FLEXIBLE ROBOT-BASED INLINE QUALITY MONITORING USING PICTURE-GIVING SENSORS

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Abstract: As part of the ROBOSENS project, the IITB developed and tested a new four-step concept for multiple sensor quality monitoring. The robot-based system uses an array of test-specific short-range and wide-range sensors which make the inspection process more flexible and problem-specific. To test this innovative inline quality monitoring concept and to adapt it to customized tasks, a development and demonstration platform (DDP) was created. It consists of an industrial robot with various sensor ports - a so-called “sensor magazine” - with various task-specific, interchangeable sensors and a flexible transport system.

1 INTRODUCTION

A substantial reason for the hesitant use of picture-giving sensors for the monitoring of inspection is the insufficient flexibility of the used monitoring concepts in relation to changing setting of tasks. At present either one (user-specific) sensor or sensors with static arrangement for a certain task of inspection are used. This rigid approach is unsuitable for the inspection of variant products.

Robots with multiple intelligent sensors will be increasingly used in the future for demanding production and assembly tasks. An especially attractive area of application is the inline quality monitoring of complex, large-area production parts such as the aircraft fuselage (see Figure 1) or parts of the bodies of road and rail vehicles. For example hundred different mounting parts on an aircraft fuselage (about 4 m x 10 m in size) must be inspected, whether proper parts have been attached correctly.

The presented new four-step concept (see Figure 2 and sections 2-5) has been developed and realized at IITB for the flexible inline quality monitoring (Sung and Kuntze, 2006) with the following characteristics:

- Multiple sensor inline quality monitoring of large complex manufacturing parts;
- Complete quality assurance with minimum inspection expenditure;
- Large flexibility regarding frequently changing test tasks;
- On-line ability by minimization of the testing period.

All sensors are placed on a sensor magazine (see Figure 1) and are ready to use immediately after docking on the robot arm. The calibration of all sensors and the hand-eye calibration have to be done before the object localization task starts.

A special transport system like a monorail conveyor will probably be needed for the transportation of large objects. Such transport systems do not allow a precise positioning. The test object is free-hanging over the ground.

2 LOCALIZATION OF UNFIXED INDUSTRIAL TEST OBJECTS

As the first step of the presented quality monitoring chain, the exact position of a production piece is determined with a wide-range picture-giving sensor (see Figure 1), which is - depending on the object size - mounted in an adequate object distance, i.e. not necessarily fixed on an inspection robot's end-effector.

A marker-less localization calculates the exact object position in the scene. This procedure is based only on a 3D CAD-model of the test object or at least a CAD-model which represents a composition of some of its relevant main parts. The CAD-model contours are projected into the current sensor images and they are matched with sub-pixel accuracy with corresponding lines extracted from the image (Müller, 2001).

Figure 3 shows a localization example. The CAD-model projection is displayed in yellow and the object coordinate system in pink color. The red pixels close to the yellow projection denote corresponding image line pixels which could automatically be extracted from the image plane. The calculated object pose (consisting of three parameters for the position in 3D scene space as well as three parameters for the orientation, see the red text in the upper part of the figure) can easily be transformed into the global scene coordinate system (displayed in green color).

Known test zones for detail inspection as well as associated sensor positions and orientations or required sensor trajectories (cf. section 3 and 4) can be defined with respect to the object coordinate system in an inspection preceding step. All the object based coordinates will be transformed online into the global scene coordinate system or the robot coordinate system with respect to the localization result, i.e. with respect to the position and orientation of the test object in the scene. The red, T-shaped overlay in Figure 3 shows an example for an optimal 3D motion trajectory (see the horizontal red line which is parallel to the object surface) together with the desired sensor's line of sight with respect to the object surface (the red line which points from a position in the middle of the trajectory towards the test object).

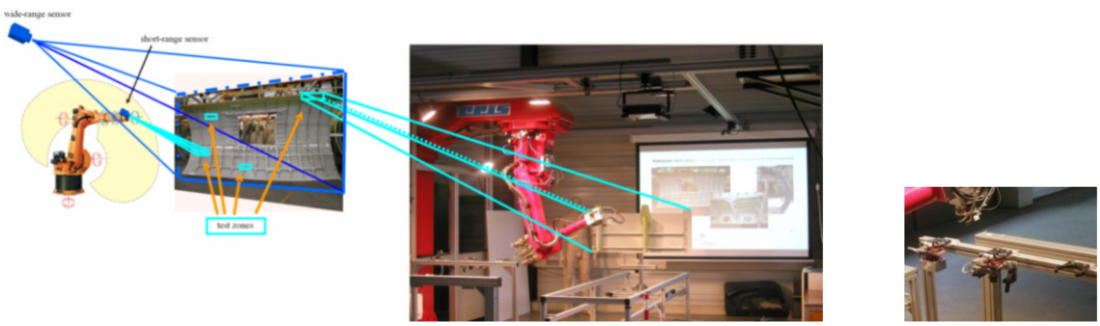

Figure 1: Quality monitoring of aircraft fuselages with wide- and short-range inspection sensors. Left: Test station and test environment. The movement of production pieces is carried out by monorail conveyors which do not allow precise positioning. Middle: Development and demonstration platform (DDP). Right: Sensor magazine.

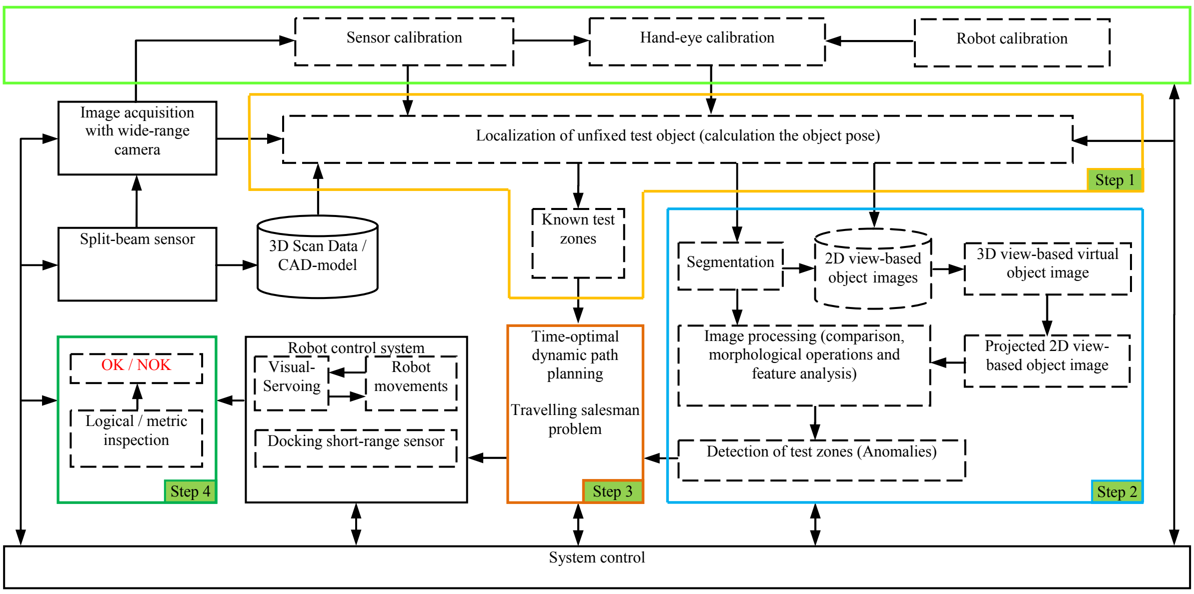

Figure 2: System overview. A new four-step concept for the flexible inline quality monitoring.

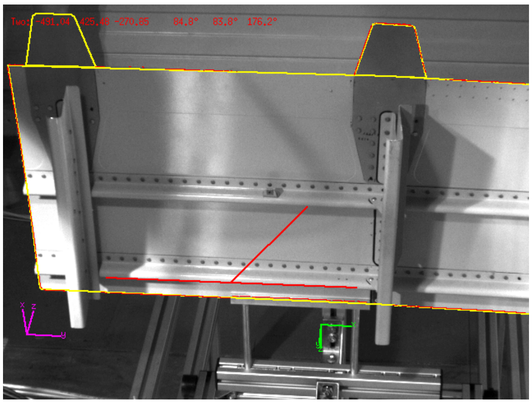

Figure 3: Localization of an object to be inspected and computation of an initial optimal inspection trajectory.

3 AUTOMATIC DETECTION OF TEST ZONES

Two approaches can be applied to find automatically anomalies on a test object. One is model-based comparison between the CAD-Model projection and the extracted image features (edges, corners, surfaces) to detect geometric differences (Veltkamp and Hagedoorn, 2001). Another one resembles probabilistic alignment (Pope and Lowe, 2000) to recognize unfamiliar zones between view-based object image and test image.

In this second step, we used purely image-based methods and some ideas of the probabilistic alignment to achieve a robust inline detection of anomalies under the assumption that the object view changes smoothly. The same wide-range camera for object localization was used for this step.

Using the result of object localization to segment an object from an image, a database with 2D object images can be built up in a separate learning step. We postulated that the views were limited either of the front side or the back side of the test object with small changes of viewing angles and furthermore postulated that we had constant lighting conditions in the environment.

We used the calibration matrix and the 2D object images to create a 3D view-based virtual object model at the 3D location where an actual test object was detected. The next process was to project the view-based virtual object model into the image plan. The interesting test zones (anomalies, see Figure 4) where detailed inspections were needed (see section 4 and 5) were detected within the segmented image area by the following steps:

- comparison between the projected view-based object image and the actual test image;
- morphological operations;
- Feature analysis.

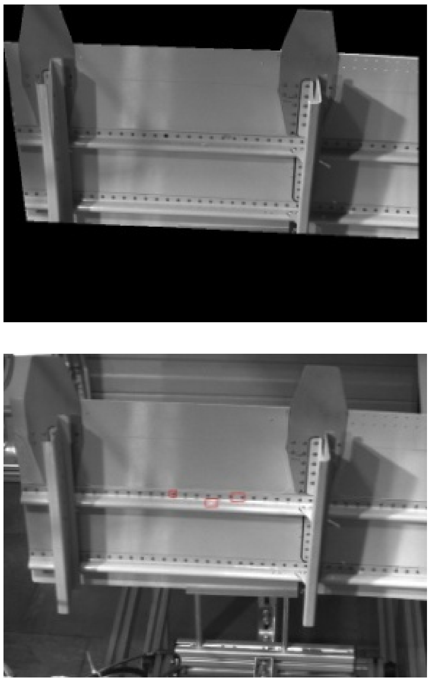

Figure 4: Upper: One of the segmented object images in the learning step. Only the segmented area in an image is relevant for the detection of anomalies. Lower: The automatic detected test zones are marked with red rectangles (overlays).

4 TIME-OPTIMAL DYNAMICAL PATH PLANNING

In the third step, an optimized inspection path plan is generated just in time, which is then carried out using various inspection-specific short-range sensors (e.g. cameras, feeler, etc.).

All the interesting test zones or the regions of interest (ROIs) have been found in the second step, but the path plan is not perfect yet. A time-optimal path has to be found from the supervising system.

The problem is closely related to the well known travelling salesman problem (TSP), which goes back to the early 1930s (Lawler et al., 1985; Applegate et al., 2006). The TSP is a problem in discrete or combinatorial optimization. It is a prominent illustration of a class of problems in computational complexity theory which are classified as NP-hard.

The total number of possible paths is calculated by: $\boldsymbol{M = (n - 1)}$. The definition of the TS-problem is based on the following assumptions:

- Modelled as a graph with nodes and edges;

- Graph is complete, this means that from each point there is a connection to any other point;
- The graph can be symmetric or asymmetric;
- The graph is metric, that means it complies the triangle inequality $C_{ij} \leq C_{ik} + C_{kj}$ (e.g. Euclidian metric, maximum metric).

Locking at the algorithms for solving TS-problems, there exist two different approaches:

Exact algorithms which guarantee a global optimal solution and heuristics, where the solution found is only locally optimal.

The most accepted exact algorithms which guarantee a global optimum are Branch-and-Cut Method, Brute-Force and Dynamic Programming. The major disadvantage of the exact algorithms mentioned above is the time consuming process finding the optimal solution. The most common heuristic algorithms used for the DSP are:

- Constructive heuristics: The Nearest-Neighbor-Heuristic chooses the neighbor with the shortest distance from the actual point. The Nearest-Insertion-Heuristic inserts in a starting path additional points;
- Iterative improvement: Post-Optimization-methods try to modify the actual sequence in order to shorten the overall distance (e.g. k-opt heuristic).

We used a heuristic algorithm with the following boundary conditions:

- The starting point has the lowest *x*-coordinate;
- The Nearest-Neighbor-Constructive heuristics look for the nearest neighbour starting with the first node and so on;
- The iterative improvement permutes single nodes or complete sub graphs randomly;
- Terminate, if there was no improvement after *n* tries.

The optimized path planning discussed above was tested at the DDP with a realistic scenario. Given a work piece of 1 by 0.5 square meter, the outputs of the second step (see section 3) are 15 detected ROIs. This would lead to a total number of about 43.6 billion possible different paths.

Starting with a 1st guess as outlined with an associated path length set to 100 %, after 15 main iteration loops the path lengths drops down to nearly 50 % of the first one, and no better achievement could be found (see Figure 5). The calculation time for the iterated optimal path was less than 1 sec. on a commercial PC, Intel Pentium 4 with 3 GHz, and took place while the robot moved to the starting position of the inspection path.

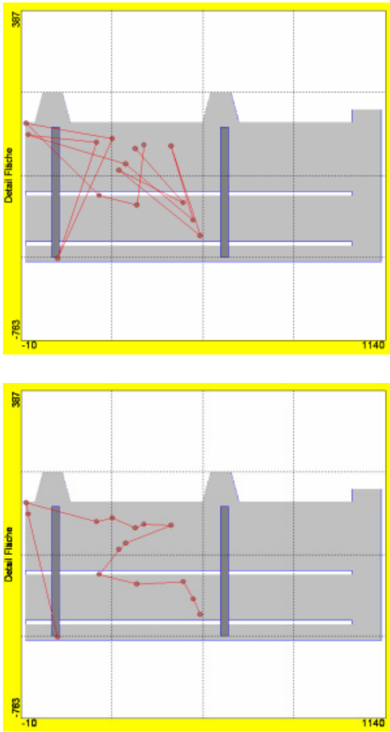

Figure 5: Upper: initial path; Lower: final path.

5 VISION-BASED INSPECTION

In the fourth step, the robot uses those sensors which are necessary for a given inspection path plan and guides them along an optimal motion trajectory into the previously-identified ROIs for detailed inspection. In these ROIs a qualitative comparison of the observed actual topography with the modeled target topography is made using image-processing methods. In addition, quantitative scanning and measurement of selected production parameters can be carried out.

For the navigation and position control of the robotic movement with regard to the imprecisely-guided production object as well as for the comparison of the observed actual topography with the target topography, reference models are required.

These models, using suitable wide-range and short-range sensors, were scanned in a separate learning step prior to the generation of the automated inspection path plan. Two sensors have been used for our work: A 3D split-beam sensor is used (Deutscher et al., 2003) for the metric test task (see Figure 6) and a short-range inspection camera with a circular lighting is used for the logical test task. For a fuselage, for example, it can be determined if construction elements are missing and/or if certain bore diameters are true to size.

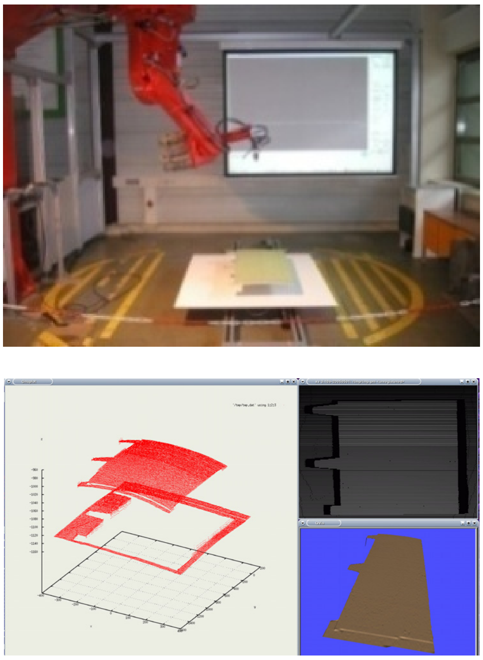

Figure 6: A split-beam technique captures the structure of a 3D object (upper part) and translates it into a graphic model (lower part).

By using the proposed, robot-based concepts of multiple sensor quality monitoring, the customary use of expensive 3D CAD-models of the test objects for high-precision CNC controlled machine tools or coordinate inspection machines becomes, in most instances, unnecessary.

An intelligent, sensor-based distance-control concept (Visual-Servoing-Principle) accurately controls the robot's movements with regard to the work piece and prevents possible collisions with unexpected obstacles.

6 CONCLUSIONS AND FUTURE WORK

A development and demonstration platform (DDP) for flexible inline quality monitoring using picture-giving sensors was created.

The primary goal of the DDP is to investigate, optimize and demonstrate to potential cooperation partners how the system can be applied to reduce effort and to increase flexibility. For example, it can be used in the robot-based coordination of short- and wide-range monitoring, for the introduction of learning-capable evaluation processes, as a tool for visualizing results and for user interaction, as well as for the flexible networking and integration of various wide- and short-range sensors.

Further inspection sensors, which are based on another measurement principle, will be developed soon on the sensor magazine and made available for the surface testing. Investigations and pre-developments for further (complex) applications can be realized with the platform at small expenditure. The applications for example can look like:

- The surface inspection of the outside and the structural examination of the inside of a car door;
- The crawler-type vehicle order supervision within the range of a car window.

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REFERENCES

Applegate, D. L., Bixby, R. E., Chvátal, V., Cook, W. J., (2006). *The Traveling Salesman Problem: A Computational Study*. Princeton University Press. ISBN 978-0-691-12993-8.

Deutscher, R., Munser, R., Hartrumpf M., (2003). Detection and Measurement of Damages in Sewer Pipes with a 3D-structured Light Projection Sensor, *In: tm - Technisches Messen 70,* 2003(07):338-345.

Lawler, E. L., Lenstra, J. K., Rinnooy Kan, A. H. G., Shmoys, D. B., (1985). *The Travelling Salesman Problem. A Guided Tour of Combinatorial Optimization*. Wiley, Chichester 1985. ISBN 0-471-90413-9.

Müller, Th., (2001). Modellbasierte Lokalisation und Verfolgung für sichtsystemgestützte Regelungen, Dissertation an der Universität Karlsruhe (TH), 8. Februar 2001.

Pope, A. R., Lowe, D. G., (2000). Probabilistic Models of Appearance for 3D Object Recognition. *International Journal of Computer Vision,* 40(2):149–167.

Sung, C.-K., Kuntze, H-B., (2006). Flexible roboterbasierte Qualitätsüberwachung mit bildgebenden Sensoren, *Sensor Magazin*, Magazin Verlag Hightech Publications KG, Bad Nenndorf, 2006(3):24-26.

Veltkamp, R.C., Hagedoorn, M., (2001). State-of-the-art in shape matching. In M. Lew (Ed.), *Principles of Visual Information Retrieval*, Springer.