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Towards ICT-Supported Bath Robots: Control Architecture Description and Localized Perception of User for Robot Motion Planning

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***Abstract*— This paper describes the general control architecture and the basic implementation concepts of a bath service robotic system. The goal of this system is to support and enhance elderly's mobility, manipulation and force exertion abilities and assist them in successfully, safely and independently completing the entire sequence of showering and drying tasks, such as properly washing their back and lower limbs. This service robotic system is based on soft-robotic arms which, together with advanced human-robot force/compliance control will form the basis for a safe physical human-robot interaction that complies with the most up-to-date safety standards. In this paper an overview of the bath robotic system components is presented, and the basic modules that contribute to the overall control architecture of the system are described. Moreover, this paper proposed an algorithm that performs efficient processing of feedback data provided by a depth sensor. This algorithm supports local shape perception and geometric characterization of user body parts and will form the basis for further implementation of surface reconstruction and robot motion planning algorithms.**

I. INTRODUCTION

Constant increase of life expectancy will cause a great growth of the elderly population. This group of people along with people with mobility disabilities are facing difficulties in performing Personal Care Activities (PCAs) such as showering, dressing, indoor or outdoor transferring, toileting and eating [1], [2]. The fulfillment of all these basic needs induces the necessity of nursing care (both in-house and clinical), great family financial burden and augmented requirements for nursing staff.

Body washing care (showering or bathing) is a very demanding procedure in terms of effort and body flexibility, so it is included among the first PCAs that are lost [1]. Robotics society has already given some answers to this early but basic PCA disability, by proposing several health care and rehabilitation solutions with physical interaction either static [3]–[5], or portable solutions [6], mounted on a wheel chair or a mobile robot [7], [8]. These solutions are mostly focused on washing specific body parts, to the treatment of particular skin diseases, or to support other PCAs such as eating or shaving. Furthermore, all these robotic systems employ rigid robotic manipulators for the interaction with the user.

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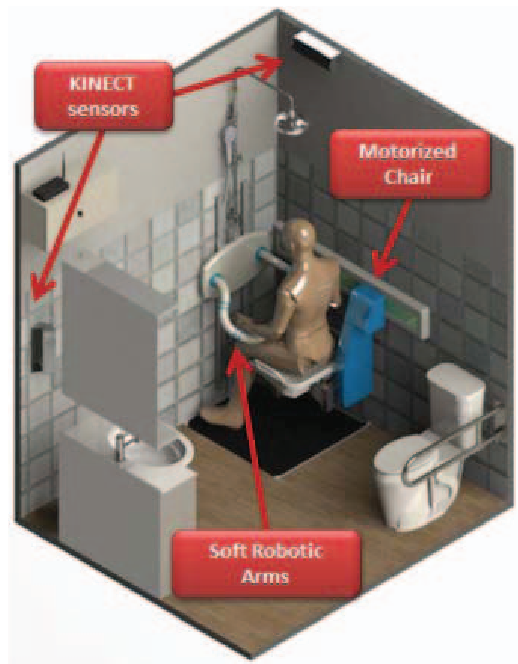


Fig. 1: Overview of the robotic bath system installed in a shower room.

The integration of soft robot arm technologies [9]–[11] to applications with physical contact with the user is not only innovative but also challenging, since all the proper technical adaptations should be considered, in order to meet the safety standards and the ease of use in showering activities. The control of a soft arm [11]–[13] in a dynamically changing environment is a challenging task, because multiple levels of control schemes should be taken into account, such as shape [14], stiffness [15], position, motion and path planning [16], and force/impedance control [17].

In this paper a brief description of the under construction bath service robotic system devices (Fig. 1) is provided based on [18], along with an overview of the control architecture of the system. Additionally, an algorithm is proposed that takes advantage of the octree data structure in order to efficiently process user perception data obtained from Kinect depth cameras and calculate local attributes that characterize a region of interest geometrically. The proposed service robotic system envisions to provide whole body showering assistance, ameliorating the daily life of frail parts of the population by increasing their independency and personal hygiene. The adaptation of the system to the user needs and preferences together with the integration of appropriate washing techniques demonstrated by professional carers is a multi-parametric problem and simultaneously a delicate issue, since the system should equilibrate between the proper elderly treatment and technical goals fulfillment.

II. SYSTEM DESCRIPTION

The functionalities of the overall system can be classified into two basic tasks:

(i) elderly mobility assistance in the showering space, with provision of appropriate transfer activities, such as sit-to-stand or stand-to-sit and human pose adjustment,

(ii) showering abilities enhancement, e.g. pouring water, soaping, body part scrubbing, etc.

In different operational modes of the system the degree of automation will vary according to the user abilities and preferences and a proper combination of the devices described below, will be used. The three basic devices, that constitute the robotic system, are accomplishing shower tasks and will meet the motion and force requirements, Fig. 1 and are briefly described below:

(a) **Motorized shower chair:** a motorized chair dedicated to the provision of the stand-to-sit and sit-to-stand functionality, for in-shower mobility enhancement and safety,

(b) **Robotic shower hose:** a soft robotic arm dedicated to specific showering activities, for example pouring water, soaping etc.,

(c) **Robotic washer/wiper:** a soft robotic arm dedicated to the provision of scrubbing wiping, drying etc., functionality.

The construction of the robotic arms will be based on soft materials (silicon, rubber etc.), which are more user friendly and are generating little resistance to compressive forces, [9], [10]. The actuation of the robotic arms will be based on tendons and pneumatic chambers. Combining these actuation techniques, the required dexterity is given to the soft-arm and adjustable stiffness in different sections of the arm can be achieved. This property can allow diversified behaviour between the sections of the soft-arm. The sections, that will have physical interaction with the human, will exhibit low stiffness, while sections that are responsible for supporting the payload (e.g. for gravity compensation) will exhibit high stiffness. In addition, customizable physical interaction in terms of contact forces can be achieved, by varying the stiffness of the robotic arm during the showering task execution.

Kinect depth cameras, mounted on the wall of the shower room in a proper configuration, as depicted in Fig. 1, will provide visual feedback to the system, by providing multi-camera view of the user. It is significant from an ethical point of view, that information only from depth measurements will be used and not from RGB camera, since depth measurements capture the shape and the geometry of the user and do not capture face and body features, revealing user's personal information. The visual information is a prerequisite not only for the human/robot perception algorithms (e.g. body part recognition and segmentation [19]–[21]), but also as a feedback closing the loop of the robot control algorithms. Furthermore, the human-system interaction will be enhanced by audio and action/gestural commands recognised via an array of microphones and the obtained depth measurements respectively. This integrated cognition system will give the appropriate assistance to the frail senior citizens, by interpreting the user's intent and preferences. This goal will be achieved by the development of cognitive robotic and learning algorithms action and gesture recognition.

The system will be able to operate in three different modes, i.e. Autonomous, direct Tele-manimultation, Shared interaction mode. In the Autonomous mode the system will execute the whole sequence without obtaining any input from the user, except for the emergency situations. Moreover, the operational mode can be switched to direct Tele-manipulation by using a remote controller, i.e. a lightweight remote controller similar to those used in video games (e.g. Wiimote), that can give the soft robotic arms the desired motion commands depending on the task of the showering sequence. The latter operational mode (i.e. Shared Interaction) includes the enrichment of human-robot interaction with a degree of autonomy, that will assist the elderly user during the task execution. In particular, if the user wants to wash him/herself, he/she will guide the soft arms to an appropriate position and then will grab and move the soft-arm, through direct physical (haptic) interaction. The robot controller is responsible for performing gravity and friction compensation, in order to ameliorate the haptic feeling this interaction creates.

III. CONTROL ARCHITECTURE

A modular, multilayered control architecture, as depicted in Fig. 2, is considered to deal with the interrelating multiple control levels of the system (i.e. shape, stiffness, position, and force/impedance control).

Decomposing this control architecture in a top-down sense, Fig. 2, the higher level module of the control architecture is the Supervisory Control Unit. This is an event based unit, that has an overview of the system and has also continuous communication with the user interfaces. Events are called all the possible situations that change the state of the system, for example emergency signal handling or user interaction commands (e.g. Voice instruction, Gestural command, Tele-manipulation input, etc.). One of the basic functionalities of this unit is to specify the operational mode

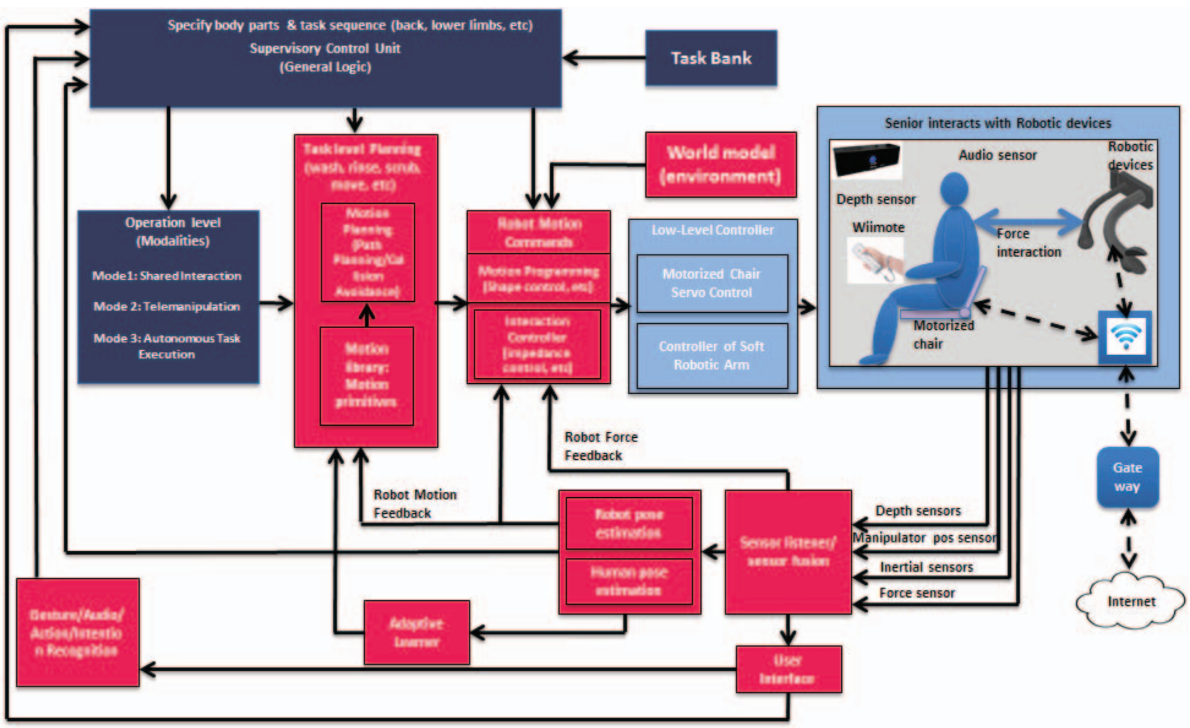


Fig. 2: Overview of the Bath Robotic System Control Architecture.

of the system and the body part onto which the robot will operate, selected via the user interface.

The medium level of the control architecture includes the Task Level Planning Module. This module is based on three components:

1) the operational mode (e.g. Autonomous, Telemanipulation, Shared Interaction),
2) the operational body area (e.g. back region, lower limbs), and
3) the specific sequence of washing execution.

The former two components are obtained as an input from the Supervisory Control Unit. In the latter component the washing execution sequence (e.g. initial position, pouring water, scrubbing, rinse, and dry) is determined by a Finite State Machine (FSM) framework. Each subtask of the execution sequence is planned based on several parameters such as Motion Primitives information [22], [23], Robot/User perception using the sensory infrastructure and collision avoidance techniques, in order to plan the proper motion of the Soft-Arm end-effector for a specific part of the sequence. The resulting motions will be simpler than the final trajectories that the end-effector of the robot will track.

In the Robot Motion Commands module, the Robot Motion Programming Submodule and the Interaction Control Submodule will be implemented. In this part, information regarding the desired end-effector trajectories from the Task Level Planning Submodule, the robot localization (position, motion, shape) from the Robot Pose Estimation Submodule, and force feedback information directly from the Sensor Fusion module will be received. Initially, the Robot Motion Programming Submodule will implement functionalities regarding position control, to ensure trajectory tracking with global convergence, collision avoidance and shape control of the Soft Robotic Arm. In addition, the Interaction Control Submodule will be responsible for the Soft Robotic Arm stiffness control, dynamic impedance/admittance integrating user adaptive features, implementing a hybrid force/position control. The output of this control level will be the actual 3D end-effector trajectories, reference shape and interaction commands (e.g. force and stiffness commands). The lower module of the architecture includes the implementation of the controllers of the motorized chair and the Soft-Arm. These controllers will be responsible for the realization of the reference commands obtained as an input from the previously described modules, by giving the appropriate motor, tendon and pressure commands respectively. In the next section, we present our first approach on data handling obtained from the depth sensors and on the characterization of the surfaces of interest (i.e. body parts), which is a prerequisite for robot motion planning.

IV. BODY PARTS REGION CHARACTERIZATION FOR ROBOT MOTION PLANNING

The general scope of robot motion planning includes the definition of a feedback dynamic control law (given the soft-arm kinematic input constraints and the operating environment), that allows the end-effector of the arm to execute surface tasks such as navigating to any feasible body part point, tracking a predefined trajectory and at

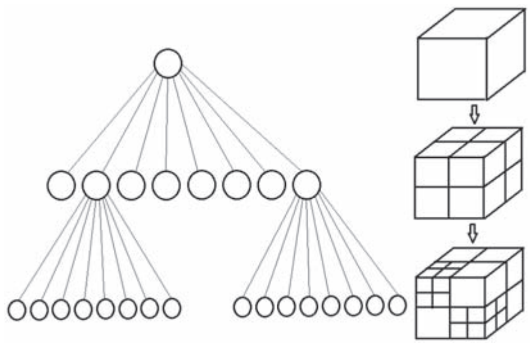


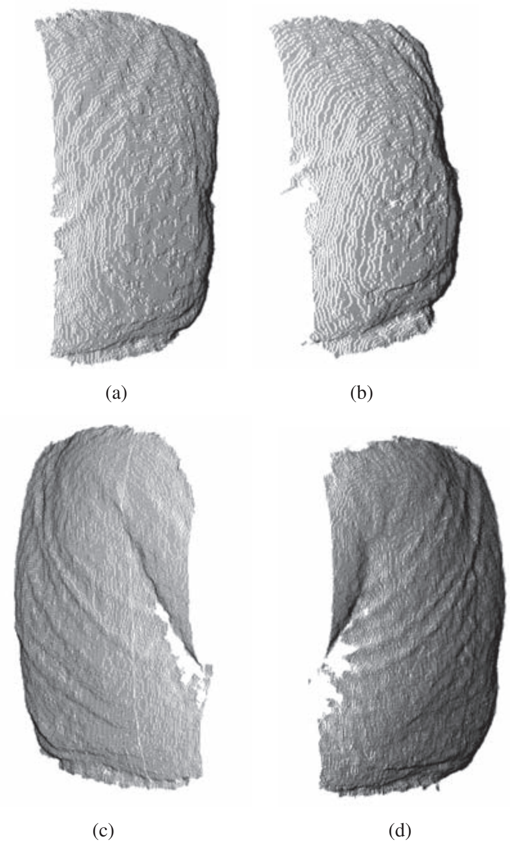
Fig. 3: Volume representation using the Octree data structure. Each level of the tree structure has direct correspondence to the division of the physical space.

the same time being compliant with this body part. This task is challenging, since many difficulties are to be faced. Firstly, we have to deal with non-planar operating surfaces, as it is shown in Fig. 4, the motion of the user, either systematic (e.g. breathing) or random motions of several body parts. Additionally, we have to cope with multiple depth cameras registration and efficient data processing. An extended analysis of the accuracy of the Kinect depth sensor is provided in [24]. Another particularly important task is body parts segmentation, which is a prerequisite not only for decision making in the Supervisory Control Unit but also for motion planning, is the body parts segmentation and labeling, [19]–[21]. Segmentation algorithms use as training data a great amount of depth images depicting the user in different poses and perform segmentation and labeling of the regions of interest, providing as an output Point-Cloud data of the recognized body parts as shown in Fig. 4.

A. Proposed Approach

The proposed approach, that meets the above mentioned challenges, is a grid based, incremental 3D mapping approach, which exploits the advantages of the Octree data structure, [25]. All the Point-Cloud data obtained from the depth sensors are inserted in the octree. Each leaf node of this tree structure corresponds to a certain volume defined by the resolution of the tree, as depicted in Fig. 3. For example, the leaves of an octree with resolution α correspond to a cube with edge of α meters. Every intermediate node divides the space into eight octants and its volume equals to the sum of the volumes of its children.

Moreover, the octree data structure can perform a down sampling of points due to its resolution attribute (e.g. two different points whose distance is less than the resolution will both be assigned to the same node), dealing with the high number of points coming as an input from the depth sensors and resulting in higher efficiency. This multi-resolutional representation of the environment, except for a simple 3D occupancy grid, can also give collision detection benefits, since the traversal of the tree at higher levels can give direct occupancy feedback related to bigger volumes and possible obstacle inflation, leading to safer obstacle avoidance techniques.



(a) (b) (c) (d)

Fig. 4: Point-Cloud representation of the back of the seated subject. (a) Subject is seated with its back straight. (b) Subject is seated with its back bending forward. (c) Subject twists its back right (occlusion of the right arm in the field of view). (d) Subject twists its back left (occlusion of the left arm in the field of view).

The surface characterization of the regions of interest, that result from the segmentation algorithm mentioned above, is implemented by calculating local attributes (e.g. normal vector) in proper neighborhoods of points (according to the task execution and the actual size of the body part) already stored in the octree. The sense of space is conceived in the octree data structure, therefore the notion of vicinity has direct correspondence to the physical environment. Each calculation is implemented by gathering a group of points $\mathbf{p}$ that lie within a certain volume:

$$\mathbf{p}_k = [x_k \quad y_k \quad z_k]^T \triangleq [p_x^k \quad p_y^k \quad p_z^k]^T$$

where x_k, y_k, z_k, are the cartesian coordinates for the number of points $k = 1, \ldots, n$, and applying eigenvalue decomposition to the covariance matrix computed from these points, as follows:

$$C = \begin{bmatrix} Cxx & Cxy & Cxz \\ Cyx & Cyy & Cyz \\ Czx & Czy & Czz \end{bmatrix},$$

TABLE I: Results: Computational Aspects

Number of Points	Insertion Time (s)	Initialization Time (s)
50718	0.0119	0.084

Algorithm performance parameters in terms of time. The average number of points per frame is presented along with the Insertion time required for the storage into the Octree data structure and the Initialization time for the computation of the local geometrical attributes.

where

$$C_{ij} = \frac{1}{n}\sum_{k=1}^{n}(p_i^k - m_i)(p_j^k - m_j),$$

and

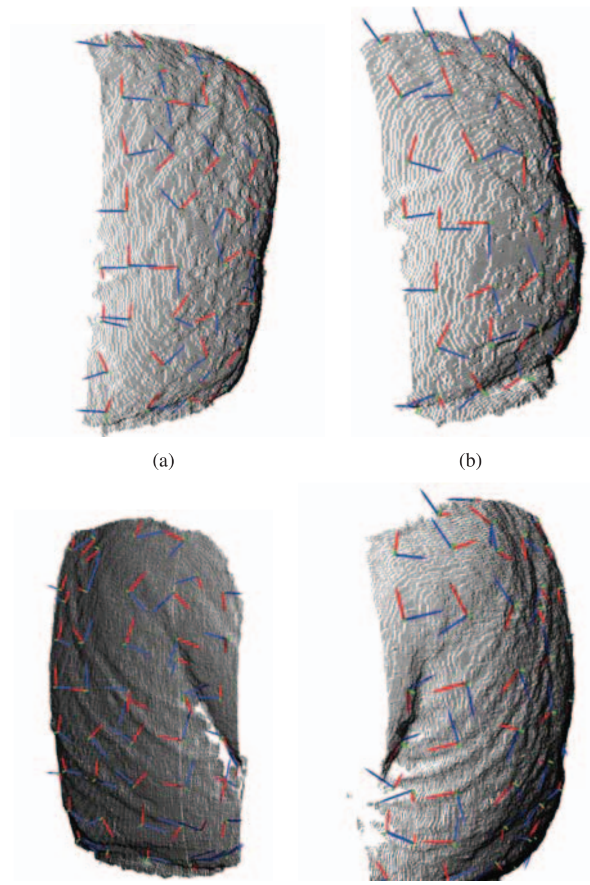
$$\mathbf{m} = \frac{1}{n}\sum_{k=1}^{n}\mathbf{p}_k \triangleq [m_x \quad m_y \quad m_z]^T$$

with $i, j = \{x,y,z\}$. The eigenvectors resulting from this decomposition will correspond to the principal axis of the gathered data and the length of each axes is determined by the square root of the corresponding eigenvalue. In particular, the local normal direction is the axis that corresponds to the minimum eigenvalue, i.e. the direction of minimum variance of the data, and the rest two of the components are defining the tangential plane of the considered region. These attributes are calculated in every level of the tree, providing more detailed attributes in lower levels and more abstract in higher levels taking into account bigger parts of the region describing the body part.

B. Results

In order to test the proposed approach, an experimental setup is used that includes a Kinect camera recording and providing depth data for the back of a randomly moving subject. The segmentation of the back region of the subject is implemented, for the purposes of of this experiment, by simply keeping the points within a window of the camera field of view, as shown in Fig. 4.

In Table I, the time performance results of the algorithm are presented. The depicted values are the average over all the frames. Both the insertion of the points into the tree and the multi-level attribute estimation (i.e. Initialization Time) execution times are low (at the order of 10 and 80 msecs, respectively), making the proposed computationally efficient for online procedures. It means that the overall algorithm, as currently implemented, can run in near real-time (10Hz). The execution times were measured in a computer system with Intel(R) Core(TM) i7-4710HQ CPU @ 2.50 Ghz and 16Gb Ram. Experimental results of the body part region characterization algorithm are depicted in Fig. 5. The green vectors correspond to the normal, while the blue and the red vectors correspond to the other two principal axis that characterize the considered region. The length of each vector is calculated through the corresponding eigenvalue, giving a rough idea of the geometric structure of the region. Despite the motion of the subject (e.g. twisting Fig. 5(d), Fig. 5(c), and bending Fig. 5(b)) and the upper arms occlusion, the algorithm is able to calculate robust attributes locally.



(a) (b) (c) (d)

Fig. 5: Point-Cloud representation of the back of the seated subject with one resolution level of local geometric attributes overlaid on the data, for the same subject configurations (a) to (d) depicted in Fig. 4. (a) Subject is seated with its back straight. (b) Subject is seated with its back bending forward. (c) Subject twists its back right (occlusion of the right arm in the field of view). (d) Subject twists its back left (occlusion of the left arm in the field of view).

V. CONCLUSIONS

This paper presents a modular description of a bath robotic system emphasizing on the basic components that contribute to the control of the system. Moreover, a brief description of the overall control architecture is given and an efficient data manipulation and region characterization algorithm is proposed. This algorithm is the initial step for several surface reconstruction and robot motion planning algorithms. For further research we aim to reduce the complexity of the problem by planning motions on a 2D "canonical" space, learned by demonstration of professional carers, with the aid of Dynamic Motion Primitives (DMP) approach [26],

[27]. The planned trajectories will be transformed to the task space, i.e. the region that the robot will operate. The latter procedure should take into account the motion of the user and be adaptive to the user needs. The tracking of these trajectories will be implemented by hybrid (force/position) control schemes. The above described approach along with the integration of cost-effective, soft-robotic arms will provide an innovative and safe solution for assisting frail older adults in showering activities, improving their quality of life.

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