2019 IEEE International Conference on Cyborg and Bionic Systems (CBS)
Munich, Germany, September 19-20, 2019

Closed loop control of a braided-structure continuum manipulator with hybrid actuation based on learning models

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***Abstract*— Design of continuum manipulators have always been restricted to simplified structures due to the modeling complexity involved. However with the success of machine learning based models, there are potentially more structures and actuation strategies that could be investigated. This paper presents a novel continuum manipulator with variable diameter and a general control strategy for closed loop task space control. The controller constitutes of an inverse kinematics based feedback component, a forward kinematics based feedforward component and a low level velocity controller. Our findings indicate how such an approach can deal with singularities and provide smooth and accurate motion.**

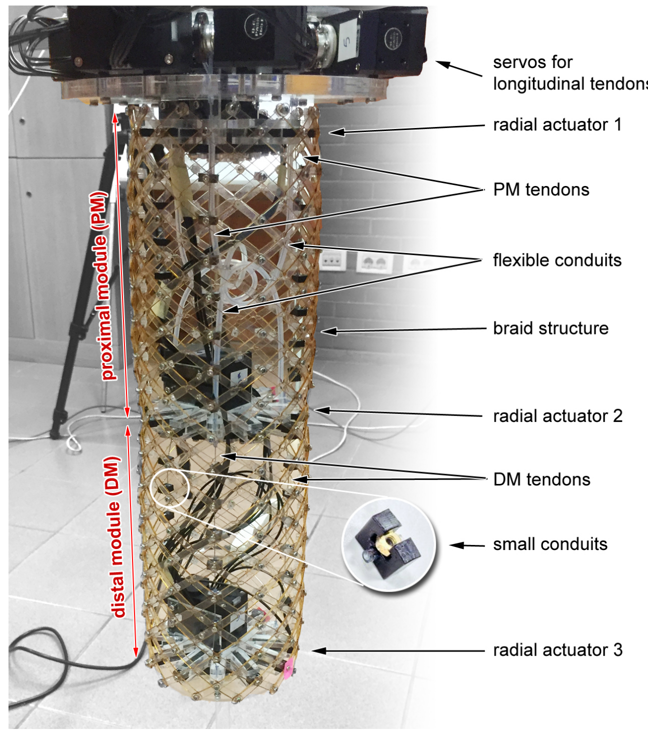

Fig. 1: Physical prototype of Active-Braid V-2.

I. INTRODUCTION

Continuum robots or ”snake like robots” [1] with their high dexterity, inherent compliance and light weight have emerged as a viable replacement for conventional hard rigid manipulators for general tasks in un-structured environments (grasping, positioning and manipulation) or situations where human/machine interaction is involved. Such systems exhibit considerable compliance and are able to produce motion by bending continuously along their length enabling them to adapt to the disturbances in the environment [2]. A variety of such systems have been reported in literature using different backbone designs and actuation principles. A segmented backbone design, actuated by tendons is proposed for the elephant trunk manipulator [3]. A similar concept is used in [4], where flexible compliant joints replaces the segmented backbone, whereas the tendril continuum manipulator [5] employs compression springs connected in series as its main body. This enables the system to contract. For such designs, the stiffness of the structure generally results from the tension in the tendons or the type of backbone used. Another common approach is to use pneumatic artificial muscles [6]. Usually three or more actuators are combined in parallel that can be actuated collectively or independently for producing a variety of different body configurations. In such approaches the muscles act as actuation units plus they form the main structural body of the manipulator. The stiffness of the overall structure can be varied by controlling the pressure in different actuators [7][8]. Similarly the Bionic Handling Assistant [9], employs three extending bellows arranged in parallel. For enhancing the manipulation capabilities, hybrid actuation (combination of different actuation principles) has also been proposed [10]. The I-Support manipulator [11], [12] uses Mc-Kibben type extending actuators in combination with tendons. For the soft robotic octopus arm [13][14], the main body consists of a braid structure embedded inside a silicone skin. A number of transverse SMA actuators along the length of the manipulator are used to actively decrease the diameter of the braid structure resulting in an increase in length. Longitudinal tendons are used to bend and shorten the soft manipulator. Stiffness variation can be achieved by using the different kinds of actuation antagonistically.

Significant amount of work on the closed loop kinematic control of continuum robots has been carried out in past decade. Principally they can be classified based on their modeling method and/or the control architecture. The model solely affects the accuracy and sensory requirements of the controller whereas the control architecture also affects the stability, robustness and speed of the controller. The

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first experimental validation of a closed loop task space controller was proposed in [15]. The model was based on the widely used constant curvature (CC) approximation. Since the controller acts directly on the task space, it is more robust to model uncertainties and therefore more accurate. However, such an approach cannot guarantee stability. Usually stability is ensured by lowering the bandwidth of the controller. Joint space controllers, on the other hand, can have more stability and smoother motions[16]. Alongside other kinematic models also were developed especially for conical continuum manipulators [17]. For a review on the different analytical modeling techniques for continuum manipulators, refer to [18]. An interesting observation from this review is the apparent discord between complexity of the model and accuracy, indicating the strong dependency of the model accuracy on the design of the manipulator. Therefore, there has been increasing interests in data driven methods as an alternative for modelling. For the active braid manipulator with variable diameter, analytical models become more difficult to obtain.

The earliest demonstration of a model-free method was shown in [19], for learning the direct inverse statics of a non-redundant soft robot using a neural network. Redundancy resolution and methods for closing the control loop was however not addressed. An efficient goal directed sampling technique that can generate unique inverse kinematic (IK) solution was described in [20] which was tested successfully on continuum manipulator. Self-organizing maps are used to learn the IK mapping with generated samples. A feedback scheme for reducing tracking error is implemented by virtually shifting the target positions proportional to the error in tracking to make the controller more robust. Later, in [21] an adaptive method for learning the direct mapping between task space and joint space is proposed for a pneumatically driven manipulator. For this a forward kinematic model was generated by means of a neural network and then inverted using Distal Supervised Learning. Afterwards an adaptive sub-controller was used to learn the mapping from the joint space to the actuator space. A similar approach based on Growing Neural Gas was proposed for the gaze control of a humnoid robot [22]. The authors own contribution to the field was learning a global differential inverse kinematics model directly from the actuator space to the task space using neural networks [23], [24]. Such an approach showed highly robust tracking performance even under the influence of unstructured environmental constraints and actuator failure [25], [24]. However, the low level actuator space control was ignored in this work which led to slower control frequencies in order to self-stabilize the motion of the manipulator between steps.

The contribution of this paper is twofold. Firstly, A new version of the Active Braid continuum manipulator is developed (shown in Figure1). A detailed description of the Active Braid manipulator along with a finite element model can be found in [26]. The following changes were introduced in the new version; 1) the overall length of the manipulator is increased, 2) A pin in slot type joint is used for the links, 3) the number of radial actuators is increased, 4) The link material is changed and 5) the servo motors are changed. In addition to this, we develop a kinematic controller that can accommodate the changes in morphology of a given manipulator and we implement and validate it on the new version of the Active Braid manipulator. Naturally, due to the complexity of analytically modeling the muscular hydrostat like structure, we employ a learning based approach. We try to develop a control architecture that can produce smooth, vibration-free motions using the learned models. This is especially important for cable driven continuum manipulators, where excitation of the inert states of the manipulator corrupts the sensory data and controller accuracy.

II. MANIPULATOR DESIGN

The manipulator design is inspired from muscular hydrostats [27], a special muscular structure, found in nature consisting of no rigid skeletal support. Examples include mammalian tongues, arms and tentacles of cephalopod molluscs and elephants trunk. The multiplicity of muscle groups enable it to produce a variety of complex movements including extension, contraction, bending and twisting. These groups of muscles are not only responsible for producing the different movements, but they also provide a unique form of skeletal support, moreover they are used antagonistically to change the stiffness of the structure. The Active Braid is made up of a compliant braid structure that is deformed by a hybrid actuation system consisting of radial actuators and longitudinal tendons. These three key components mimics the behavior of the oblique, radial and longitudinal muscle groups, found in muscular hydrostats. A new prototype of the manipulator is developed consisting of two independently actuated modules; the proximal module (PM) and the distal module (DM). The radial actuator 2 acts as a transition from the PM to DM. The length of the manipulator can be extended by adding more modules in series. The different parts of the manipulator are shown in Figure 2. Compared to the previous version the overall length of the manipulator is increased in-order to enhance the reachable workspace. The structure/ body of the manipulator and the hybrid actuation units are briefly explained in the following sub-sections.

A. Manipulator Structure

The structure/body of the manipulator resembles a braid structure in form and functionality. A braid structure is a cylindrical shell consisting of clockwise and anti-clockwise sets of mutually interlaced, helical fibers(idealy non-extensible yet flexible) [28]. When extended or contracted axially, the structure is capable of considerable accommodation of strain since the angle between the fibers and the longitudinal axis of the structure can change. The structure acts like a constant volume structure, as the length increases the diameter decreases and conversely as the length decreases the diameter increases. Moreover, the structure is able to bend smoothly without kinking under external or internal unbalanced forces. For the Active-Braid V2 (as

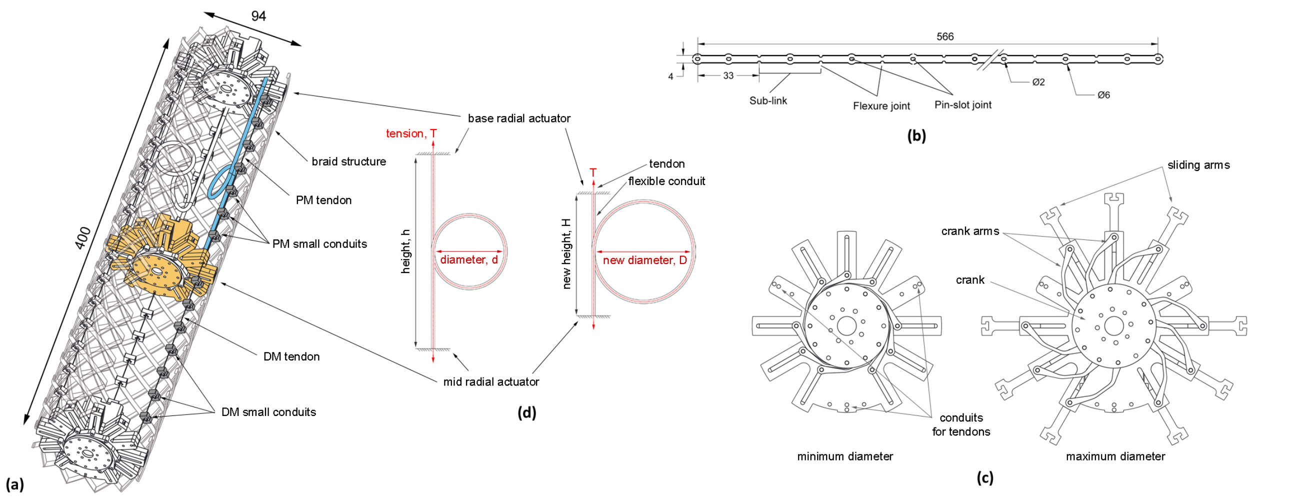

Fig. 2: Different parts of the Active-Braid V-2.(a) isometric view of the manipulator (deformable braid structure + the hybrid actuation unit), (b) cad drawing of a single link, (c) detail view of the radial actuator both in the minimum and maximum diameter state, (d) As the height 'h' changes between the radial actuators, the loop diameter changes automatically but the total length of the conduit remains constant, hence keeping the tendon inside in tension. Dimensions in mm

shown in Figure 2(a)), the structure is made from flexible links, laser cutted from polycarbonate sheets with a thickness of 1mm (Figure 2(b)). A total of 24 such links are used, arranged in two layers like the clockwise and anti clockwise helical fibers of a braid. A single link is further divided into 17 sub-links. Flexure type joints are provided between the sub-links, in-order to localize the effect of torsion, experienced by the whole link (along its length) during the deformation of the structure. Instead of interlacing the links, "pin in a straight slot" type joints are provided at the center of each sub-link, to keep the separate layers of links together and also produce the structural deformation required. The pin in slot type joint permits relative rotation and some translation between the two layers of the links. It is believed that the small translation increases the bending capabilities of the structure. The material for the links is changed in the new version because with the previous version bulging of the structure was noticed during bending.The new material provides more lateral stiffening, which reduces the bulging and enhances the workspace of the manipulator.

B. Hybrid Actuation

The Active-Braid uses two types of actuation units for producing the deformations required in the braid structure (shown in Figure 2(a)). A total of three independent radial actuators are provided along the axis of the braid structure, with the primary function of reducing and constraining the diameter of the manipulator. Reduction in diameter produces an extension in the length of the braid structure, moreover constraining the diameter is useful in bending. The radial actuator achieves this by employing a modified crank slider mechanism that is able to convert the rotation motion of a smart servo motor (Robotis-Dynamixel XM430-W210-R) into translational motion of 9 individual sliding arms, arranged in radial configuration. The radial actuators further provides structural support to the deformable braid structure. A detailed view of the radial actuator, both in the minimum and maximum diameter state is shown in Figure 2(c). The previous manipulator version consisted of only two radial actuators, one at the base and the other at the mid section. A third radial actuator at the end of the distal module enhances the motion capabilities produced by the manipulator. For producing the bending and contraction motion, six longitudinal tendons are employed, with three tendons for each section. The tendons are arranged 120 degrees apart, around the axis of the manipulator. The tendons are kept close to the inner surface by passing them through small conduits provided at the pin joints on the inner surface of the braid structure. Each tendons is independently actuated using the smart servo motor (Robotis-Dynamixel XM430-W210-R), located at the base of the manipulator. Bending can be achieved by retracting any one or two of the tendons while contraction of the braid structure can be achieved by retracting all three tendons simultaneously. In-order to decouple the bending and shortening of the distal module from the proximal module, flexible conduits are used for the distal module tendons, located between radial actuator 1 and radial actuator 2. Working like a Bowden-cable, the flexible conduit is able to transfer the tension applied on the tendons at the base of the manipulator to the mid radial actuator, in this manner the PM is isolated from the effect of the three tendons for the DM. Furthermore when the PM is actuated, the loop in the flexible conduit is deformed to accommodate the height change automatically while the overall length of the conduit remains constant, keeping the DM tendons in tension (refer to Figure2(d)). For the new version smart servos are used for both the actuation systems. The new servos have five operating modes namely; Position control mode, Current control mode, Velocity control mode, Current based position control mode and PWM control mode. Moreover they can be used as an actuator and a sensor

III. TASK SPACE CONTROLLER

As mentioned in the first section the focus of this paper can be addressed in two parts. The first part deals with the modeling problem and the second part deals with the integration of the low level and high level control architecture.

The presence of the radial actuators pose difficulties in modeling due to cable slackening. Given the actuator space configuration $q \in \Re^n$ and the task space variable $x \in \Re^m$, the forward kinematic model can be well defined as :

$$x = F(q) \tag{1}$$

Inverse of this equation which defines the inverse kinematic equation is also possible when the Jacobian matrix (2) is non-singular. However when the tendon actuators become loose due to the radial actuators, the Jacobian matrix loses its rank. Naive learning of the differential inverse kinematics like in [24], can lead to incorrect learning in certain regions of the actuator space.

$$\dot{x} = J(q)\dot{q} \tag{2}$$

To solve this problem we use the fact that the forward is still well defined even with cable loosening. Therefore a learned forward model can be used as a feedforward component to compensate for possible errors that the learned differential IK model incurs. We use the same differential IK model proposed in [24] along with the feedforward component. The IK model is obtained by learning local IK mappings. Therefore, given the current actuator configuration q_a, the current task space configuration x_a and the desired task space configuration x_d, the learned IK network outputs the next desired actuator configuration q_d. Note that just this controller can provide decent tracking accuracy as long as we provide enough settling time between targets and the motion and it does not go near singular configurations.

For improving the accuracy of the controller near singular configurations we add a feedforward component to the solution provided the differential IK (See Figure 3). By assuming we can generate an accurate forward model (1), the Jacobian can be inverted using the damped least squares method [29]. Refer to the next section for the description of the learned models. The damped least square (DLS) method is widely used because of its superior performance near singularities. Given the predicted error e_p, obtained using the forward model and the output from the IK model, the incremental change in actuator configuration, required to reduce the future error, would be given by:

$$\Delta q_d = J^T(JJ^T + \lambda^2 I)^{-1} e_p \tag{3}$$

The damping constant λ is tuned by hand and must be large enough for the given solutions to be well-behaved near singularities. Higher values of the damping constant increase the convergence time of the controller. Since we only have a learned model of the forward model, the kinematic Jacobian is estimated numerically. Since the addition of feedforward component increases the computational burden of the controller, it is also possible to deactivate this part when the tracking error is low.

The architecture of the low level controller is dependent on the actuator properties also. For our experiments we use a high gear ratio DC motor. The inbuilt controller is provided with position, velocity and current control. In order to reduce vibrations of the manipulator and provide smooth motions, two factors must be considered:

- The impulses applied by the actuator are minimized while being fast enough to reach the desired actuator position.
- The bandwidth of the task is low enough that the manipulator dynamics can be ignored.

Since we do not have direct torque control it is difficult to ensure that the impulses applied by the motors are low. Even if load cells were available for each tendon, friction compensation techniques had to be employed to avoid abrupt motions due to the high static friction in the gears. To reduce the effect of the nonlinear static friction, we use a low level velocity controller in the actuators. By ensuring that the desired velocities are never going to zero, we can always stay in the region of dynamic friction. As we have a high gear ratio, it is possible to reduce the motion of the actuators to very low values without stopping the motors. The scheme we designed to employ the low level controller with the previously mentioned high level controller is depicted in Figure 3.

The desired change in actuator configuration, $\Delta q_d + (q_d - q_a)$, is first normalized and multiplied by a constant matrix K. The constant K, which is a parameter to be tuned, decides the range of velocities for each actuators. For our case all the radial actuators have the same values for K and likewise for the longitudinal actuators. To ensure smoother convergence to the target position, we also multiply this signal proportionately with the tracking error. The desired trajectories are kept smooth to test the controller.

IV. LEARNING AND CONTROL PARAMETERS

The differential IK model is the structured and learned in the same way as [24]. The sampling is however performed differently with motor babbling in the velocity level (Figure 4). This allows for faster sampling. A multilayer perceptron (MLP) with 60 hidden layer size was used to learn the IK model. For the forward model, we employ an extended forward kinematic mapping to account better for time dependent factors like material hysteresis. An analytical version of the same was first described in [30]. This can simply be achieved by defining the forward kinematic equation as:

$$x_i = F(q_i, x_{i-1}) \tag{4}$$

This defines the tasks space variable (x_i) to be dependent on the actuator variables (q_i) and the previous task space configuration (x_{i-1}). The underlying assumption is that the

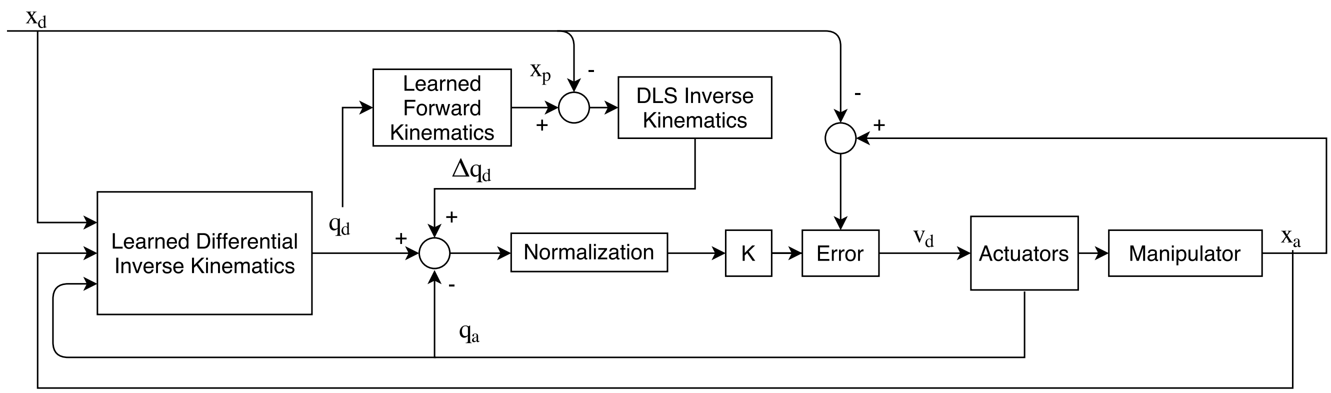

Fig. 3: Control diagram of the proposed controller.

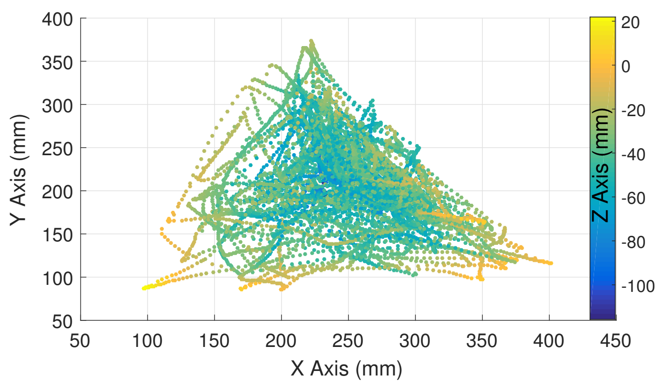

Fig. 4: Manipulator workspace obtained by motor babbling.

motions are localized. For calculating the Jacobian matrix, only the actuator space variables are varied: this allows to maintain the dimension of the Jacobian matrix to $m \times n$. The forward model was learned with a MLP of 90 hidden units. The training, testing and validation samples were divided in the ratio 70:15:15 to avoid overfitting. The prediction accuracy of the forward model was 1.17 ± 0.73 mm. K is 2 for the longitudinal actuators and 0.2 for the radial actuators. The damping constant λ is 0.31.

V. RESULTS

Due to the various level of control and feedback that a continuum manipulator has, it is important to have an appropriate low level controller along with the high level models. This is clearly evident from the experiments with the manipulator for a smooth linear trajectory (see Figure 5). The total length of the trajectory is 160mm divided into 98 steps. We perform a comparison between the proposed controller and a position controller working in the position space [23], [24]. We conduct four kind of tests using both controllers: position control and normal motion (PN), position control and slow motion (PS), velocity control and slow motion (VS), velocity control and normal motion (VN). The slow motion is achieved by reducing the speed of the tracking motion by manually adding delays. This allows enough time for the manipulator to settle and provides more accurate sensory data. Figure 6 shows the Cartesian Error of the 4 experiments. It is worth to notice that the velocity controller outperforms in both cases (normal and slow motion) the position controller reaching an accuracy that is less than $5mm$ in the slow motion case and less than $13mm$ in the normal motion case. The improvement in the performances is due to the use of the forward model (being more accurate then the inverse one) that allows to adjust, at each step, the position of the manipulator by regulating the velocity output to the motors. Not only the accuracy of the controller improves with the same control frequency (see Figure 6), but also the smoothness of the trajectory (see Table I for mean accuracy, velocity and jerk during the motion). Note that the tunable control parameters are kept the same for all tests. This could help in improving the performance of the controller even for faster motions.

We perform also two experiments where the robot is asked to follow two parallel trajectories perpendicular to the Z axis of the manipulator (see Figure 7). The second trajectory is generated in the lower region of the workspace where few points have been collected during the motor babbling phase (it is a border region not completely reachable by the manipulator). This causes an increase of the error (22,1mm for this trajectory and 8.1mm for the other one). We perform this experiment in order to demonstrate the capability of the manipulator to move perpendicular to the Z axis by exploiting the radial actuators (this task could not be performed by using only the longitudinal ones). Figure 8 shows the different contribution of the three radial actuators in the two tasks.

VI. DISCUSSION AND CONCLUSIONS

In this paper we present the new Active Braid 2 manipulator. We present the changes compared to the previous version that involve the structure and the actuation system. We present a controller for such a manipulator (working in the velocity space) based on a model-free approach and implemented using two neural networks that are able to learn the direct and inverse model of the manipulator. We show that this model is more accurate compared to a position-based

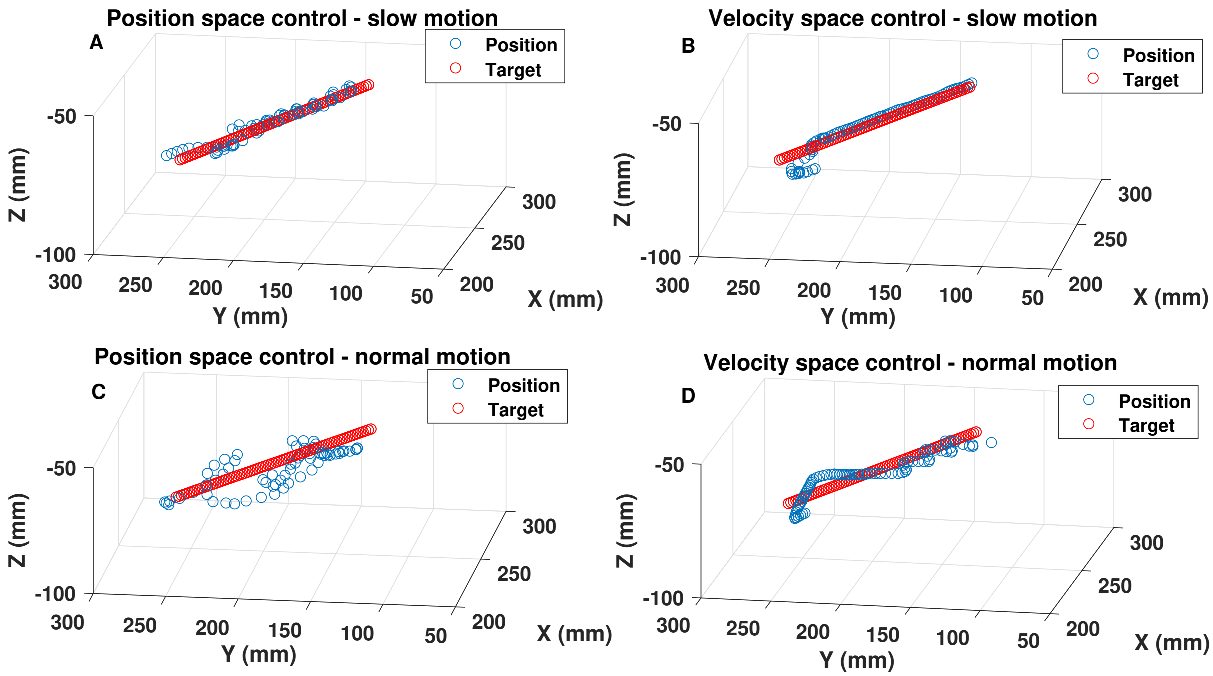

Fig. 5: Trajectory of the end effector during the tracking task for the low level position controller and the low level velocity controller.

TABLE I: Trajectory quality during tracking. In the third column it is listed the time needed to complete the task.

Task	err (mm)	time (s)	vel (mm/s)	jerk (mm/s^3)
PN	21.3	9	26.5	3115
VN	12.8	9	11.6	942
PS	9.7	36	14	710
VS	4.4	36	4.8	170

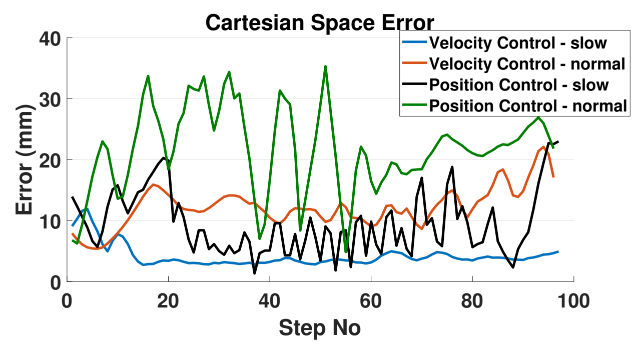

Fig. 6: Error in tracking for the same trajectory with the low level position controller and the low level velocity controller.

approach and produce more smooth motion. In addition to this, in order to validate the effectiveness of the new actuation system of the Active Braid V2 manipulator, we show a task that involves the motion perpendicular to the Z axis where the use of all the three radial actuators is essential in order to accomplish such a task. Future works will involve the design and implementation of dynamic controllers in order to enhance the capability of the manipulator.

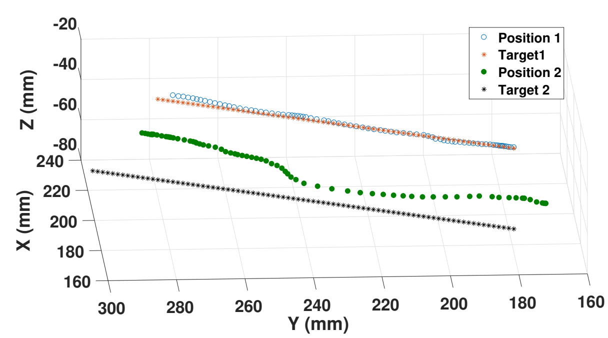

Fig. 7: Parallel trajectories perpendicular to the Z axis of the manipulator

VII. Acknowledgments

The authors would like to acknowledge the support by the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme FP7/2007-2013/ under REA grant agreement Smart-e, number 608022. This project/research has also received funding from the European Unions Horizon 2020 Framework Programme for Research and Innovation under the Specific Grant Agreement No. 785907 (Human Brain Project SGA2).

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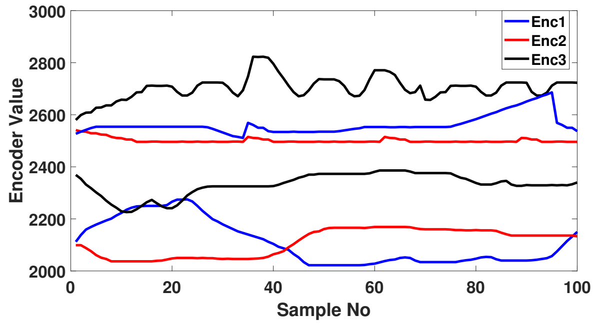

Fig. 8: Encoder values of the radial actuators

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