Automated inspection of door parts based on fuzzy recognition system

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Abstract— **The article presents a comprehensive strategy of door parts (locks, handles, doorplates etc.) examination as a paradigm of active sensing. It covers the whole process – from segmentation, through initial hypothesis generation based on fuzzy inference, to final recognition and precise localization of the keyholes in a robot base coordinate system. The strategy is a preliminary stage of a door locks opening procedure. The image analysis process is divided into three steps. First, an initial region of interest is localized using a RGB-D low resolution camera mounted on the robot's head. It is then categorized, based on its properties, as a lock, handle, doorplate etc. Finally it is inspected using 2D camera mounted on the robot's arm. Thanks to the preliminary localization with the head camera the robot can look at the point of interest at sight, without time-consuming thorough inspection of the whole door. The whole system was formally specified as an embodied agent. For that purpose a system modeling language was used to specify embodied agent subsystems behaviors. The proposed strategy is verified experimentally using Velma prototype service robot.**

I. INTRODUCTION

The demographical processes in modern societies all over the world motivate research on service robots as companion for elderly people [1]. These robots need to operate indoor, e.g. in kitchens [2]. Robot navigation in such environment requires robust methods of door detection and identification, and the localization of handles and locks. When the robot needs to enter a room with door, the manipulation subsystem's role is to unlock the door, e.g. by pushing the handle [3]. Then, the robot can open the door by moving its arm in stiff contact with door plane [4] or alternatively by pulling a doorknob [5] or handle [6] using versatile multifingered grippers. The problem of how to deal with door locks remains open for research.

In current work we present a comprehensive strategy of door parts (locks, handles, doorplates etc.) examination as a paradigm of active sensing [7], [8]. It includes image segmentation, initial hypothesis generation based on fuzzy inference and final recognition and precise localization of the keyholes in a robot base coordinate system. The strategy is a preliminary stage of a door locks opening procedure.

For coarse localization of door features RGB-D data is used. It allows to determine the distance between the floor and analyzed objects, and also their absolute size. When the region of interest placement is initially determined using the RGB-D low resolution camera mounted on the robot's head, the next step is labeling, i.e. assignment of one or more known categories to each segment. This process uses fuzzy inference system with features such as size, shape, position used as input variables [9]. The last step depends on the task – in this article, a precise detection of a keyhole is used as an example. To achieve this, a close view inspection using a 2D camera mounted on the robot's arm is conducted.

For precise localization of a door lock, or generally a planar object, two different approaches may be applied – either template matching [10] or feature points matching [11]. Thanks to the preliminary localization with the head camera, the robot can look at the point of interest at sight, without time-consuming, thorough inspection of the whole door. For a robot equipped with multiple, independently moved vision receptors (cameras mounted on head and arms), image acquisition actions can be performed using an adequate sensor, taking into account cameras properties (e.g. effective image capture frame of the analyzed region of interest). The whole system was formally specified as an embodied agent [12]. For that purpose a system modeling language [13] was used to specify embodied agent subsystems behaviors [14] with special attention to vision virtual receptor [15].

The key part of our approach is flexibility. New object classes can be added with ease, by adding a new set of rules to the inference system. Similarly, additional algorithms for object examination can be added, as those are selected in the last step depending on the object label.

The article is organized as follows. Section II presents general system assumptions and the resultant system structure in the form of an embodied agent. The following sections describe the subsystems of the proposed embodied agent, i.e. the control strategy formulated as theirs behaviors. Section III describes the control subsystem of the agent, and its effectors and receptors are presented in sections IV and V. The proposed strategy is verified experimentally on Velma robot (section VI). Section VII concludes the work.

II. SYSTEM STRUCTURE

A service robot that performs presented analysis of the door objects needs to posses an active head with camera to briefly analyze the door from distance and to detect areas for further close view investigation. The other camera mounted on the arm, next to its wrist, is vital for the last step, to get a close view of particular areas of interest. In practice the robot should be equipped with movable torso to extend the workspace of the arm. A large workspace is needed to take pictures of the door elements placed on various heights with the optical axis of the arm camera perpendicular to the door plane while the camera looks directly at the currently examined feature.

To facilitate subsequent implementation of the control system of such a robot, an agent approach has been utilized.

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The inner structure of the robot, represented by a single *embodied agent*, has been decomposed into five types of internal subsystems: its effector E, receptor R, virtual effector e, virtual receptor r and a control subsystem c . The former two of above subsystems form the agent's corporeal body, whereas the latter three its control system. The embodied subsystems communicate with each other through dedicated input and output communication buffers.

In the proposed embodied agent the active head has its RGB-D camera represented by the real effector R_{hd} and the neck motors with encoders and servo controllers, which are represented by the head real effector E_h, controlled by the head virtual effector e_h. The 2D camera mounted on the arm is represented by the real receptor R_{ac}. The virtual receptor r_v processes the visual data from both cameras. The robot needs to control two additional real effectors: for arm – E_a and for torso – E_t, with the virtual effector e_{ta}. The role of the above subsystems will be described in detail in the following sections.

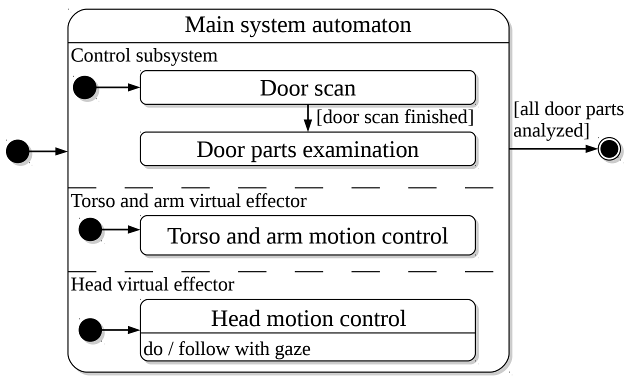

Fig. 1. Main system automaton

The control subsystem behaviors are executed simultaneously with virtual effectors behaviors as it is presented in main system automaton depicted in Fig. 1.

III. CONTROL SUBSYSTEM

The control subsystem automaton (Fig. 1) consists of two behaviors. The behaviors execute the postulated stages of door objects analysis: an initial door scan (sec. III-A) and a subsequent door parts examination, i.e. keyholes localization (sec. III-B).

A. Door scan behavior

We assume that the initial robot position allows to scan the door with a RGB-D camera mounted on its head, without the need to move the robot's base. „Door scan" is the first behavior to launch (Fig. 2). The position of head target point A_t expressed in robot base frame ${}^{0}_{A_t}P$ is initially set as the door top coordinates, e.g. on the height of 2 meters in front of the robot. The ${}^{0}_{A_t}P$ is sent to the head virtual receptor – e_h. The control subsystem waits until the head motion is completed. Then a measured head camera pose ${}^{0}_{D'}T$ is sent to the vision virtual receptor r_v and its „detect points of interest" behavior is activated. The control subsystem collects desired arm camera poses ${}^{0}_{C}T$, adequate for the localized points of interest computed by r_v, enriched with generated hypotheses about type of particular feature. The system makes succeeding scans, changing the z coordinate of ${}^{0}_{A_t}P$ until the whole door is analyzed. The list of desired arm camera poses ${}^{0}_{C}T$ is updated with subsequent scans, taking into account the possible duplicates of particular points of interest.

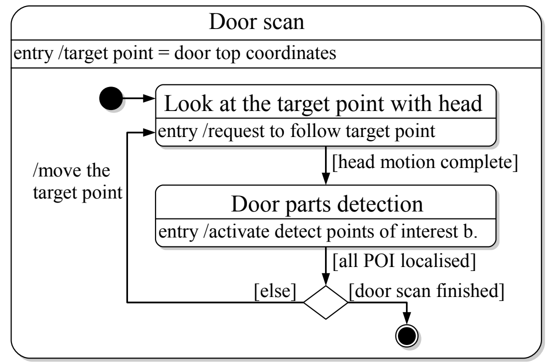

Fig. 2. „Door scan" control subsystem behavior

B. Door parts examination behavior

The „door parts examination" behavior (Fig. 3) analyzes all of the initially localized points of interest, represented by a list of desired arm camera poses ${}^{0}_{C}T$. For presentation purposes, we focus on door locks. As a result the list of detected keyholes position ${}^{0}_{K}P$ is returned. In every cycle, a desired arm wrist pose ${}^{0}_{W}T$ is computed

$$ {}^{0}_{W}T = {}^{0}_{C}T \left({}^{W}_{C}T\right)^{-1} \tag{1} $$

where ${}^{W}_{C}T$ denotes constant camera location expressed in arm wrist coordinate system. Then the arm and torso virtual effector e_{ta} interpolates the trajectory, while control subsystem waits until the trajectory execution is finished. Measured arm camera pose ${}^{0}_{C'}T$ can slightly differ from the desired one, depending on arm manipulator control properties (especially when impedance control with noticeable friction and relatively low control stiffness is applied). Each door part is analyzed by the virtual receptor e_v „detect keyhole position" behavior that takes into account measured camera position ${}^{0}_{C'}T$.

IV. ROBOT EFFECTORS

The effectors are presented from the point of view of their control. The arms and torso virtual and real effectors are described in sec. IV-A. The head virtual and real effectors are described in sec. IV-B.

A. Arm and torso control

The task of door lock recognition is one of the steps that constitute the process of door opening, hence the whole robot should be controlled in a way that ensures that it's ready for contact with any object, obstacle or person that may appear in its surroundings. The movable torso is needed to

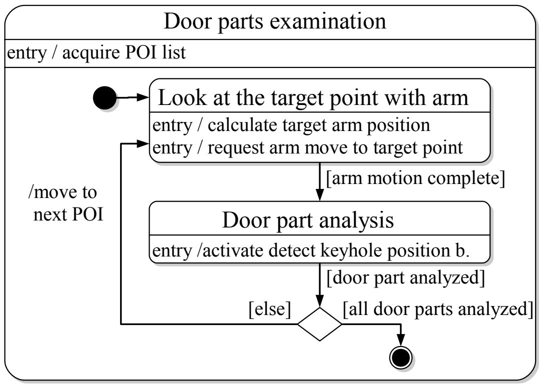

Fig. 3. „Door parts examination" control subsystem behavior

extend the workspace of arms, that makes the kinematic chain redundant. One of the approaches studied so far to satisfy above conditions is impedance control [6] with null-space control [16]. The virtual effector receives E_{ta} desired wrist pose ${}^{0}_{W}T$ from the control subsystem c and computes the trajectory under certain constraints, e.g. maximum velocity and acceleration of the joints, obstacle avoidance etc. (e.g. [17]). Finally, the trajectory is executed.

B. Head control

The robot's susceptibility (e.g. while the redundant kinematic chain is impedance controlled in external space) causes that its joints' position cannot be considered as fixed and highly depends on external forces that are applied to the robot. That phenomenon complicates position control of the robot's head [18], when the goal is to point a camera axis on a specific object with global coordinates specified. One inverse kinematics calculation for every target point is insufficient. The desired position of head's joints must be frequently updated, taking into account current torso position. Thus, the inverse kinematics is calculated at the same rate as position regulators on motor controllers run. Each time a target head joints position is calculated, a trajectory generator is applied to assure that joint acceleration and velocity limits are kept.

V. Robot Receptors

The system receptors' functionality is described with the two behaviors of vision virtual receptor e_v. The first behavior depends on the head camera data and performs „detect points of interest" activity (sec. V-A), as well as the labeling of detected elements (sec. V-B). The second one uses the arm camera in „detect keyhole position" activity (sec. V-C).

A. Head camera perception and data analysis

People gather information about their surroundings mainly using their sense of vision. To make a robot capable of working on human everyday tasks, in environments that are not intentionally adapted for machines, it must be equipped with a set of vision sensors. For looking around and quick localization of interesting regions the main solution are cameras mounted on active head. A wide-angle camera, possibly with ability to sense depth information, makes it possible to scan the robot's surroundings. Commonly, a pair of stereo-cameras or structured-light sensors [19] are used for this purpose.

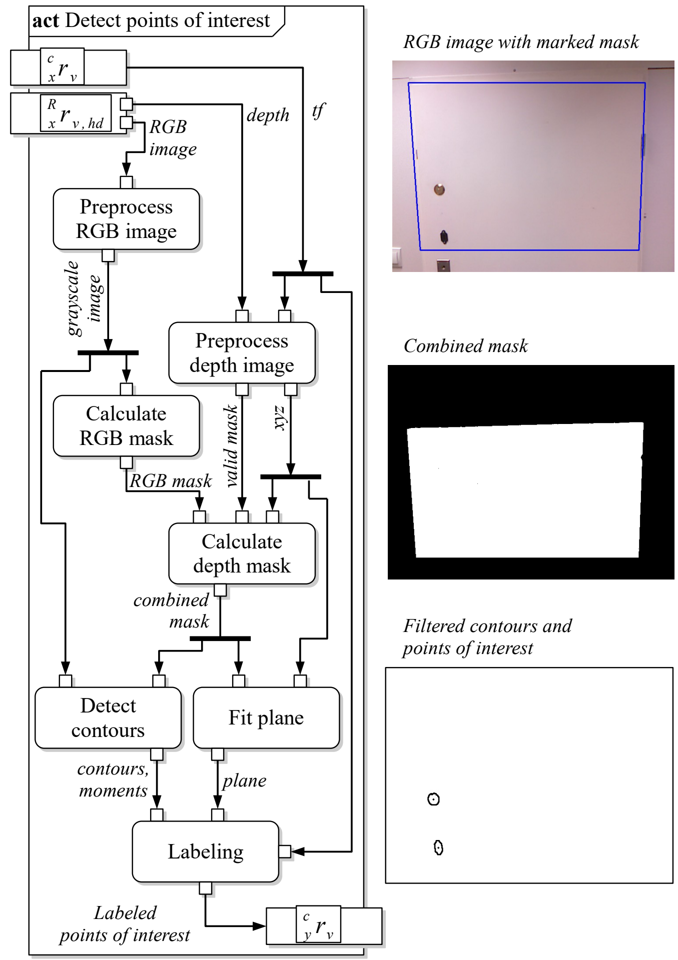

Fig. 4. The data flow of points of interest detection behavior of the vision virtual receptor

In the first behavior, RGB and depth data from the head-mounted sensor are processed to extract positions of interesting points (Fig. 4). First, color image is preprocessed (undistorted and converted to grayscale). Then, based on contour image, line segments are extracted (Hough line transform) and filtered to select only the strongest ones (i.e. having high score, length bigger than threshold and angle not bigger than 30^o from vertical). The two strongest lines, laying on opposite sides of the image, are selected as a door frame (used to produce *RGB mask*). During depth preprocessing, using measured head camera pose ${}^{0}_{D'}T$, a cloud of points is produced (expressed in robot frame). Based on this cloud, mask from color image and additional mask describing valid depth readings, combined mask is produced, which selects only the part of the door between the frames, and with vertical coordinates between 0.1m and 1.9m.

If it is the first view, then using a set of door points extracted from the cloud, door-plane parameters (point on plane p_0 and normal vector n) are calculated using RanSac approach [20] and stored in memory, otherwise plane parameters are read from internal memory. Combined mask is also used to select contours laying on doors. Mass centers (u, v) of those contours are used to calculate line pointing from the camera to them, described by point:

$$[l_0, 1]^T = {}_{D'}^{0}T\,[0, 0, 0, 1]^T \tag{2}$$

and direction vector pointing through (u, v) pixel:

$$[l, 0] = {}_{D'}^{0}T \left[\frac{u - c_x}{f_x}, \frac{v - c_y}{f_y}, 1, 0\right] \tag{3}$$

calculated using camera intrinsic parameters f_x, f_y, c_x and c_y. The intersection of this line (expressed in robot frame) with the door plane (4) gives the final coordinates of interesting point:

$${}_{L}^{0}P = l_0 + l\frac{(p_0 - l_0) \cdot n}{l \cdot n} \tag{4}$$

This position is then moved along a vector normal to the plane towards robot to calculate final desired arm-camera position ${}_{C}^{0}T$, which is sent back to the control subsystem.

B. Fuzzy system for region-of-interest labeling

The procedure was adapted from the recent work of the authors [9]. The previously detected regions can be of many different kinds: light switches, door plates, door locks, handles, etc. In our system, we defined classes for said objects, supplemented with unknown objects. We don't limit any region allocation to only one of the above classes. As objects can be found in different locations and there are no simple rules to distinguish between them, fuzzy rules were prepared to describe every class, based on a few, basic properties – location in a door plane (horizontal and vertical), object size and its shape regularity. Appropriate fuzzy sets are presented in Fig. 5.

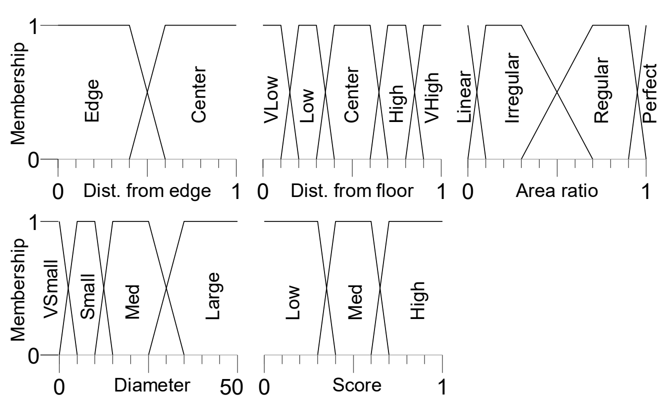

Fig. 5. Fuzzy sets for linguistic variables in presented system [9]

For object's horizontal position there are two possibilities – `Edge` and `Center`, which are based on a normalized distance from the door edge. Vertical position relies on absolute distance from the floor and its proper values are `VeryLow`, `Low`, `Center`, `High` and `VeryHigh`. Shape regularity is computed using rectangle and ellipse circumscribed on segment according to given rule:

$$Ratio = \max\left\{\frac{A_S}{A_R}, \frac{A_S}{A_C}\right\}$$

where A_S, A_R and A_C is area of segment, circumscribed rectangle and ellipse accordingly. A segment can has `Perfect` shape, when it is elliptical or rectangular. Alternatively, `Regular`, `Irregular` or `Linear` values characterize shapes composed from linear segments only. The available Size values are `VerySmall`, `Small`, `Medium` and `Large`, according to diameter of circumscribed circle. All output variables (class scores) have uniform distribution, and can be `Low`, `Medium` or `High`.

A rule database describing relationships between input and output variables is another part of our system. It can be created in a simple way, because input variables are close to straightforward description of door elements. The following operators are used: basic `min` and `max` for AND/OR, `min` for implication and `max` for accumulation. A defuzzifier uses a bisection.

To create a final, numeric measure for proceeded segment, defuzzification process is conducted on every output variable. Any results with score lower than arbitrary set threshold S_{low} are dropped, and, if we drop all possibilities, the segment is labeled as unknown. The last step is removing Handle and Lock labels from segments placed outside of doors (on the wall), and Switch label is removed from segments placed inside. The exemplary results for a few, different doors are presented in Fig. 6.

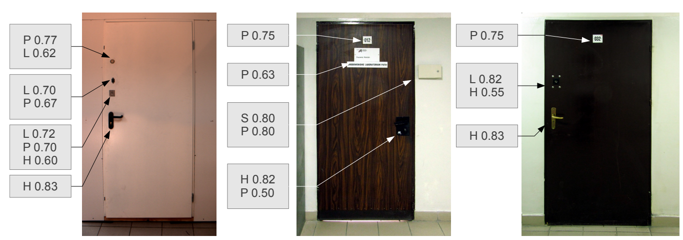

Fig. 6. A sample of labeling results. Labels shown for classes with membership bigger than 0.4. H - handle, L - lock, P - plate, S - switch [9]

C. Arm camera perception and data analysis

Sometimes, head-mounted sensors are not able to gather sufficient information about interesting object, which may be placed inside a cabinet or so low, that the picture from top mounted cameras is skewed and unusable. Humans motion capabilities greatly exceed these of the current service robots, for which it is almost impossible to lean or bend enough to obtain a clean view of the interesting object. For this reason, additional sensors may be mounted near the end of the robot's arm, either on the wrist or the gripper. These sensors could be either wide-angle to aid manipulation tasks and be useful in visual servoing, or narrow angle to look even closer on objects to take precise measurements.

allow taking detailed photos of door locks. After preprocessing the image from the camera, it is passed to ORB keypoint detector [21]. The same detector is used to extract keypoints from model images. After matching features between camera image and all models, the model with the best matches ratio is selected as the proper one. Then, based on those well matched pairs, a homography between the model and image is calculated, which is then used to transform keyhole coordinates from model image to camera coordinate system (Fig. 7). From this point, the processing is similar to the previous behavior – a line is generated in a camera frame, which goes through the camera center and the interesting point, which is then (after transforming to the robot frame) intersected with plane coordinates remembered in internal virtual receptor memory. Resulting point coordinates ${}^{0}_{K}P$, in the robot base frame, define the final keyhole position.

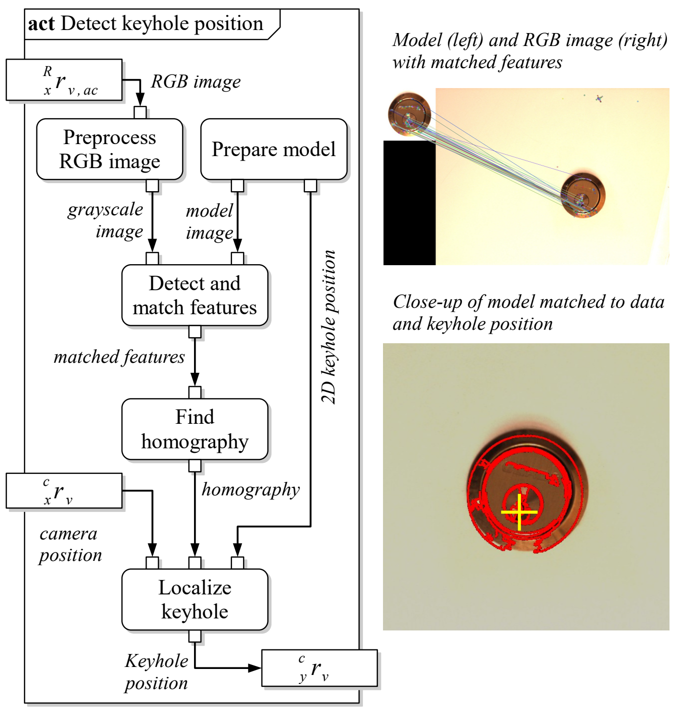

Fig. 7. The data flow of keyhole detection behavior of the vision virtual receptor

VI. EXPERIMENTS

The article specifies a general structure of a robotic system capable of door elements localization and investigation with use of an RGB-D sensor and a camera. There are many robotic platforms that may be used for such task without any or with minor modifications, including Willow Garage PR2 [2] or TUM Rosie [22]. The experiments have been conducted on Velma robot (Fig. 8). It is a two-arm robotic system, developed in the Institute of Control and Computation Engineering, Warsaw University of Technology in 2013. It has a torso capable of rotation, on which two Kuka LWR-4+ manipulators are mounted. Velma's head is mounted on a pan-tilt unit, attached to the torso. The head has two RGB cameras and Microsoft Kinect RGB-D sensor (giving 640x480px images) with rather wide horizontal field of view (57^o). Velma is equipped with two BarrettHand grippers and the left arm has a Prosilica GC1290C camera (giving 1280x960px image), with 12mm lens with much narrower, 23^o horizontal field of view, fixed to the manipulator's flange. The whole virtual receptor has been implemented using DisCODe framework [23], with each of the actions presented in figures 4 and 7 being divided into simpler components. The control subsystem has been implemented in Robot Operating System [24], that cooperates with virtual effectors implemented in OROCOS. The kinematic parameters of the robot were calibrated using method described in [25].

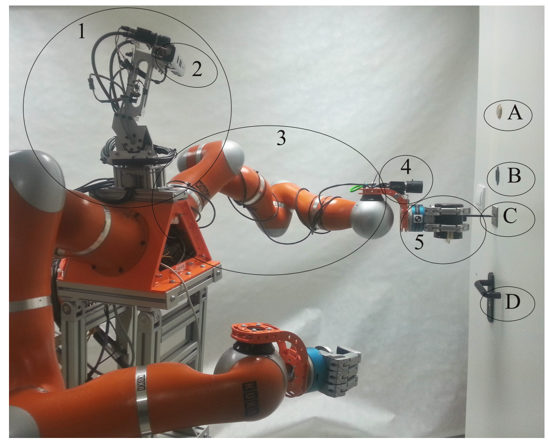

Fig. 8. Velma robot performing verification experiment, where: 1 – active head, 2 – MS Kinect RGB-D camera, 3 – LWR arm, 4 – arm camera, 5 – Barrett Hand gripper holding verification tool with skewer, A–D – door locks front covers with keyholes

The result of door lock keyholes visual localization was evaluated by comparison with the reference positions in robot base coordinate system. Hence a method of an alternative keyholes position measurement was developed. The method utilized a pointing device held with one of robot Velma's arms. The whole hand together with the pointing device was treated as a single tool, attached to the flange of the manipulator.

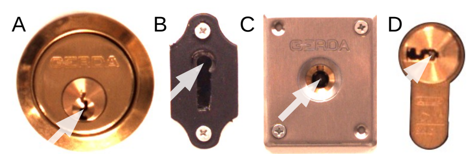

Fig. 9. Doorlocks used in experiments with marked keyhole position

For each lock (depicted with keyholes pointed out in Fig. 9), the pointing tool tip was placed in a keyhole in three different orientations. Then the measured keyhole position was averaged to minimize the impact of tool calibration error and robot susceptibility. The results were compared with keyhole positions measured with the vision system. The average difference between those positions was calculated for each of the keyholes on each coordinate. The results are presented in tab. I and concluded in the section VII.

TABLE I
AVERAGE DIFFERENCE BETWEEN KEYHOLE POSITION CALCULATED BY VISION SYSTEM AND REFERENCE POSITION FROM POINTING DEVICE

	X [mm]	Y [mm]	Z [mm]
Lock A	1.7	0.6	2.1
Lock B	4.6	1.3	0.2
Lock C	2.7	1.9	0.2
Lock D	4.8	2.5	1.9
Average	3.4	1.6	1.1

VII. CONCLUSIONS

The examined algorithms successfully localize different door elements and investigated locks (localize their keyholes) with satisfactory precision. The applied methods may be suitable for use in a more complex application which covers the whole process of door lock opening. Taking into account the resultant keyholes positioning error, we expect that a few trails of key insertion on the area of approximately 1 square cm will be sufficient to succeed.

The proposed system itself can be further developed. Having a robot equipped with multiple, independently moved vision receptors (cameras mounted on head and arms), some actions can be taken in parallel, reducing processing time. Door scan behavior may be optimized by introducing a visual feedback. Taking into account the position of characteristic points, an overlap of subsequent door images may be obtained instead of moving the target point by a constant interval.

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