Learning Manipulator Behaviors Based On Visual Demonstration

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Abstract

As opposed to the usual approach of programming robot arms by giving a complete description of the trajectory (e.g. *direct programming*) this work is based on the idea of *Programming by Demonstration*. Only few intermediate positions, which approximate the trajectory, are given and recorded by a stereo-camera-system. The idea is to extract the path of the manipulator gripper from the images by geometrical connecting this positions to form a smooth trajectory. This is done by tracking the appearance of the gripper in the sequence of stereo images. The gripper position in previous images and the gripper appearance are used for locating it in the next images. Based on this sequence of positions a *trajectory-structure* is formed, which allows to execute a vision based movement. The trajectory is general in the sense that the starting position and the orientation can be specified variable. The approach can be used in the assembly industry for approaching a working tool to a certain object and handling it (e.g. a screw spanner).

1 Introduction

Instead of programming a robot by giving a complete description of the trajectory (e.g. *direct programming*) this approach is based on the idea of *Programming by Demonstration*, which means to indirect program a system by giving examples. Basic ideas and related work on this topic can be found in [Heise 92] and [Friedrich96].

The operator uses the control panel to move the gripper in discrete steps to intermediate positions of the desired trajectory. A stereo-camera-system records this sequence and a computer-vision-system reconstructs a smooth 3D-trajectory. This trajectory only serves as an example for a whole class of trajectories having variable starting position and orientation. In the application phase this two unknowns have to be determined (e.g. manually by the operator or, perhaps, automatically with the help of a vision system). Furthermore, the information of the gripper trajectory can be used to anticipate collisions with unexpected objects in order to early interrupt the course.

The gripper is tracked in the images by using its appearance in the previous image as decribed in section 2. Section 3 briefly explains the calibration used. In section 4 a *trajectory structure* is defined, which allows to execute a vision based movement. Figure 1 shows the whole system and the way the components depend on each other.

2 Tracking the gripper

To extract a series of gripper positions from a sequence of images, the gripper has to be located in every single image. To be more precise, in every single image a certain *reference point* of the

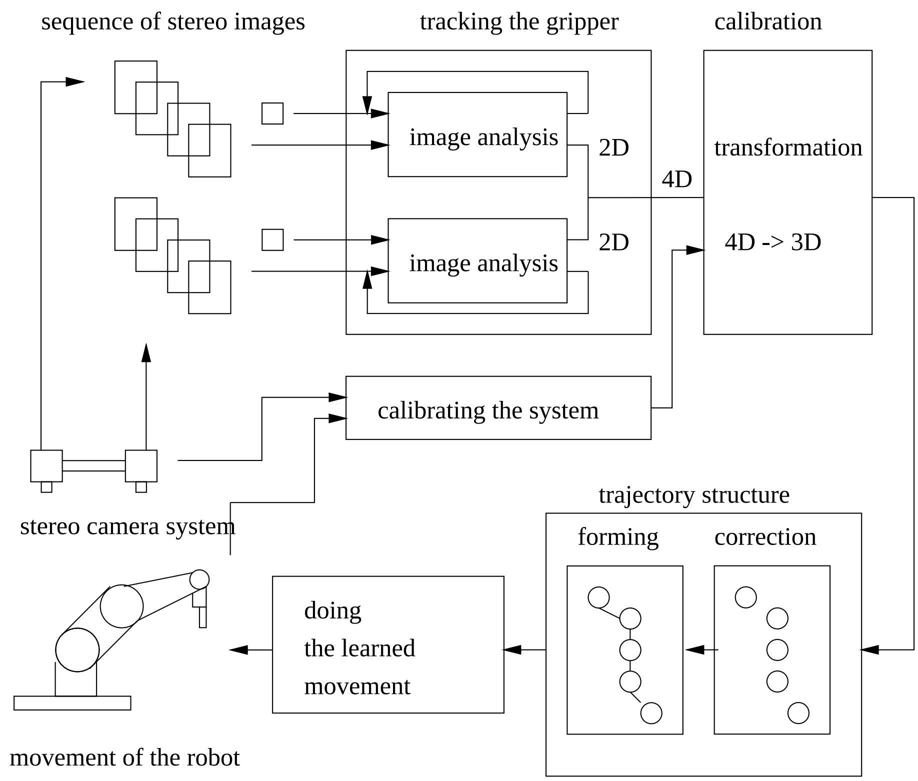


Figure 1: The components and their interaction.

gripper must be detected. Based on this precondition it is possible to consider the extracted positions as intermediate points of the movement. A two step procedure is applied to extract the reference point from the images:

(i) roughly locate final segment of the gripper by using its appearence (greylevels) from previous image

(ii) exactly determine the reference point by geometrical analysis in the selected *gripper image region* (in the following named *patch*).

In figure 2 the procedure is illustrated graphically.

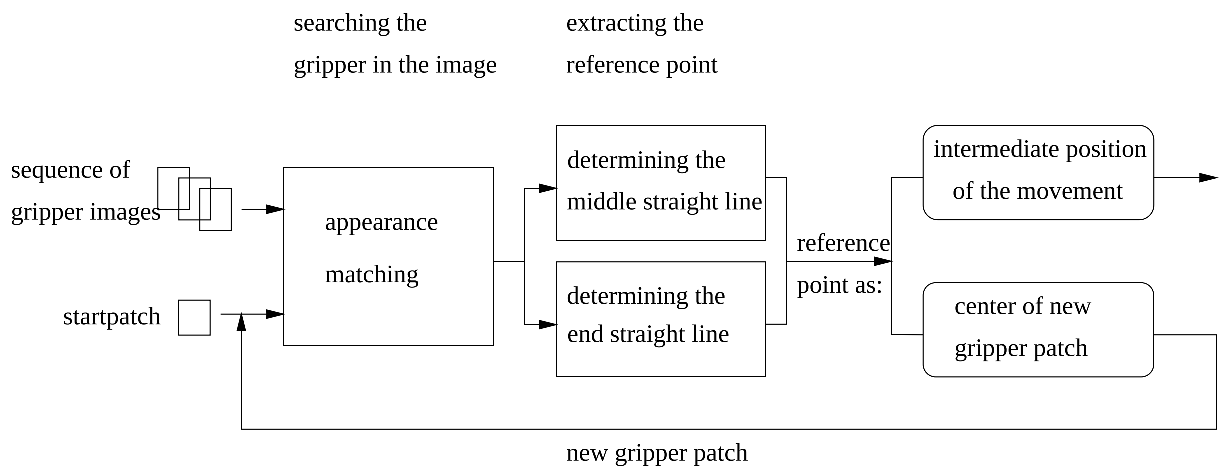


Figure 2: Tracking the gripper - a two step procedure.

The input of the procedure is a sequence of stereo images representing the movement of the gripper in discrete steps. Furthermore, two image patches are supplied - one for each image sequence - which depict the appearance pattern of the gripper in the starting position of the movement. Both image sequences of the stereo cameras are analysed the same way but independently.

2.1 Locating the gripper region

The gripper image region is located by correlation matching using the expected gripper appearance (instead of using a model of the gripper). An $(m \times m)$-image B depicts the whole scene in which the robot arm is working and an $(n \times n)$-patch P contains the final segment of the gripper. Now a correlation image C is computed, by defining $C(k,l)$ as sum of squared distances
$C(k,l) = \sum_{\substack{i \in \left\{k-\frac{n}{2},\ldots,k+\frac{n}{2}\right\} \\ j \in \left\{l-\frac{n}{2},\ldots,l+\frac{n}{2}\right\}}} \left(B(i,j) - P(i-(k-\frac{n}{2}), j-(l-\frac{n}{2}))\right)^2$ for each image position (k,l).
Figure 3 shows a scene, the relevant gripper image region and the resulting correlation image (brighter greylevel indicates better correlation).

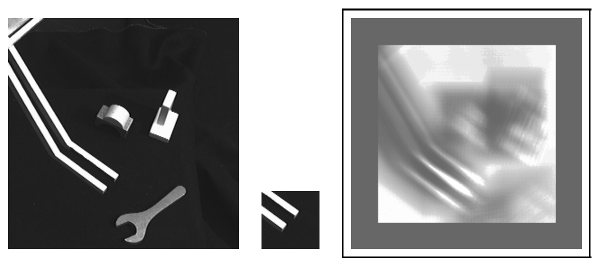


Figure 3: Scene, gripper image region and resulting correlation image.

The position of maximal correlation is looked for by starting the search in the position of the patch located in the previous image and expanding the catchment area (for reasons of efficiency). The position with the least sum of squared distances is expected to be the center of the relevant $(n \times n)$-region containing the tip of the gripper fingers.

2.2 Locating the reference point

Next, a certain reference point on the depiction of the gripper must be defined and located in the image as exact as possible. It will be used both as an intermediate position of the whole movement and as the center of the gripper image region for locating the gripper in the following image of the sequence. Figure 4 shows graphically the reference point of the gripper defined for this purpose. It is the virtual point of intersection between the *middle straight line* and the *end straight line* of the robot gripper. To extract these straight lines it is necessary to first recognize the top faces of the gripper.

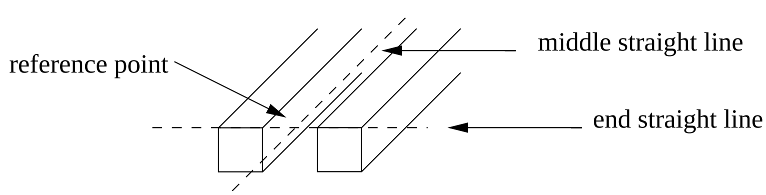


Figure 4: Definition of a reference point of the gripper.

2.2.1 Extracting the top faces of the gripper

This is done in two different ways using simple heuristics, depending on whether an object is grasped or not. In the case of a free gripper it is assumed that the image patch can be segmented into regions as follows. The background area of the gripper is approximately homogenous and therefore can be segmented in one region, which is expected to have the largest area of all regions. Furthermore, the gripper fingers are spacely disconnected, the top faces of the two gripper fingers are homogenous and can be segmented into one region for each, and they are the second and third largest areas. Figure 5 shows exemplarily the validity of these heuristics in the case of a free gripper. However, if an object is grasped these preconditions are no longer valid and that is why another heuristic is needed. It has to be mentioned, that the scene is lighted quite well and the gripper is made of reflecting material. This guarantees the top faces to be those parts of the image with the highest greylevel. Figure 6 illustrates the validity of these heuristic in the case of a grasped object.

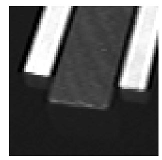


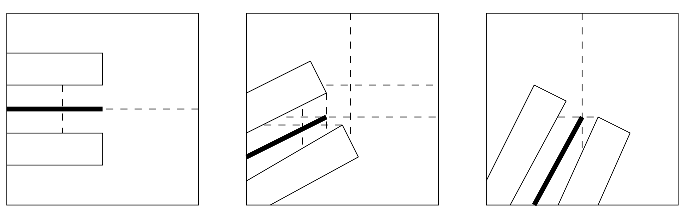
Figure 5: Gripper patch without object and its segmentation image.

Figure 6: Gripper patch with grasped object and its segmentation image.

From the segmentation result a reference point of the gripper must be extracted as intersection between the middle straight and the end straight line.[1]

2.2.2 Detecting the middle straight line

For this a middle straight line is determined exactly between the extracted regions of the two gripper fingers which come from the top faces of the gripper. Each point on this middle straight line is characterized such that the Euclidean distance to both regions is equal. Alternatively, a city block metric, which computes distances only in x- respectively y-direction, works as well (see figure 7). If the distance in positive and negative x- (y-) direction is equal this point is added to a set M of points near or on the middle straight line. The middle straight line is obtained by fitting a straight line through the points of M.



(a) (b) (c)

Figure 7: Determining points between top faces of fingers to extract a middle straight line.

[1] For other robotic equipment special attributes must be explored which are suitable to detect the gripper in the image (e.g. specific gripper color or an identity tag) and extract a certain gripper reference point.

2.2.3 Detecting the end straight line

First a set of relevant grey level edges is extracted from the gripper image region by computing the gradient magnitudes and setting a threshold. Care must be taken with this threshold to guarantee that at least two corner points of the final segment of the two gripper fingers are in the set of edges. In a second step the relevant corners have to be detected in the binary image of edges. A binary correlation mask (see figure 8) is used having edge points at the middle vertical axis. The mask is applied at every edge of the binary gripper image and rotated in discrete steps of angles in the interval of $[0, 360]$ degrees.

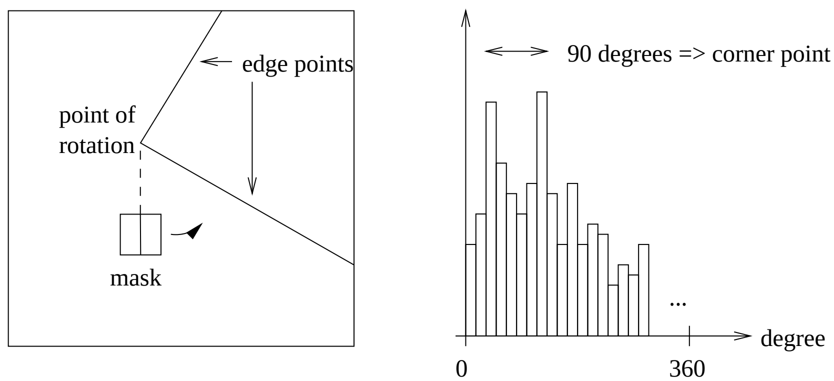


Figure 8: Rotating a squared mask to detect corners of the gripper fingers.

For each rotation step a value is retained which describes how many edges of the middle axis of the mask correspond to edges of the gripper. If two maximum peaks are found, being about 90 degrees apart from each other, then the rotation point belonging to that situation is taken as corner point. Only those points are considered, which are close to the top faces. The end straight line is obtained by fitting a straight line through these corner points.

3 Calibrating the camera system

Calibrating a stereo camera system means to find the relation between *image coordinates* ($2 \times$ 2D) and *world coordinates* respectively *robot coordinates*. Figure 9 shows the dependencies.

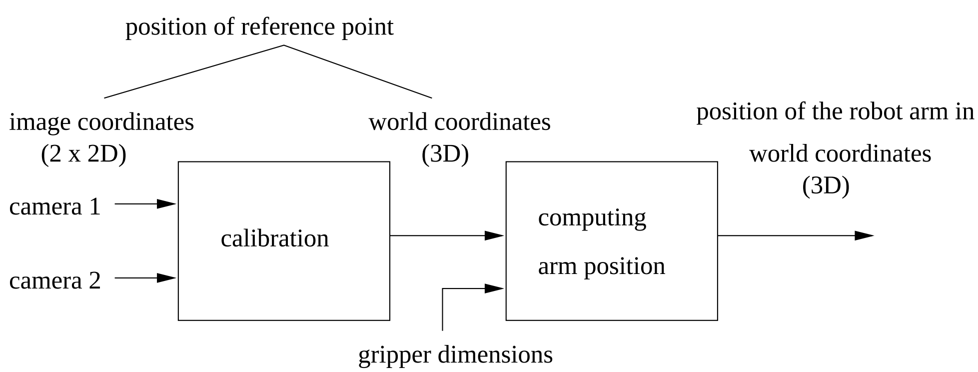


Figure 9: Transformation from 4D-image coordinates to 3D robot coordinates.

To obtain the function $calib : 4D \rightarrow 3D$ we use the technique proposed in [Faugeras93]. For each camera a matrix

$$P_i = \begin{pmatrix} p^i_{11} & p^i_{12} & p^i_{13} & p^i_{14} \\ p^i_{21} & p^i_{22} & p^i_{23} & p^i_{24} \\ p^i_{31} & p^i_{32} & p^i_{33} & p^i_{34} \end{pmatrix}$$

($i = 1, 2$) is computed by using pairwise combinations of 3D world points and the 4D stereo points. The usage of the matrix is specified within the following context. Given a point in world coordinates (x_w, y_w, z_w) the position in image coordinates can be obtained by solving

$$\begin{pmatrix} x_i \\ y_i \\ 1 \end{pmatrix} \cdot \delta_i = P_i \cdot \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix},$$

where δ_i is an arbitrary scale factor. However, starting with a stereo image point (x_1, y_1, x_2, y_2) a transformation is needed for computing the world coordinates (x_w, y_w, z_w).
By combining P_1 and P_2 an overdetermined linear equation system ($\vec{b} = P\vec{a}$) is obtained. It can be solved for the vector $\vec{a}$ which contains the unknown 3D world coordinates and the two unknown scale factors by computing the pseudo inverse matrix of P. The matrix P and the vector $\vec{b}$ contain given calibration attributes and the given stereo image point for which the 3D world coordinates are requested.

$$\vec{a} = (P^T P)^{-1} \cdot P^T \cdot \vec{b}$$

In order to compute the calibration attributes a set of associations between 3D world points and 4D stereo image points is needed. For the purpose of this work it is possible to compute the relation between image and robot coordinates directly without an intermediate world coordinate system. Due to the dexterity of the robot manipulator only one 3D world point is needed namely the reference point of the gripper described in section 2. The manipulator is moved in discrete steps through the working space and along this course the reference point is recorded in 3D (known from the control unit of the robot) and is additionally detected in the stereo images to acquire the series of 4D stereo points.

4 Trajectory structure

Using the calibration result the reference point of the gripper can be reconstructed into 3D robot coordinates for arbitrary positions of the gripper in the working space. Furthermore, taking the same coordinate system into account, the position of obstacles could be determined by reconstruction from stereo data. Based on both, Euclidean relations between the robot gripper and obstacles could be represented. In order to learn a trajectory (possibly through a collection of obstacles) the system user is asked to demonstrate an example trajectory. For this, the user steers the gripper through the working space and stops at certain intermediate places, and the system computes a sequence of 3D positions $(x_1, y_1, z_1), ..., (x_n, y_n, z_n)$ extracted from the series of stereo images. This section describes how to acquire and use a smooth trajectory.

4.1 Definition

A trajectory structure will be defined by having in mind, that the operator should demonstrate just an example of a class of congruent trajectories. That is, during the application phase the example trajectory will be adapted to any desired starting position and orientation. Therefore, it must be possible to easy include the concrete starting position and orientation as soon as they become known. Accordingly, during the demonstration phase a trajectory structure will be constructed, which represents only the geometric relationship between intermediate points and not the absolute positions and orientations.
The trajectory structure is a sorted sequence $(k_1, ..., k_m)$ of nodes. Each node refers to an intermediate point of the trajectory and is defined by three components:

- vector $(v_x, v_y, v_z) \in IR^3$, written as $k_i.(v_x, v_y, v_z)$
- increment to the following node $(dx, dy, dz) \in [-1, 1]^3$, written as $k_i.(dx, dy, dz)$
- orientation $\varphi \in [0, 2\pi]$, written as $k_i.\varphi$

Vector $k_i.(v_x, v_y, v_z)$ decribes the relation between point (x_i, y_i, z_i) and (x_1, y_1, z_1), defined as

$$k_i.(v_x, v_y, v_z) = (x_i, y_i, z_i) - (x_1, y_1, z_1) \quad , \qquad \text{for all} \;\; j \in \{1, ..., n\}$$

The increments are given by

$$k_i.(dx, dy, dz) = k_{i+1}.(v_x, v_y, v_z) - k_i.(v_x, v_y, v_z)$$

for a node k_i $(i \in \{1, ..., n-1\})$.
The orientation φ of the gripper at node k_i can be chosen free. In the implementation reported here it should keep an orthogonal orientation to the tangent at every point of the trajectory.

4.2 Using the structure

To perform a movement the trajectory has to be defined absolutely by incorporating the starting point (x_s, y_s, z_s) and three rotation angles $\varphi_{xy}, \varphi_{xz}, \varphi_{yz}$ (describing the rotation in the xy-, xz- and yz-coordinate-plane). The structure is moved into the starting position, which means every node is translated with (x_s, y_s, z_s), and then it is rotated as defined by $\varphi_{xy}, \varphi_{xz}, \varphi_{yz}$. Figure 10 shows a simple example (for simplicity in 2D).

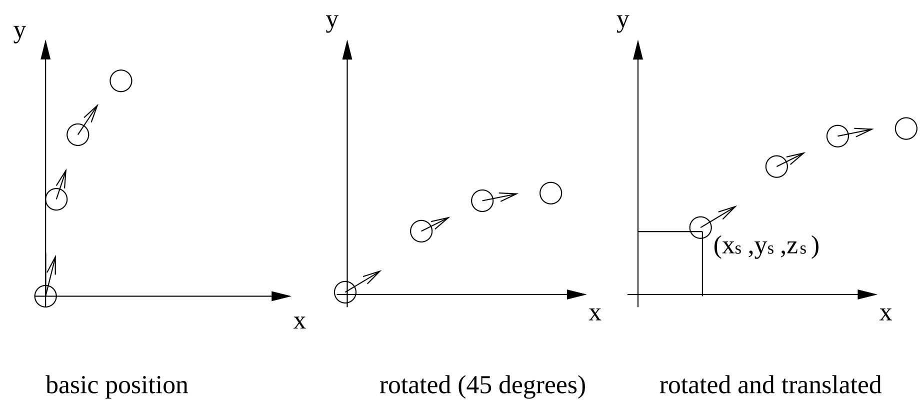


Figure 10: Moving the trajectory structure in the starting position and orientation.

When the robot starts to move the fingers beginning from (x_s, y_s, z_s) the second node works as an *attractor* until it is reached. Now the next node comes into play and the procedure is repeated for all nodes of the trajectory structure. A criterion is needed to test, whether a node is passed or not. For this a plane defined by the position of the node $k_i.(v_x, v_y, v_z)$ and the stored increment $k_{i-1}.(dx, dy, dz)$ is used. When the robot continues to move the fingers it is tested node by node whether the respective plane is passed. For a position (x_p, y_p, z_p) of the fingers the difference vector $(x_d, y_d, z_d) = (x_p, y_p, z_p) - k_i.(v_x, v_y, v_z)$ and the scalar product s between (x_d, y_d, z_d) and $k_{i-1}.(dx, dy, dz)$ is calculated. There are three cases to deal with:

- $s > 0 \Longrightarrow -90 < |\angle((x_d, y_d, z_d), k_{i-1}.(dx, dy, dz))| < 90$
- $s = 0 \Longrightarrow |\angle((x_d, y_d, z_d), k_{i-1}.(dx, dy, dz))| = 90$
- $s < 0 \Longrightarrow 90 < |\angle((x_d, y_d, z_d), k_{i-1}.(dx, dy, dz))| < 270$

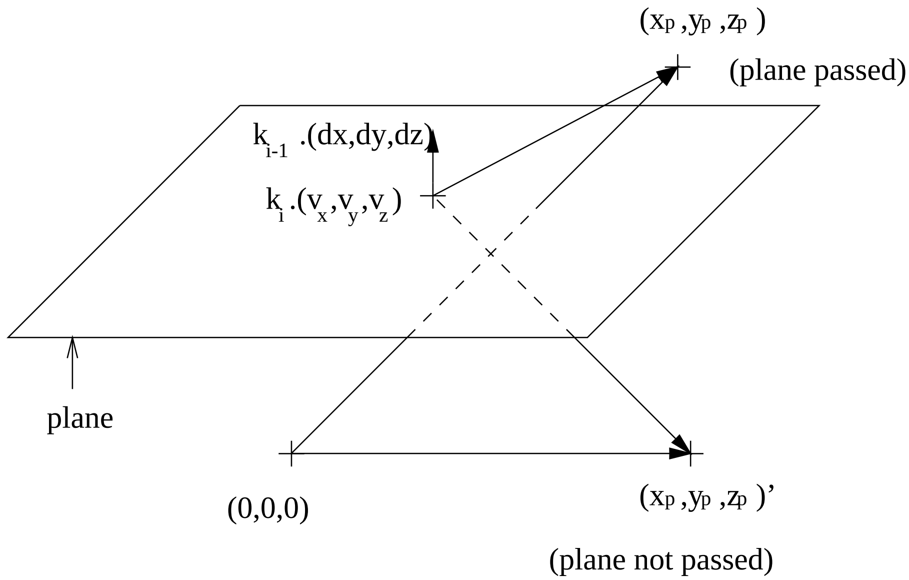


Figure 11: Testing whether an intermediate position of the demonstrated trajectory is passed or not.

If $s < 0$ then the fingers have not yet reached the plane belonging to a certain point of the trajectory, if $s = 0$ then the plane is reached, and $s > 0$ means that it is passed.
Figure 11 illustrates this criterion. Finally the orientation of the gripper at a certain point on the trajectory has to be found. This is done by first calculating the distances to attracting node k_i and preceding node k_{i-1} as

$$dist_v = \sqrt{(x_p - k_{i-1}.v_x)^2 + (y_p - k_{i-1}.v_y)^2 + (z_p - k_{i-1}.v_z)^2}$$

and

$$dist_a = \sqrt{(x_p - k_i.v_x)^2 + (y_p - k_i.v_y)^2 + (z_p - k_i.v_z)^2}$$

and then computing the orientation of the gripper as weighted mean of $k_{i-1}.\varphi$ and $k_i.\varphi$:

$$\varphi' = \frac{dist_a \cdot k_{i-1}.\varphi + dist_v \cdot k_i.\varphi}{(dist_a + dist_v)}$$

Figure 12(a) shows a simple example of the path from node to node. Furthermore, figure 12(b) shows an interesting behavior if a certain intermediate point can not be reached exactly, maybe due to an obstacle at that place. In this case the subsequent node attracts the gripper and thus it comes back to the original trajectory. Therefore, the course of the robot gripper can partially deviate from the learned trajectory at local areas due to certain requirements and adaptively return back to the target trajectory afterwards.

4.3 Smoothing

Usually the positions extracted from the images are unprecise, because of resolution limit of the image or errors in calibration. To get a smooth trajectory a simple method can be used by considering the position of the neighbouring nodes. For a node k_i the position is adjusted by first calculating the distance between k_{i-1} and k_{i+1} as

$$d_1 = \sqrt{(k_{i+1}.v_x - k_{i-1}.v_x)^2 + (k_{i+1}.v_y - k_{i-1}.v_y)^2 + (k_{i+1}.v_z - k_{i-1}.v_z)^2}$$

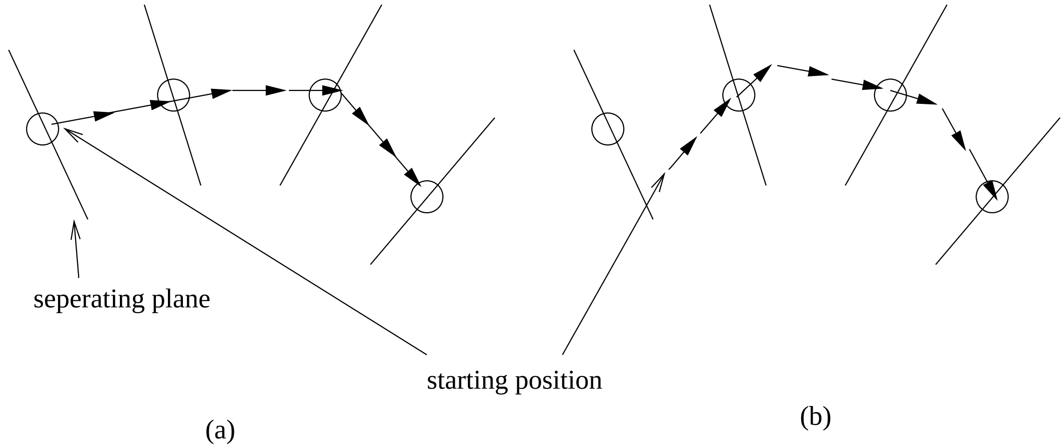


Figure 12: Example showing the resulting movements beginning in the starting point (a) or somewhere beside of it (b).

Then
$$(x_m, y_m, z_m) = k_{i-1}.(v_x, v_y, v_z) + \frac{d_1}{2} \cdot k_{i-1}.(dx, dy, dz)$$
is the point in the middle position between k_{i-1} and k_{i+1}. The distance between $k_i.(v_x, v_y, v_z)$ and (x_m, y_m, z_m) is

$$d_2 = \sqrt{(k_i.v_x - x_m)^2 + (k_i.v_y - y_m)^2 + (k_i.v_z - z_m)^2}$$

To do the adjustment two parameters $\varepsilon_1, \varepsilon_2 \in [0, 1]$ are defined. ε_1 defines whether a correction has to be done (e.g. in the case of large distances between points) and ε_1 says *how strong* it should be done. With $(x_d, y_d, z_d) = (k_i.v_x - x_m, k_i.v_y - y_m, k_i.v_z - z_m)$ the new position is

$$k_i.(v_x, v_y, v_z)' = \begin{cases} k_i.(v_x, v_y, v_z) + \varepsilon_2 \cdot (x_d, y_d, z_d) & , \text{ if } \quad d_2 \geq \varepsilon_1 \cdot d_1 \\ k_i.(v_x, v_y, v_z) & , \text{ otherwise} \end{cases}$$

This adjustment is done for the position of every single node starting with k_2.

5 Experiments

The experiments have been carried out with an industrial articulation robot having six rotational degrees of freedom and a two-fingered gripper. Image processing is done in the KHOROS environment on a SUN workstation 10/40. Exemplarily, the system was engaged to learn to handle a screw spanner. This means that a course of the manipulator must be learned such that the screw head will be turned around in a circle. In order to automatically learn the required trajectory of the robot gripper the system user steered the robot in 30 discrete steps of 3 angle degrees and according to that a quarter of a circle is approximated. Figure 13 shows for three intermediate steps on this course some processing results involved in visually evaluating the trajectory of the gripper fingers. The three images in the first row depict these intermediate steps. The second row shows pairwise the located regions of the finger tips of the gripper and corner points of the fingers. Finally, the images in the third show the result of computing the middle straight line and the end straight line of the fingers and the intersection point between both which is used as reference point. This point is extracted in all 90 images of the quarter cycle demonstration and a smooth gripper trajectory is approximated and reconstructed thereof. To get an impression for the accuracy of the learned movement the deviation from the radius has been measured. This deviation was at most 3 mm for a screw with head radius 15 mm.

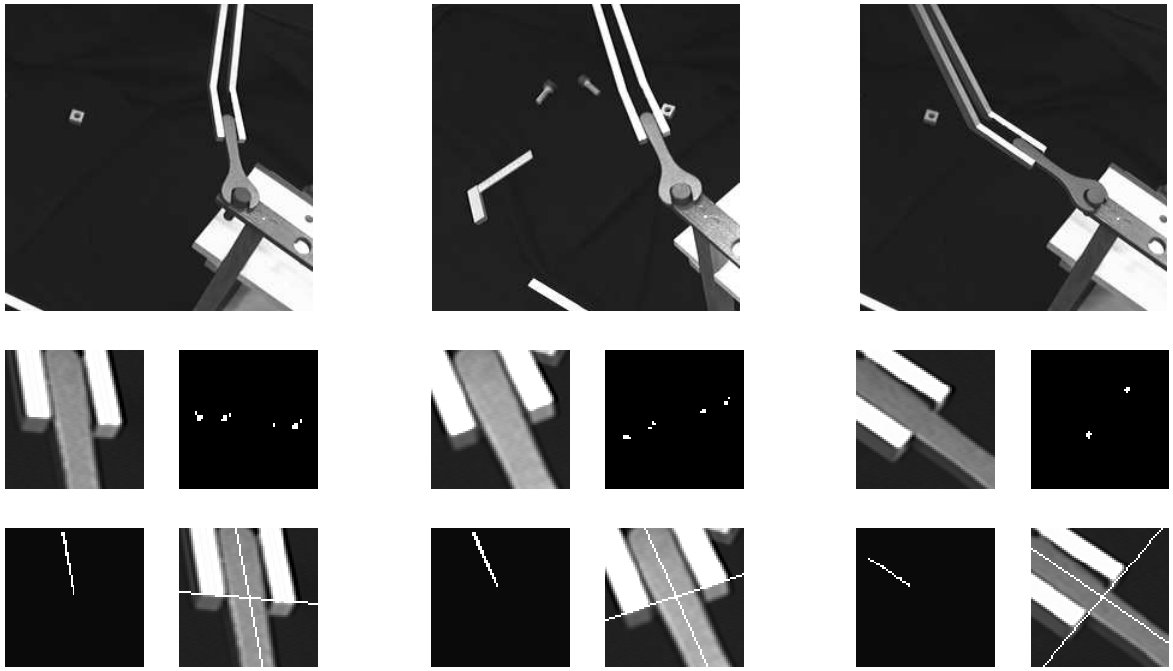


Figure 13: Intermediate steps of handling a screw spanner, and visual processing.

6 Conclusions

The proposed framework enables an operator to program a robot by just giving intermediate positions recorded by a stereo camera system. For the operator there is no need for exact knowledge of how to program the robot. Instead, it is possible to use the example trajectory in various starting position and orientation by simple translation and rotation of it. Furthermore, it is possible to involve a computer vision system, which analyses the sequence of stereo positions for an early avoidance of collisions with new objects in the scene. The ability to react on unexpected appearance of obstacles and return to the original trajectory is one of the most important features of robot systems to be used in praxis.

References

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