the path for every handled part in the sequence population. However, optimization of the path planning can influence the efficiency of the overall maintenance process. Obstacles and the location of the parts can be considered as path-planning factors. A short path is required to achieve the optimal assembly of mechanical parts. Therefore, the path-planning optimization formula tries to find an optimal setting for the path planning variable. For path planning potential field method was used and the repulsive force (ρ_0) as path-planning variable was selected. The potential field method involves attractive and repulsive forces and The variable (ρ_0) is the condition value to evaluate the influences of repulsive force on the parts [16]. Therefore, the setting of (ρ_0) will affect the overall outcome path. Each successful path is then stored as path population (PP) as shown in Table 1.

TABLE I
SP AND PP SETS TABLE

Sequence	ρ_o	Orientation	Grippers	G
1,2,4,3,6,5	2.87,3.81,2.97,3 .48,3.24,4.12	X+,Y-,X- ,Z+,Y+,X+	G1G1G2 G2G2G2	1

* *Table shows the sequence orientation and gripper count.*

Once, sequence and path population sets are collected, the genetic algorithm is utilized to generate the optimal solution for sequence sets. The optimized sequence is then used by the genetic algorithm to generate optimal path. A cost function is defined as an evaluation index to determine the cost of each population set. The overall cost depends on the distance cost, the sequence cost and the gripper exchange cost. Hence, the cost function components are the number of gripper exchanges (G), the number of assembly direction changes (O), and the actual distance of the path (D_{act}). The number of gripper change and direction change was considered as elements of optimal assembly contribution on maintenance process efficiency, whereas the actual distance of path was considered as path planning contribution. The optimized variables were sequence of parts and the value of ρ_0. The number of gripper changes and assembly direction changes were calculated respect to the order of part sequences. Then, the actual distance of path was calculated based on path planning of every single part.

Finally, in third stage the passive haptic control mode is applied to the virtual environment. In this mode the optimized 3D path trail is generated for user guidance. The user when in training mode selects the part and follows the exact path. After finishing the assembly of the path the user returns to an initial position of next part. In the whole process the user movement is limited to the trail boundary using haptic force guidance.

A. 3D Path planning for the handled parts

MAD path planning is process to find a 3D trail for each handled from its initial position to the final position. In a 3D environment each part is defined in a 3D plane in the form of geometrical shapes and an origin (O) represents the center of the part. The bounding box technology was used to draw bounding boxes around the handled parts to highlight the boundary of the part as shown in fig. 3. The positions of a part and its bounding box in a frame O_1 with respect to the reference frame O_0 can be represented as the transformed points of parts vertex using a 3D homogenous transformation matrix (1). The configuration of the parts is represented by $q = [d_{xi}\ d_{yi}\ d_{zi}\ \theta_i]$.

$$H = \begin{bmatrix} 1 & 0 & 0 & d_{xi} \\ 0 & cos\theta_i & -sin\theta_i & d_{yi} \\ 0 & sin\theta_i & cos\theta_i & d_{zi} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

Where:

d_{xi}, d_{yi}, d_{zi} = translation along the *x*-axis, *y*-axis and *z*-axis of the workspace coordinate.

Θ_i = angle between *x*-axis of workspace coordinate and *x*-axis of local/frame part coordinate.

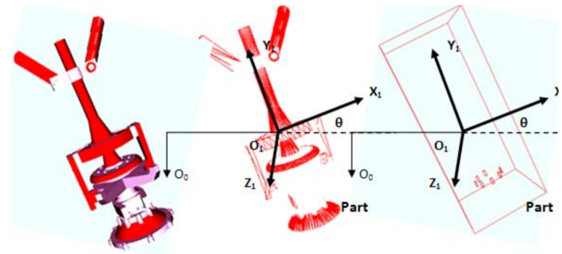

Fig. 3. The orientation & configuration of a handled part q = $[d_{xi}\ d_{yi}\ d_{zi}\ \Theta_i]$ and the bounding box calculation.

The part from its start position to the final position moves with an attractive force. This attractive force pulls the part to its final position. Similarly, Parts which already reached their final position became an obstacle for the upcoming parts. This rule ensured that handled part will not collide with the pre-assembled parts. In case the path is blocked by an obstacle; each obstacle has its own repulsive force that repels the part from the obstacle avoiding collision of part and obstacle. As the part reaches its final position, from initial to final a 3D trail is formed. The attractive and repulsive forces are represented as:

$$\text{If } \rho(o_i(q)) \le \rho_0$$

$$F_{rep}(q) = -\eta \left[\frac{1}{\rho(oi\,(q))} - \frac{1}{\rho_0}\right]\delta \quad (2)$$

$$\delta = \frac{1}{\rho^2(o_i(q))}\nabla\rho(o_i(q))$$

$$\text{If } \rho(o_i(q)) > \rho_0$$

$$F_{rep}(q) = 0$$

$$If\ |o_i(q) - o_i(q_f)| \le d$$

$$F_{att} = -\zeta\,(o_i(q) - o_i(q_f)) \quad (3)$$

$$If\ |o_i(q) - o_i(q_f)| > d$$

$$F_{att} = -d\zeta\,\frac{(o_i(q) - o_i(q_f))}{|(o_i(q) - o_i(q_f))|} \quad (4)$$

Where:

q_f = final configuration of a part at its final position

d = evaluation value of distance from the current position to the final position

ζ = scale factor
F_{att} = attractive forces
q = configuration of the parts
F_{rep} = repulsive forces
ρ_o = repulsive force radius
o_i (q) = point on the workspace
η_i = scale factor
i = index of the i[th] part

The repulsive force has a provisional value $\rho(o_i(q))$, which is the distance from the center of a part to the center of an obstacle. The summation of the attractive and repulsive forces gives the direction for movement as a normalized vector as follows:

$$q = [\ qx\ ,\ qy,\ qz\ \ \theta]$$

$$\vec{f} = [\ f_x\ f_y\ f_z\ ]$$

$$\vec{f}\ =\ \Delta q\ \frac{F_{att} + F_{rep}}{||F_{att} + F_{rep}||}\ S \qquad (5)$$

Where:
q = Coordinates of the handled objects
$\vec{f}$ = Force applied to move handled part
S = Step size between path points

This 3D path planning process based on 3D potential field method is utilized by the optimal planner (Sect. C) that generates the best population having optimal sequence and optimal path.

B. *Assembly Sequence and Gripper (SG) Planner*

A sequence planner was implemented to find out all the possible sequences as each part must have a predefined assembly direction to prevent obstruction between parts. To solve this problem a 3D relationship matrix is used to get all possible assembly directions. The planner randomly examines the 3D relationship between succeeding and the parts those already reached the final position. Table 2 shows the geometric relationships between parts for each X, Y, Z direction with respect to the local reference frame of final positions. In the matrix (1) specifies that the part can be assembled in the given direction, whereas (0) indicates that the handled part cannot be assembled in the given direction because other parts will interfere with the movement.

The planner randomly generates the part number and then examines the relationship matrix for succeeding part valid direction. For example the planner would randomly select 4 and then it selects 6. Since part 6 can only succeed from direction X+ and Z- (1 in relationship matrix) would be counted as valid sequence. Similarly, for part 6 a valid succeeding part is searched that can be part 2 from Y- and Z+. The proposed direction-finding algorithm only considers the directions of the principal axes of the part, which is sufficient for this case. Each valid assembly sequence is stored as sequence population for optimization process in later stage and all invalid sequence population are cut short as bad population. Table. 3 shows some of the valid sequence populations computed by the planner.

TABLE II
CONNECTION MATRIX

X+ X-

Parts	1	2	3	4	5	6
1	0	1	0	1	0	0
2	1	0	1	1	0	0
3	1	0	0	0	1	0
4	1	0	1	0	1	0
5	0	1	0	1	0	1
6	1	1	1	1	1	0

Parts	1	2	3	4	5	6
1	0	0	1	1	1	0
2	1	0	0	1	1	0
3	1	1	0	0	0	0
4	0	0	0	0	1	1
5	0	1	0	1	0	0
6	0	0	0	0	0	0

Y+ Y-

Parts	1	2	3	4	5	6
1	0	0	1	0	1	1
2	0	0	1	1	0	1
3	0	1	0	0	0	1
4	1	0	1	0	0	0
5	0	1	0	0	0	1
6	0	0	0	0	0	0

Parts	1	2	3	4	5	6
1	0	0	1	0	1	1
2	1	0	1	1	0	1
3	1	1	0	0	0	1
4	1	0	1	0	0	0
5	1	1	0	0	0	1
6	1	0	0	0	0	0

Z+ Z-

Parts	1	2	3	4	5	6
1	0	1	1	1	1	1
2	0	0	1	1	1	1
3	0	0	0	1	1	1
4	0	0	0	0	1	1
5	0	0	0	0	0	1
6	0	0	0	0	0	0

Parts	1	2	3	4	5	6
1	0	0	0	0	0	0
2	1	0	0	0	0	0
3	1	1	0	0	0	0
4	1	1	1	0	0	0
5	1	1	1	1	0	0
6	1	1	1	1	1	0

TABLE III
VALID SEQUENCE TABLE

Sequence	$\mathbf{G_{val}}$
1,2,4,3,6,5	2
4,3,5,6,2,1	1
1,3,4,2,5,6	2
5,2,4,3,1,6	2

* Grayed color row shows the best optimal sequence chromosome

TABLE IV
GRIPPER TABLE

Part	1	2
1	GR1	GR2
2	GR1	
3	GR3	GR2
4	GR3	GR2
5	GR2	
6	GR3	GR2

* *GR1,GR2,GR3,*are the type of grippers associated to each part.

These sequences are then optimized using genetic algorithm developed by Holland [17]. Initial sequences are randomly picked from the table as parent chromosomes and evaluation index gripper change value (G) is defined. To reduce the number of gripper exchanges for each handled part a gripper table was proposed in our prior work (Shown in table 4) and similar methodology for gripper count was used. The chromosome having less number of G value is considered to be the best. A preliminary ranking based on natural selection was performed to sort the population and select good chromosomes. Chromosomes with poor cost values were removed from the population. The partially matching crossover (PMX) method [18] was used to produce new off-spring. The resulting optimal sequence has valid sequence directions and least number of gripper changes. This sequence is then used by the path planner to find optimized path.

C. *Optimization planner for MAD population*

The final stage of the planner deals with finding the optimal sequence and path for the handled part. The optimization method involves Genetic algorithm developed by Holland with an extension to 3D computation [18]. Initial sequences were randomly picked from the table and path populations were randomly generated. The population consisted of 50 chromosomes, and each chromosome had two main components: the sequence of all parts and a path cost (ρ_0) array. The sequence was encoded as a series of integer values, whereas the path (ρ_0) array was encoded as binary values. These two components were the optimization design parameters (optimized variables). The series of (ρ_0) were ordered in sequence. A cost value was calculated for each chromosome in the population. The inputs for the cost (C) value were the number of gripper exchanges (GR), the actual path distance of each part (D_{act}) and the number of orientation changes (O):

$$C = \alpha + \omega + \varepsilon \qquad (6)$$

$$\alpha = w_1 \left[1 - \frac{O}{n-1}\right],$$

$$\omega = w_2 \left[1 - \frac{G}{n-1}\right],$$

$$\varepsilon = w_3 \left[1 - \frac{\sum_{i=1}^{n} \frac{(D_{ref})i}{(D_{act})i}}{n-1}\right]$$

Where:

w1, w2, w3 = random weight values

n = number of total parts

The actual path distance (D_{act}) in eq. 6 is a summation of single distances from one path point (o_i) to another path point until reach the final position. D_{ref} is the shortest distance from the initial position to the final position. The comparative value between D_{act} and D_{ref} gives the efficiency of the path. The path is efficient if the comparative value is close to 1 and inefficient if the comparative value is close to 0.The preliminary ranking based on natural selection was performed to sort the population and select good chromosomes. Chromosomes with poor cost values were removed from the population.

D. Haptic Guidance planner for trail

To make the user follow the path from start position to the final position, a control composed of a force $\vec{f}$ (eq. 5) is directly applied to haptic device for guiding the user by generating the directions drawn as trails in the virtual environment. When handled part is perpendicular to its final assembly position all the repulsive forces disappear to let it freely assemble. Each handled part when assembled in its final position becomes an obstacle and start generating repulsive force. This approach offers a more direct, intuitive control over the interaction activity, thus speeding up the MAD process and its configuration controls.

This haptic-assisted feature particularly supports the user in maintenance training as, in the reality, operators usually employ tools and parts to be maintained that have well-known mass and stiffness properties, and the simulator is expected to transmit them the same sensation.

IV. Path Planning Experiment

The presented experiment has been done using the C++ platform and Open Inventor for 3D virtual environment. A single computer with a Pentium (2.14 GHz) CPU and 2 GB ram is used to run the MAD simulations. The simulation scene contains 6 objects with a total weight of 84193 faces. The computed workspace is (4.0x4.0x4.0) environment as it can be seen in fig. 4. The optimized sequence and path are then visually displayed in the simulator with haptic based interaction as shown in fig.6.

The optimization task was to find the optimal sequence and appropriate repulsive force value to achieve an efficient assembly task under the condition that the optimized variables (*optimal sequence and repulsive force radius*) satisfy the assembly rules. If a path should become restricted in local minima, the cost value of that chromosome will be small almost close to 0. Then, that chromosome will automatically be cut off in the next generation. The algorithm stops processing if it is running short of time or when getting constant results for 40 generations.

The inputs for the cost value were the number of orientation changes (w_1), the number of gripper exchanges (w_2), and the actual path distance of each part (w_3). The best sequence from the sequence table was selected. The weighting values for optimization were set to w1 = 0.2, w2 = 0.2, and w3 = 0.5 to consider both the sequence and path planning. The best sequence found by the intelligent planner was [4,3,5,6,2,1] with the gripper change value of 1 as shown in Table 2. 250 generations were processed and the best cost value graph of all the populations that was taken from 0 to 250th generation is shown in Fig. 5. Initially 50 random populations were populated in algorithm and finally, value 0.425 among all was found as best fitness cost to complete the process. The results for the optimization of repulsive force radius (ρ_0) value for each part and sum of actual distance (ΣD_{act}) for the whole maintenance process is shown in Table 5.

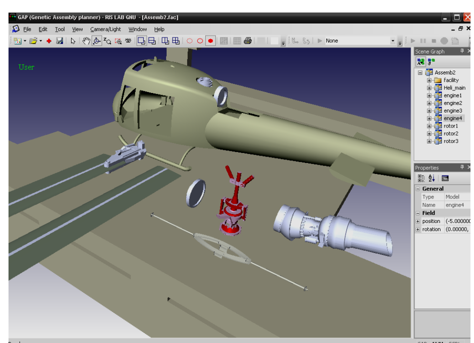

Fig. 4. virtual environment for assembly and disassembly simulations showing un-assembled parts at initial position.

Once the trail for the obtained path is found, the haptic guidance planner is implemented for user guidance as shown in fig 6(a) and 6(b). For each part a trail is shown in the simulated environment. This scheme for passive haptic guidance with the optimal path results is considered as optimized haptic path.

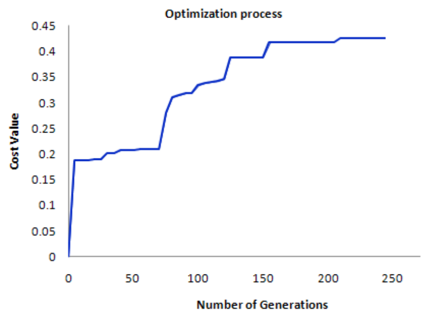

Fig. 5. The Best Cost Value Optimization results graph

TABLE V
MEASURING FOR ACTUAL DISTANCE

Sequence	ρ_{01}	ρ_{02}	ρ_{03}	ρ_{04}	ρ_{05}	ρ_{06}	ΣD_{act}
4,3,5,6,2,1	5.23	4.44	4.71	4.37	3.28	4.26	479.42
4,3,5,6,2,1	**3.20**	**3.52**	**3.73**	**4.38**	**4.27**	**3.15**	**287.06**
4,3,5,6,2,1	4.44	4.69	4.48	4.73	3.49	2.78	367.54
4,3,5,6,2,1	4.69	3.23	3.32	4.17	3.85	3.44	623.2

Optimization process of ρ_0 to find optimal actual distance.
**Gray color indicates the best chromosome.*

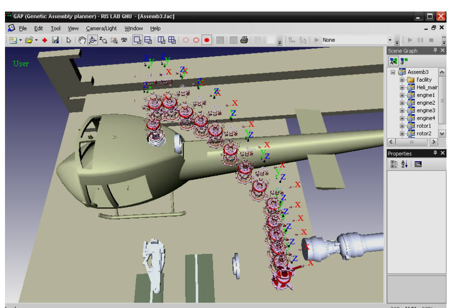

Fig. 6a. Simulation results, trail generated for optimized planned path.

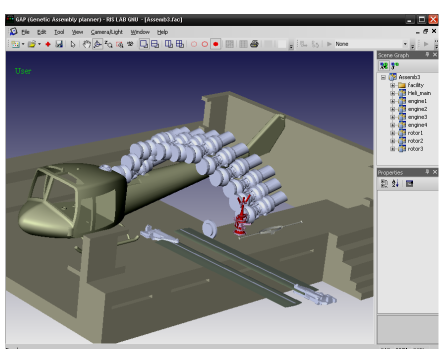

Fig. 6b. The part follows the trail and reaches its final assembly position.

V. CONCLUSION

The proposed 3D algorithm is novel MAD optimization technique based on 3D potential field and genetics algorithm. The algorithm covers both the stages for achieving valid assembly sequence and the optimized path to the goal that can help planner reach optimal MAD. Simulation result shows that the proposed approach can be implanted in complex 3D MAD. Furthermore, it becomes possible to use optimal combination of tele-operations and assembly sequence algorithms in a virtual maintenance system. Despite of computational time, the algorithm results can become the approach to obtain empirical data before path planning. The results of the proposed algorithm can be used for an active haptic guidance application; this haptic feedback appears very useful, especially when the user is not acquainted with the simulation process. Future work will consist of utilizing neural network for learning by the user input for the path planner.

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