

A Bio-inspired Approach for Regulating and Measuring Visco-elastic Properties of a Robot Arm

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Abstract

This work focuses on interaction control of robot manipulators in unstructured environments, with special regard for situations of unpredictable contact/non-contact transitions. It is basically addressed to those environments where a high level of robot adaptability is required and no information on the geometry of the environment is available.

By pointing out the main limitations of standard interaction control schemes in managing situations of contact/non-contact transitions, this paper proposes a new control solution that is inspired by the biological model of motor control in voluntary movements. It consists of a combination of a feedforward loop and a proportional-derivative plus gravity compensation control in the feedback loop.

The control law is named coactivation-based compliance control in the joint space since a unique function, called coactivation function, is evaluated for regulating robot visco-elasticity in an unpredictably variable environment. It resumes the mechanism of adjustable visco-elastic properties acting on the agonist and antagonist muscles of a human arm.

The work also proposes a methodology for evaluating performance of interaction control schemes

that is based on stiffness graphical representation through ellipses. The method replicates the experimental setup used in neuroscience to measure stiffness in human limbs. It is regarded as a powerful tool for evaluating robot behavior over space and time, since it allows both a visual representation of stiffness variation during motion and a quantitative measure of robot performance.

It is shown how the method can be used to evaluate a control scheme and how it can provide indications to improve a control law. In this paper, an application to the standard compliance control in the joint space and the coactivation-based compliance control is presented.

1 Introduction

The control problem of robot interaction with the working environment was originally investigated in industrial scenarios for the execution of tasks such as assembly or parts mating. A series of control solutions ranging from the concept of active compliance [1], [2] to the concept of mechanical impedance [3], [4], [5] up to the hybrid position/force control approach [6] were proposed. They are still referred to as the basic approaches to interaction control, although the working environment is getting more and more complex and industrial tasks can no longer be reduced to a set of repetitive and well-defined motions.

In the new industrial scenarios, robots should be capable of facing a variety of tasks, which cannot be always pre-programmed. Robots should be required to operate in environments where part sizes and positions may vary, or where the materials may have different levels of flexibility. They should be required to cooperate with other machines or robots, or even to interact directly with human operators (see [7] for a survey).

Further, robots are being introduced in many other application fields, e.g. rehabilitation robotics, surgery, neuroscience, etc., where the variability of the workspace is typically higher than in industry and where contact with humans is often experienced. In all these contexts, the need for a high level of robot adaptability in the interaction control is very strong.

Apart from the specific application, a distinction can be always made between interaction with an unstructured environment and interaction with a structured environment. Whenever the environment can be accurately characterized and it is possible to discriminate between constrained directions of motion and unconstrained directions of motion, one can resort to a hybrid position/force control strategy to face the interaction control issue. On the other hand, when the geometry of the environment is unknown, interaction can be controlled by means of compliance or impedance control laws [8].

This work focuses on interaction between a robot and an unstructured environment, by concentrating on situations of unpredictable contact/non-contact transitions, i.e. situations where unforeseen transitions from free space to constrained space or vice versa can occur. The main objective of this work is to provide a contribution to the study of robot adaptability to an unpredictably variable environment. For this analysis contact/non-contact transitions are regarded as a meaningful case, especially when the presence of humans is a peculiarity of the robot working environment. In such situations, safety becomes the target with maximum priority during interaction at the expense of accuracy, while accuracy has not to be compromised when the robot returns to free space. The level of accuracy required in free space is strictly dependent on the application field; on the other hand, the maximum force value that the robot can exert in the interaction depends on the stiffness of the interaction environment.

The approach followed in the development of this research work consists of three main phases.

The first phase is aimed at acquiring an accurate knowledge of the control problem, by carefully analyzing the control solutions proposed in the literature.

The second phase consists of extending the analysis to biological motor control. Observing how humans face situations of constrained motion and contact/non-contact transitions may suggest new improvements of standard interaction control schemes. Therefore this phase is aimed at investigating the basic mechanisms of biological motor control which may be used in revisiting standard interaction

control laws. It culminates in a new formulation of compliance control.

The third phase is dedicated to the evaluation of the proposed compliance control scheme through standard analysis methods, in order to quantify the effective improvements with respect to the standard compliance control. Furthermore, a new evaluation methodology is proposed to validate the control law. It has been named the *stiffness ellipse method*, and is borrowed from an experimental method used in neuroscience to measure stiffness in the human upper limb.

As regards interaction control and, in particular, the adaptability to unpredictably changeable environments, the analysis of the literature has pointed out the basic limitations of classical interaction control schemes in unstructured environments.

Basically, compliance control turns out to be really easy to implement, since it does not require prior knowledge either of the environment or the robot dynamics; as a counter side, it is weak in managing situations of contact/non-contact transitions. At least a variable compliance function is needed to improve the level of robot adaptability to the environment.

On the other hand, impedance control can ensure higher performance than compliance control in contact/non-contact transitions. However, it requires computing robot dynamics model thus increasing the algorithmic computational effort.

Further, both compliance and impedance control require setting a number of control parameters that can vary linearly with the number of joints, when the robot is controlled in the joint space, or with the operational space cardinality, if the robot is controlled in the Cartesian space.

This research work resumes compliance control in the joint space by improving its level of reactivity and adaptability to a variable working environment. The choice of focusing on control in the joint space rather than in the Cartesian space is determined by different factors. The most obvious is the simplicity of implementation. Another factor is that this control offers the advantage of being applicable to very different mechanical structures, ranging from a classical industrial robot up to robots with elastic transmission systems or cable actuation systems [9], [10], [11]. Finally, a similar

control strategy is conceived as being used by the central nervous system to control hand stiffness: neurophysiological studies suggest that the viscoelastic properties of the human arm are controlled through joint stiffness and muscle activity [12]. When designing robots that attempt to mimic the versatility of human arm motion, it seems appealing to consider such biologically inspired control strategy.

A parallel control action is proposed here, based on a combination of a feedforward control loop and a feedback control loop. The feedforward control increases system reactivity and stability in fast as well as slow movements, while the feedback control improves the system adaptability to the constraints. In particular, an adaptive stiffness function is proposed for the proportional-derivative plus gravity compensation control in the feedback loop, which presents the following three basic properties (see our previous work [13]):

- A unique function, evaluated on line, is required to update the stiffness of all the joints during motion.
- The use of a variable function for the proportional and derivative parameters makes the controller independent of the task and the working conditions, and as such it is especially suitable for interaction with unstructured environments.
- The dependence on position error and interaction force conveys a high level of adaptability to the constraints without losing accuracy in free space.

The control law proposed in this paper has been named *coactivation-based compliance control in the joint space*. A unique parameter is used to modulate joint compliance in the interaction and is named *coactivation*, by analogy with the homonymous biological mechanism which regulates stiffness in the human arm (see Section 2).

The control law is evaluated in experiments of contact/non-contact transitions through standard evaluation techniques and through the proposed stiffness ellipse method. This is a powerful method to

visualize stiffness variation over space and time and also to extract a quantitative measure of control performance. Indeed, in addition to a measure of accuracy, stiffness direction and interaction force, it conveys an immediate graphical representation of the robot behavior during a task by describing stiffness variations through ellipses.

Recent advancements in neuroscience and biology that have inspired the coactivation-based control law and the stiffness ellipse method are presented in Section 2.

The work goes on with the mathematical formulation of the coactivation-based compliance control in the joint space (Section 3) and its validation on an 8-d.o.f. robot arm through standard evaluation techniques (Section 5). The stiffness ellipse method is presented in detail in Section 4 and is applied to a standard compliance control in the joint space. It turns out to be a suitable tool for evaluating performance of interaction control schemes and providing indications for the design of new control laws. Thus, it is used to carry out a compared analysis between the standard compliance control and the coactivation-based compliance control and extract evaluation parameters for interaction control schemes (Section 6) .

2 Recent advancements in investigating human motor control and hand stiffness

Biological motor control. Ideally, a motor control based on actions that are not affected by the output signals of the controlled object (i.e. feedforward control) ensures a null error between the reference and the controlled variable [14], [15].

In biological systems, however, feedforward control cannot ensure alone the desired behavior without the action of a feedback control [18], [16], [17]. The rationale is that feedforward control cannot reject unexpected disturbances which are unavoidably present in all biological systems.

On the other hand, the control of a biological system cannot be based only on a feedback action, because of the significant delay in the transmission of neural information [19]. The total feedback loop delay could reach 130 ms for oculomotor control [20], 110ms for proprioceptive control [21] and about 200–250 ms for visuomotor control [22].

Therefore, to achieve stability and reactivity in the motor control of a biological system, the combined action of feedforward and feedback control seems to be fundamental, especially in the control of voluntary movements of the arm. Stability, which can be degraded by delay in the transmission of neural information, is ensured in low as well as fast movements thanks to feedforward [16], [14], [15] whereas unskilled movements and interaction with an unknown environment are allowed thanks to feedback [17], [23].

In human arm control, feedback seems to act in the interaction control by regulating the muscular activity in accordance with the movement error [17]. A biological mechanism called *coactivation* acts on the agonist and antagonist muscles by regulating arm visco-elastic properties at the level of muscles and joints and indirectly at the level of end effector.

The phenomenon of neural adjustable mechanisms for the visco-elastic property is particularly evident in the spinal reflexes in human beings (especially the stretch reflex) [24], [25], where the coactivation between alpha and gamma motoneurons allows muscle contraction as well as perception of the contraction (Figs. 1, 2).

The concept of coactivation is often mentioned in works on the human arm modeling or else in studies on the human spring-like behavior [17], [25], [26]. Also impedance control, which dates to some twenty years ago, was born as a dynamic generalization of stiffness at the human arm limbs [27], [28], [3] and, in the last few years, other scientists working in robotics and neuroscience have discovered new areas of collaborations [17], [29]. They propose using robots as physical models to address specific biological questions and incorporate aspects of human or animal biomechanics and neural control in the design of robotic artifacts, in order to improve robot versatility and robustness for a given task [30], [31].

Here, the concept of coactivation and the studies on the combined action of feedforward and feedback control are borrowed for improving robot performance in situations of interaction with an unstructured environment and, particularly, in contact/non-contact transitions. The resulting inter-

action control scheme is presented in Section 3.

Measure of human arm stiffness. Neuroscience can also provide robotics with instruments for developing new evaluation methods, which can be regarded as an alternative or improvement of standard evaluation methods for robot control schemes. They could be used both for analysis of a known control scheme and for synthesis of new control solutions.

The main idea developed in Section 4 of this work consists of using methods for the measurement of the human hand stiffness, in static as well as dynamic tasks [32], [33], [34], [28], to evaluate performance of control schemes for control of robot end-effector stiffness.

In neuroscience, the classical approach to the measurement of the mechanical properties of a human arm is based on the use of a haptic device and on the measure of force and displacement of the subject’s arm, constrained by the device. The model of the human arm as well as the stiffness variation is derived by the collected force and displacement data.

The idea of using an ellipse to study human arm stiffness during tasks of posture maintenance was suggested in the late eighties [35], [28]. The experiments consisted of small displacements of the hand while maintaining a given posture. The subject’s hand was displaced from an equilibrium position by a two-joint manipulandum and the restoring forces were measured at the steady state. The relation between the force f and the displacement dx was modeled as: $f = Kdx$, where K was the stiffness matrix. Matrix K could be decomposed in a symmetric component K_s , representing the forces which could be derived from a potential function, thereby conferring muscles a spring-like behavior, and a skew-symmetric component K_a , representing the forces which had non-zero curl and which could not be derived from a potential function. The plot of the set of points $f = K_s dx$, for $\| dx \| = 1$, described an ellipse in the Cartesian space, called the *stiffness ellipse*.

The experiments showed that the stiffness ellipses for different subjects were very similar (at any given location, the shape and orientation of the ellipses did not change from one subject to another), while the stiffness magnitude varied. Also, they revealed that the stiffness ellipse size was a function

of how stiff the subject was keeping the arm, while the stiffness ellipse shape and orientation were a function of the posture of the arm [36], [35], [37].

More recently, the computation of the stiffness ellipse based on the joint stiffness matrix in lieu of the Cartesian stiffness matrix has shown that different stiffness ratios between shoulder and elbow joints (depending on different muscle co-contraction level) can produce changes in the shape and orientation of the stiffness ellipse [12]. Moreover, during force regulation tasks the orientation of the stiffness ellipse varies as a result of the joint stiffness changes. This result has been confirmed also by the compared analysis of the multi-joint tasks of posture maintenance, unconstrained point-to-point movements and constrained movements (Fig. 3) [38], [39], [40], [41]. The experimental data have shown that the size of stiffness ellipses during point-to-point movement is larger than during posture maintenance tasks and that the orientation slightly changes. Conversely, changes in stiffness ellipse orientation are remarkable during constrained multi-joint arm movements. For, the movement of the robot arm has been restricted to a transversal straight path and small force perturbations have been applied while the subject was moving. The data have shown that, in the middle of the movement, stiffness in the constrained direction decreases with respect to that during the unconstrained movement; as a result, the major axis of the stiffness ellipses largely changes in orientation, by pointing perpendicularly to the force direction.

The same set of experiments has been repeated in this work in order to measure robot end-effector stiffness in the three tasks of posture maintenance, point-to-point motion and constrained motion. The experimental setup and the results are shown in Section 4.

3 Control law

In the following a combined action between a feedforward control mechanism and a feedback control mechanism is proposed, like in biological motor control, in order to increase robot reactivity and stability by means of the feedforward loop, and control interaction force and accuracy by feedback. It is concentrated especially on the role of the feedback loop in the regulation of the arm visco-elastic

properties.

Basically, the robot arm control scheme consists of two torque contributions (Fig. 4): the first one (τ_{FF}) is produced by the feedforward loop through the inverse dynamic model and the second one (τ_{FB}) is evaluated by the feedback controller through a proportional-derivative plus gravity compensation control law.

The realization of the forward action is based on a partial or complete knowledge of the arm dynamical model, which allows calculating the feedforward torque vector as

$$\tau_{FF} = B(q_d)\ddot{q}_d + C(q_d, \dot{q}_d)\dot{q}_d + F\dot{q}_d \quad (1)$$

where

- $B(q)$ is the $(n \times n)$ joint inertia matrix
- $q, \dot{q}, \ddot{q}$ are the $(n \times 1)$ joint position, velocity and acceleration vectors, respectively
- $C(q, \dot{q})\dot{q}$ is the $(n \times 1)$ vector of centrifugal and Coriolis torques
- F is the $(n \times n)$ diagonal, positive definite matrix of joint viscosity coefficients

and the subscript ‘ d ’ indicates that such quantities are computed for the desired motion.

As regards the evaluation of the arm motor commands in the feedback loop, a proportional-derivative action in the joint space is proposed [42], with special emphasis on the adjustable mechanism of K_P and K_D parameters. The standard compliance control law is expressed as

$$\tau_{FB} = K_P\tilde{q} - K_D\dot{\tilde{q}} + g(q) \quad (2)$$

where K_P and K_D are $(n \times n)$ constant diagonal gain matrices. Quantity $\tilde{q} = q_d - q$ is the joint position error and $g(q)$ is the best available estimate of the gravitational torques acting on the joints.

On the other hand, the proposed control law, named *coactivation-based compliance control in the joint space*, can be written as

$$\tau_{FB} = K_P(c)\tilde{q} - K_D(c)\dot{\tilde{q}} + g(q) \quad (3)$$

where c is a variable factor. It allows regulating the robot stiffness and damping through the proportional and derivative gain matrices K_P and K_D .

3.1 Coactivation-based PD adaptive law

An adaptive law is chosen for c in the control law (3) which tries to mimic the biological mechanism of visco-elastic regulation acting on the human arm joints and agonist/antagonist muscles. The c factor is called *coactivation*, as in the human case, and is used to update the proportional and derivative gains of the robot control law both in unconstrained and in constrained motion.

An appropriate choice for the c function could improve arm accuracy in free space, by increasing stiffness, and increase arm compliance and elasticity in constrained space, by decreasing stiffness when an external bound is sensed. In both cases, the gains of diagonal matrices K_P and K_D evolve from an initial value (experimentally evaluated) as a function of a unique factor, that is the coactivation. The presence of contact is revealed by a force sensor on the robot wrist which allows switching from free space to constrained space and vice versa.

In the case of unconstrained motion, the arm can freely move in the execution of the task, without damaging objects or persons. Hence, emphasis is posed on the improvement of robot behavior in terms of accuracy, by addressing a reduction of the position error.

In the biological motor control, feedback control ensures high precision and fine positioning tasks; moreover, it is hypothesized that position error can contribute to regulate arm visco-elastic properties [17]. The same approach is resumed here to stiffen the robot arm in unconstrained motion by using only information on the current joint position, recorded by the position sensors. An adaptable law is proposed for the stiffness parameters that is depending on the robot position error. The i -th element of K_P increases from its minimum value as

$$k_P(c) = \begin{cases} k_{Pmin} & \text{if } c = 0 \\ k_{Pmin} + \bar{k}_P c & \text{if } c \neq 0, \quad k_P < k_{Pmax} \\ k_{Pmax} & \text{if } c \neq 0, \quad k_P \geq k_{Pmax} \end{cases} \quad (4)$$

where the coefficient $\bar{k}_p$ can be different for each joint, in order to allow regulating the level of coactivation for each of them. In (4), k_{Pmin} is the minimum gain allowing a quite accurate motion and k_{Pmax} is the maximum gain which still ensures stability in the motion. The updating law for c is an increasing monotonic function of the sole position error, i.e.

$$c = \beta \sqrt{\tilde{q}^T \tilde{q}} \quad (5)$$

as presented in [17] for the human visco-elastic regulation. In (5), β is a positive coefficient.

An analogous adaptable law is proposed for the viscosity parameters. The i -th element of K_D matrix evolves over time like (4), but with a slower increasing rate, i.e.

$$k_D(c) = \begin{cases} k_{Dmin} & \text{if } c = 0 \\ k_{Dmin} + \bar{k}_d c & \text{if } c \neq 0, \quad k_D < k_{Dmax} \\ k_{Dmax} & \text{if } c \neq 0, \quad k_D \geq k_{Dmax}. \end{cases} \quad (6)$$

Whenever an interaction force is sensed by the force sensor mounted on the arm, situations of danger or damage must be avoided and, despite the loss of accuracy, the maximum level of compliance in the interaction direction has to be ensured. In this case, the control law has to make the arm capable of adapting to the constraints in accordance with the level of force exerted at the end effector by the environment. From here the idea of using the force sensor information to decrease the k_P function from its initial value k_{Pin} with a law similar to the free space, i.e.

$$k_P(c) = k_{Pin} \bar{h} c \quad (7)$$

$$c = c_{min} + \alpha \frac{1}{\sqrt{f^T f}} \quad \text{if } f^T f \neq 0 \quad (8)$$

where $k_{Pin} \bar{h}$ is the maximum value for the proportional parameter, and $\bar{h}$ is a scalar coefficient playing the same role of $\bar{k}_p$. The viscosity parameters k_D in constrained motion observe the same law as in (7).

In (8) the coactivation function depends on the interaction force. When the force value f increases, the coactivation decays until a minimum value which still allows the arm to move, but sufficiently

low to ensure a high level of compliance. The necessity of setting a constant minimum value of coactivation (c_{min}) emerged during experimental trials in constrained motion. In fact, robot stability must be ensured even in the presence of very high interaction forces which cause too low coactivation values.

Finally, as regards the upper limit for c , it is natural to choose it unitary, so that during the period of application of interaction force stiffness cannot overcome its maximum value.

4 Stiffness ellipse method

The stiffness ellipse method is an experimental protocol developed for the validation of interaction control strategies and based on the graphical representation of the robot hand stiffness matrix (i.e. the Cartesian stiffness matrix) through ellipses. It resumes the ellipse-based approach used by neuroscientists in the evaluation of human arm stiffness and completes it with evaluation parameters suitable to measure performance of a robot arm.

In the following three geometrical parameters, which allow an ellipse to be uniquely determined in the plane, will be used to measure performance of a control scheme before, after and during interaction. They are:

- the *area*, which defines the ellipse magnitude;
- the *shape eccentricity*, which is calculated as the ratio between the minor and the major axis, thus providing information on the shape;
- the *ellipse orientation angle*, which is described in terms of the direction of the major axis.

The stiffness ellipse method requires estimating the hand stiffness matrix, as a first step, and extracting the listed three parameters, as a further step, in order to move from a numerical to a graphical stiffness representation.

In the case of interaction control in the Cartesian space, the hand stiffness matrix is known, as it is the proportional parameter imposed to regulate the end-effector interaction force.

In the case of interaction control in the joint space, like the coactivation-based compliance control and the standard compliance control in the joint space, the robot stiffness is regulated in the joint space through the joint proportional matrix. As a consequence, the Cartesian behavior is indirectly dependent on the joint stiffness matrix and the relation between the hand stiffness and the joint stiffness has to be extracted. To this purpose, the virtual work principle is invoked as follows.

Similarly to the manipulability ellipsoids described in [43], the ellipse derives from the relation

$$\tau = J^T f \quad (9)$$

between the joint torque τ and the interaction force f , where J is the robot Jacobian matrix. In the stiffness ellipse method, relation (9) is used to evaluate the robot behavior in correspondence of small perturbations as

$$\frac{\partial \tau}{\partial q} = \frac{\partial J^T}{\partial q} f + J^T \frac{\partial f}{\partial q}. \quad (10)$$

Then, by resorting to the variational equation of robot dynamics (see [39]), i.e. the robot dynamics model in correspondence of small perturbations, the joint stiffness R matrix can be expressed as

$$R = -\frac{\partial \tau}{\partial q} \quad (11)$$

and the hand stiffness K matrix can be defined as

$$K = -\frac{\partial f}{\partial x}, \quad (12)$$

where x is the Cartesian position of the robot end effector.

Substituting (11) and (12) in (10) yields

$$-R = \frac{\partial J^T}{\partial q} f - J^T K \frac{\partial x}{\partial q} \quad (13)$$

$$-R J^{-1} = \frac{\partial J^T}{\partial q} f J^{-1} - J^T K \quad (14)$$

and finally

$$K = \left(J^T\right)^{-1} \left(R + \frac{\partial J^T}{\partial q} f\right) J^{-1}. \quad (15)$$

Having calculated matrix K , the graphical representation of the stiffness can be carried out by means of the matrix singular value decomposition. This allows expressing K as

$$K = U \cdot S \cdot D^T \quad (16)$$

where

$$U = \begin{bmatrix} U_{max_x} & U_{min_x} \\ U_{max_y} & U_{min_y} \end{bmatrix} \quad (17)$$

being U_{max_x} and U_{max_y} the x and y components of the maximum resisting force vector for unit displacements, respectively.

Relations (16) and (17) are used to compute the three ellipse parameters. In particular, the ellipse orientation angle is calculated as

$$\varphi_e = \tan^{-1} (U_{max_y}/U_{max_x})$$

where $0 \leq \varphi_e < \pi$, while the shape eccentricity and the area are expressed, respectively, as

$$s = \alpha_{min}/\alpha_{max}$$

and

$$A = \pi \alpha_{max} \alpha_{min}$$

where $\alpha_{max} = \left(\lambda_{max} (K^T K) \right)^{1/2}$ and $\alpha_{min} = \left(\lambda_{min} (K^T K) \right)^{1/2}$, being λ_{max} and λ_{min} the maximum and the minimum eigenvalues of $K^T K$ matrix, respectively.

For each task, the graphical representation allows obtaining ellipses with different geometrical features in correspondence of different stiffness behaviors in the Cartesian space. Qualitatively, the major axis represents the direction of the highest stiffness while the minor axis indicates the direction of the minimum stiffness. The variations in length and direction of the major and the minor axis with respect to time and tasks provide information on the regulation of the arm stiffness in time and in different working conditions.

5 Validation of coactivation-based compliance control through standard techniques

The combined control action (1), (3) has been tested on an 8-d.o.f. robot arm, namely the Dexter arm (presented in detail in our previous work [11]), by means of standard evaluation techniques. This means that a suitable interaction scenario has been set up and position error and interaction force have been measured. Further, the coactivation factor has been recorded and drawn.

The experimental setup basically includes the Dexter robot arm and a force sensor mounted on the arm wrist (Fig. 5). The control law runs on a PC Pentium II and the motor commands are transmitted to the eight DC motors through two 4-axis board controllers (i.e. two MEI board controllers) with a sample rate of 10 ms. The force sensor is a three-component ATI force sensor capable of reading a maximum force value of 210 N. The sensor is used to verify the presence of dynamic perturbations on the trajectory and switch the arm from a stiff and accurate behavior to a more flexible and adaptive one and vice versa. The C++ Programming Language is used to integrate the control law with the sensor information.

The main objective of this experimental session is to demonstrate how efficiently a unique parameter is able to regulate the PD gains in the joint space in the transition from unconstrained to constrained motion as well as during interaction. To this purpose, the position error is used to extract a measure of robot accuracy in free space while the coactivation is used to derive information on the variation of robot visco-elastic properties in free space as well as in constrained space.

The experimental scenario tries to reproduce an unstructured environment which offers situations of unpredictable contact/non-contact transitions. The robot arm is neither provided with visual feedback nor with any other sensors which could give information on the geometry of the environment. Only eight encoders (for reading the angle joints) and the force sensor are used. Further, no a priori knowledge of the environment is assumed, except for the dimension of the robot workspace.

The experimental trials consist of repeating a point-to-point motion in four different situations: i.e. free space, constrained space, transition from free space to constrained space and, finally, transi-

tion from constrained space to free space.

The motion in the free space is described by a polynomial function of fifth degree from an initial position to a final position. Then, the constraint is realized by means of an obstacle on the motion direction, having a parallelepiped shape. It can be modelled with a stiffness value of $K_e = 5 \cdot 10^4$ N/m, and the assumption is made that the experienced force acts only at the robot end effector.

The first phase of motion in free space is addressed to evaluate the effect of the coactivation mechanism on the robot accuracy in the unconstrained motion. Hence, the c graph is reported together with the position error in the Cartesian space (Figs. 6, 7) in order to emphasize that, when the robot moves freely, coactivation increases and the Cartesian error decreases from 0.020 m to an average value of 0.003 m at steady state.

The c factor acts directly on the joints and indirectly on the Cartesian position; hence, changes in Cartesian position error are delayed with respect to changes in the c factor and also depend on the choice of $\bar{K}_P$ parameters which regulate the rate of variation of joint stiffness.

For the experiments, $K_{Pmin} = \text{diag}\{60, 40, 10, 9, 8, 1, 0.2, 0.2\}$ and $\beta = 1.5$. The $\bar{K}_P$ matrix is fixed at the beginning as it depends on the inertial properties of each link and defines the range of variation of c for each joint. For the Dexter arm, $\bar{K}_P = \text{diag}\{3, 2.5, 2.5, 2, 1.8, 1, 0.2, 0.2\}$.

In the second phase the constraint is placed in the robot workspace. The arm is constrained during the whole duration of the task by the constant force produced by the obstacle, except for a short time interval during which the force is released. The coactivation, modulated by the sensed interaction forces, is recorded and shown in Fig. 8. Around $t = 5$ s, in correspondence of a force reduction, the c factor makes the position error decrease for a short time and then increase again until 0.08 m (Fig. 9) when the force grows. For K_P , $K_{Pin} = \text{diag}\{60, 40, 15, 10, 8, 4, 1, 1\}$, $\bar{H} = \text{diag}\{1, 0.8, 0.8, 0.7, 0.7, 0.5, 0.1, 0.1\}$, $c_{min} = 0.4$ and $\alpha = 1$ have been chosen.

Finally, the last two phases focus on the transition from the stiff behavior in unconstrained motion to the adaptable (i.e. compliant) behavior in an unexpected constrained workspace and the reverse

transition. To this regard, a sole experiment is reported, which considers both transitions. The graph of the coactivation in Fig. 10 shows the change in compliance around $t = 5$ s due to a contact and a subsequent release of the contact. The error increases as soon as the compliance increases and then reduces with respect to the interaction instant (Fig. 11).

It is worth noting that the arm is stable in all the four phases thanks to the high rate of adaptability to a constraint. The role of c is of paramount importance to preserve stability of the arm control since it allows imposing the rate of stiffness variability as well as a minimum level of visco-elasticity through c_{min} , that is experimentally determined.

6 Validation of compliance control schemes through the stiffness ellipse method

This section presents the experimental protocol of the stiffness ellipse method. The validity of the method is tested on a standard control law, i.e. compliance control in the joint space (2), whose performance are already known in the literature. Further, it is applied to the coactivation-based compliance control in the joint space (3) and a comparison with the standard control (2) is carried out.

The stiffness ellipse method requires evaluating the hand stiffness matrix in terms of joint stiffness matrix R , as in (15). Matrix R corresponds to K_P matrix in control laws (2) and (3) and is assumed to be diagonal in order to simplify the process of parameter setting required by the control scheme. This assumption, however, does not weaken the ellipse-based methodology, since the double-joint stiffness values are generally lower than the single joint values (corresponding to the coefficients on the main diagonal) both in static and in dynamic case [39], and thus prove to be inefficient to produce shoulder and elbow torque in force control [44].

The graphical representation of hand stiffness based on ellipses is obtained through the singular value decomposition (16), (17) of matrix K .

As regards the experimental setup, the robotic platform described in the previous section has been simplified into a 2-d.o.f. robot arm, moving in a (x, y) plane. The rationale is that the adherence to

the original protocol used by neuroscientists is considered to be fundamental to verify the feasibility of the proposed methodology in validating a control scheme.

Hence, the Dexter arm has been transformed into a planar arm, with two joints (i.e. the shoulder and the elbow joint) and two links (Fig. 12). All the other joints are not controlled and mechanically blocked. The robot joint positions are measured by means of two incremental encoders located on the 2 motors and the force perturbations exerted at the end effector are sensed by the three-component ATI force sensor, mounted at the robot wrist.

Similarly to the method in [40], [39], [12], [38], the reference frame is fixed on the shoulder, with the z -coordinate fixed at the level of the shoulder. The x -axis indicates the rightward direction while the y -axis indicates the frontal direction away from the body. The frame origin $[x, y] = [0, 0]$ is set on the shoulder and transversal movements from $[x, y] = [-0.2, 0.65]$ m to $[x, y] = [0.2, 0.65]$ m have been performed. It is worth noting that the y -coordinate is different from [40], [39], [12], [38] because of the different link lengths.

A series of intermediate positions are considered between the initial and final postures and the experiments have been performed several times for each posture. Mean values are reported for each case.

By analogy with the experiments on human subjects, hand stiffness has been evaluated in three different working conditions: posture maintenance (static case), point-to-point motion (dynamic case) and finally constrained motion. For each of the three cases, the same experimental assumptions and the same setup are considered.

The complete set of experiments has then been repeated with different values of the proportional matrix, in order to analyze and discuss the corresponding changes in the ellipses. Also the analysis over time has been carried out, since it appears to be meaningful in describing the dynamic evolution of ellipses for different proportional gains. For each posture, a time window of 10 samples is moved three samples ahead, starting from the instant of perturbation, as recorded by the force sensor.

Static case: posture maintenance. In the static experiments of posture maintenance, the robot arm is controlled to maintain the position in spite of short perturbations. To estimate the stiffness changing during static tasks, the end effector has been pushed and pulled back in eight randomized directions $\pm x, \pm y, \pm x \pm y, \pm x \mp y$ for short time instants. The applied forces are small enough to move the end effector in the eight directions of about 6-8 mm in very short periods (less than 0.3 s).

Considering the transversal path from $[x, y] = [-0.2, 0.65]$ m to $[x, y] = [0.2, 0.65]$ m, the stiffness ellipse has been estimated in 5 different equidistant postures (Fig. 13). The robot arm has been positioned in each posture and then perturbed from the eight different directions. The matrix K has been extracted from (15) by imposing $\frac{dJ}{dq} = 0$ and the corresponding ellipses have been calculated on ten samples, starting from the instant of perturbation.

The procedure has been repeated 40 times (8 times for each posture).

Dynamic case. In the dynamic experiments the robot arm is moved from the initial position $[x, y] = [-0.2, 0.65]$ m to the final position $[x, y] = [0.2, 0.65]$ m while short perturbations are exerted at the end effector. The velocity of the robot end effector is 0.2 m/s.

To estimate the changes in stiffness, matrix K has been calculated from (15) with $\frac{dJ}{dq} \neq 0$ and five different equidistant positions have been taken on the transversal path. During motion, in correspondence of each posture, the end effector has been pushed and pulled back in the eight randomized directions $\pm x, \pm y, \pm x \pm y, \pm x \mp y$ for short time instants. The procedure has been repeated 72 times.

Similarly to the experimental protocol reported in [40], 9 ellipses corresponding to 9 time instants have been estimated for each path, as shown in Fig. 14. In particular, 2 ellipses have been calculated in the starting position, before the motion (ellipse 1 and 2), and 2 ellipses in the rest position, after the motion (ellipse 8 and 9). In both cases, the robot is in static conditions and the ellipses are the same as in the posture maintenance experiment. The five remaining ellipses correspond to the motion starting point (ellipse 3) and to the other 4 positions reached while moving from the initial to the final position (ellipse from 4 to 7). The three parameters evaluated for drawing the ellipses have been

averaged on ten samples, starting from the instant of perturbation.

Constrained motion. The last set of experiments has been carried out similarly to the dynamic case. The robot arm is moved from $[x, y] = [-0.2, 0.65]$ m to $[x, y] = [0.2, 0.65]$ m and is randomly perturbed in eight directions with small forces. The difference with respect to the point-to-point motion is that the motion is restricted to a transversal straight path by a barrier on the y -direction. Hence, the force sensor measures constantly a force due to the constraint.

The 9 ellipses are calculated in correspondence of five equidistant postures starting from the instant of perturbation (Fig. 15). A total of 72 trials has been carried out.

6.1 Validation of compliance control in the joint space

The experimental protocol described above has been repeated for two different choices of K_P matrix. Firstly, $K_P = \text{diag}\{32, 4.5\}$ has been considered. Note that higher values do not allow realizing the experiment since they make the system unstable during interaction. Then, the experiments have been repeated with $K_P = \text{diag}\{15, 2.5\}$.

A compared analysis of static and dynamic cases has been carried out by means of the combined graphical representation of the 2-link robot arm and the stiffness ellipse in the 5 postures reached during the transversal motion. In this way, information on the area, the shape and the orientation of the ellipses with respect to the arm configuration is conveyed through the graphical representation, like in neuroscience [39].

As shown in Figs. 13, 14, in each posture the ellipse has a different area and a different orientation. In particular, the area reduces when the robot moves from the lateral positions to the central positions and the orientation changes according to the position of the elbow, i.e. the major axis is always oriented towards the elbow, both in static and in dynamic case.

The comparison between static and dynamic behavior has pointed out that the ellipses do not enlarge or thicken in the point-to-point motion; indeed Figs. 13, 14 and Tabs. 1, 2 demonstrate that the magnitude decreases whereas the eccentricity increases with respect to the posture maintenance.

This behavior, that is also confirmed by the experiments with the lower K_P matrix ($K_P = \text{diag}\{15, 2.5\}$) (Tabs. 3, 4), differs from the results in the human subjects.

Using two different K_P matrices for the experiments, i.e. $K_P = \text{diag}\{32, 4.5\}$ and $K_P = \text{diag}\{15, 2.5\}$, has shown that an increase of proportional gains causes an evident increase in the area. For the static case, the analysis of the data for different choices of K_P has pointed out that the ellipse area can be approximated with a quadratic polynomial function of K_P , while Tabs. 1–4 show that the shape eccentricity decreases when the accuracy increases. The orientation, instead, does not change. Stiffness ellipses during posture maintenance for four different values of K_P are drawn in Fig. 16.

Moreover, the time analysis shows that the ellipses do not evolve over time and the area is always constant (Fig. 17). Besides the lack of correspondence with the biological model, this translates into a static behavior before, during and after the perturbation. If K_P is high (e.g. $K_P = \text{diag}\{32, 4.5\}$), the robot arm is more accurate but it is not capable of adapting to different interaction situations (Figs. 16, 18). Decreasing K_P (e.g. $K_P = \text{diag}\{15, 2.5\}$) ensures a safer interaction (stiffness ellipses are smaller), but at the expense of the accuracy even when the perturbation is finished (Figs. 16, 19).

The last experiment of point-to-point constrained motion, performed in presence of a barrier along the y -axis, allows showing that, in a constrained environment, the standard compliance control cannot adapt to a constraint. Some values of K_P cannot be used, since they cause instability in the interaction with the constraint. Thus, the higher K_P , i.e. $K_P = \text{diag}\{32, 4.5\}$, turns out to be unsuitable for tasks of interaction and the results reported in Fig. 15 are related to the lower K_P , i.e. $K_P = \text{diag}\{15, 2.5\}$. In correspondence of the central ellipses a slight inclination can be observed with respect to the unconstrained case (Fig. 20) without reduction in magnitude. Indeed, the central ellipses appear to enlarge with respect to the unconstrained case.

6.2 Validation of coactivation-based compliance control in the joint space

As for the compliance control in the joint space, the experiments in posture maintenance as well as in point-to-point motion result in a set of ellipses which, drawn with the 2-link robot arm in the 5 configurations, differ in shape and magnitude in each configuration and are oriented always towards the elbow.

The experiments have been repeated 8 times for each posture for different values of α in the coactivation function (8).

A parametric analysis of stiffness ellipses as a function of coefficient β in (5) has not been considered, as it does not act in the interaction but only in the free space.

Both in the posture maintenance experiments and in the dynamic case, the initial value for K_P matrix has been set as $K_{Pmin} = \text{diag}\{40, 8\}$ for the free space and as $K_{Pin} = K_{Pmin}$ for the interaction case. The matrices $\bar{K}_p$ and $\bar{H}$ of coefficients $\bar{k}_p$ and $\bar{h}$ are respectively $\bar{K}_P = \text{diag}\{2.5, 1.8\}$ and $\bar{H} = \text{diag}\{0.8, 0.7\}$ and β is equal to 1.5. The parameter $\alpha = 1$ has been chosen for the first set of experiments and then a higher value ($\alpha = 2$) has been used.

As shown in Figs. 21, 22, ellipses 1 and 2 in the point-to-point motion are analogous to ellipse 1 in the posture maintenance. The scenario is similar for ellipses 8 and 9 in Fig. 22 with respect to ellipse 5 in Fig. 21. When the motion begins, the ellipse slowly evolves by enlarging and by thickening with respect to the static ellipses. Tables 5, 6 show that the area slightly increases as well as the shape eccentricity, while the orientation is unaltered. These results are consistent with the experiments on human stiffness [39].

Changing the value of α in (8), which regulates the rate of variation of stiffness in the interaction, the ellipse behavior is almost unchanged as regards shape and orientation, but notably changes in magnitude. At each time instant and for each position, the area becomes greater when α is higher (Tabs. 5–8). In particular, for the static case, the data extracted in correspondence of different values of α allow approximating the variations of the ellipse magnitude with respect to α through a poly-

nomial function of fourth degree.

Changing α modifies the interaction behavior (e.g. the ellipse magnitude in correspondence of small perturbations) but does not compromise accuracy, which is depending on β . Leaving β unchanged ensures comparable values of the position error and unaltered values of eccentricity in the two considered cases of transversal movement, as evident in Figs. 23, 24 and Tabs. 5–8.

Figure 25, which shows four overlapped ellipses for four different α values in the same static posture, reminds the variation of stiffness ellipses with the level of muscle co-contraction in human subjects [12]. This suggests that also for the robot it could be feasible to regulate the level of contraction at the shoulder and/or at the elbow according to the interaction task. Whether different levels of shoulder or elbow contraction are required to perform different interaction tasks, two different values of α in the coactivation-based control law can be considered, one for the shoulder and one for the elbow. In such a case, the interaction will depend on the ratio between the two levels of contraction, like in humans.

Further, the time analysis of the stiffness ellipses has confirmed that the coactivation-based compliance control can effectively adapt to the perturbation and is closer to the biological behavior than the standard compliance control in the joint space.

Studying how the stiffness ellipse changes over time when small perturbations are exerted at the end effector means verifying that the robot (initially stiff) dynamically returns to the initial stiffness when the perturbation is finished. Indeed, the robot stiffness, and correspondingly accuracy, continues to slightly increase after the perturbation because of the coefficient β in (5). Figures 26 and 27 illustrate the ellipses changing in time in a static posture and in a dynamic case, respectively. As expected, in the static case the ellipse magnitude dynamically increases while the orientation and the eccentricity remain unchanged. In the point-to-point motion, instead, the orientation evolves towards the orientation of the next point. The evolution of the ellipse area over time is drawn in Fig. 28 for the two values of α . The area increases over time and during the perturbation (i.e. until about 0.2 s)

for $\alpha = 2$ is always higher than for $\alpha = 1$.

The last set of experiments is concentrated on the issue of constrained motion. The results reported in Fig. 29 have been obtained with $\alpha = 1$. As it was expected, ellipses 1 and 2 and even 8 and 9 are unchanged with respect to the point-to-point motion (Fig. 22), since they are not influenced by the horizontal constraint along the y -axis. Ellipses begin changing when the robot starts moving. In particular, ellipses 4, 5 and 6 become smaller and change in orientation. They are more inclined with respect to the static and dynamic case and have a smaller area because of the force exerted by the constraint on the force sensor. The inclination reduces when the robot approaches the end of the movement and returns to a static condition, as evident in ellipses 6 and 7 in Fig. 29.

The major inclination indicates that the axis of major stiffness tries to dispose perpendicular to the constraint. This means that the arm regulates the stiffness in order to rotate the minor axis towards the obstacle and exert a minor force in the direction of interaction.

It is worth noticing that the ellipse orientation changes in the middle of the movement even if the coactivation factor does not explicitly depend on force direction. This is due to the different behavior of elbow stiffness with respect to the shoulder stiffness during motion.

In the robot arm, in fact, elbow and shoulder parameters in the constrained motion have a similar rate of variation (i.e. $\bar{H} = \text{diag}\{0.8, 0.7\}$) and a different initial value. Elbow initial stiffness has been set at a lower value than shoulder stiffness, as it can be seen in $K_{Pin} = \text{diag}\{40, 8\}$. This choice derives directly from biology. It seems that humans control directional characteristics of hand stiffness by opportunely varying joint stiffness [12]. Particularly, when the human arm is constrained to move under conditions similar to the conditions chosen for the robot in the constrained motion experiments, changes in the ellipses seem to be mainly due to the elbow joint. In fact, in constrained motion elbow stiffness results in lower values than in unconstrained motion, while shoulder stiffness is quite unchanged [38].

6.3 Data analysis

The data collected during the experiments with the stiffness ellipse method seem eligible for providing qualitative as well as quantitative information on performance of interaction control schemes. Whereas figures of ellipses overlapped to a 2-link robot arm convey qualitative information on the variations of the ellipse features over space and time, the numerical data provide a measure of three important factors: the stiffness magnitude, the level of accuracy and the direction of the major stiffness. The advantage is that changes in robot behavior are immediately visible through the figures and a careful data analysis is possible by means of the three measured parameters.

The stiffness magnitude can be measured through the area of the ellipse. The evidence that, in the static case, the ratio between the areas remains constant for all the five postures while changes for different values of proportional gains turns out to be useful to derive a law of variation of stiffness as a function of K_P matrix or α coefficient. In particular, the analysis of the data measured for different values of K_P and α has pointed out that:

- The ellipse area as a function of K_P is approximately a polynomial function of second degree.

It depends both on the joint proportional gain k_P and on the posture. Hence, for a 2-link robot arm five different functions (each for a different posture) can be extracted for each joint. In general, they can be expressed as

$$A(k_P) = a^* k_P^2 + b^* k_P + c^*$$

where a^* , b^* , c^* depend on the joint and the posture.

- The ellipse area as a function of α can be approximately described by a polynomial function of fourth degree. It is strongly dependent on α and slightly on the posture and can be expressed as

$$A(\alpha) = a\alpha^4 + b\alpha^3 + c\alpha^2 + d\alpha + e$$

where a , b , c , d and e are the polynomial coefficients.

The level of accuracy, instead, can be measured by means of the shape eccentricity, as well as of the position error. Tables 1–4, corresponding to the static and dynamic case for two different K_P in the standard compliance control show that the eccentricity decreases when accuracy increases, while Tables 6 and 8 show that the eccentricity remains unchanged if only α is varied in the coactivation-based compliance control. This was expected, since in the coactivation-based compliance control the coefficient α is responsible for the interaction, while the coefficient β , which in the experiments was never changed, is responsible for the accuracy.

Finally, the direction of the greater stiffness and, thus, of the major accuracy is indicated by the ellipse orientation angle ϕ . The data demonstrate that ϕ does not depend on the level of compliance and accuracy, but it depends only on the arm posture. For a given posture, it does not change when α or K_P are unchanged. Further, for each posture, ϕ represents the direction of the major force exerted by the robot on the environment.

7 Conclusions

This paper has focused on the interaction control of a robot arm in an unstructured environment, with special emphasis on the need for adaptability to unpredictable changes in the environment. In such a case, the standard interaction control schemes suffer from a number of limitations. Hence, studies on the biological motor control have been taken as a possible inspiration source for new control solutions.

The work has proposed the coactivation-based compliance control in the joint space as an improvement of standard compliance control, by showing its performance through standard evaluation techniques. The control scheme combines a feedforward and a feedback control loop in order to enhance rapidity of response and system stability in free space as well as in constrained motion. Special attention has been dedicated to the feedback control: a human-like mechanism (i.e. the *coactivation*) has been introduced in the PD control to regulate the visco-elastic arm properties. This allows choosing a single function to modulate the proportional and derivative gains for all the arm joints; further,

it permits to regulate robot compliance independently of the accuracy.

The paper has also presented a new evaluation method for robot interaction control schemes, i.e. the stiffness ellipse method, that has been borrowed from an experimental method used in neuroscience for measuring hand stiffness in humans. It seems eligible for measuring performance of interaction control schemes as well as for providing indications on the design of new control solutions.

The same experimental setup used in neuroscience has been replicated for a robot arm and measurements of stiffness have been carried out for the standard compliance control in the joint space. In this way, the validity of the proposed evaluation method has been verified.

A compared analysis between standard compliance control and coactivation-based compliance control has been carried out by means of the stiffness ellipse method. The results obtained have a twofold validity. On one hand, they have shown that the coactivation-based compliance control in the joint space can manage contact/non-contact transitions in a fashion that is quite close to the behavior observed in humans. The same consideration does not apply to the standard compliance control in the joint space.

On the other hand, a careful analysis of the data collected during the experiments has provided three measures of performance of interaction control schemes, that are the ellipse area, the shape eccentricity and the ellipse orientation angle. They give information on the stiffness magnitude, the level of accuracy and the direction of the major stiffness, respectively. The law of variation of the area with respect to K_P and α has been finally extracted.

Future researches will be addressed to pursue two main objectives. The first one concerns the analysis of the role of the elbow coactivation or else of the shoulder coactivation in the execution of different tasks. Like in humans, it could be possible that only one of the two robot joints needs to be highly adaptable for the execution of some tasks [12]. The effects of two separate values of α , one for the shoulder and another for elbow, will be evaluated.

The second objective is more related to the experiment of constrained motion. The role of force direction and force magnitude in the variation of the ellipse inclination in constrained motion will be deeply investigated. This could help improve the mathematical relation between force and coactivation factor in robotics, and further understand the biological mechanism of visco-elastic regulation in neuroscience.

Finally, the possibility of including adaptive or learning mechanisms for developing an internal model of the robot dynamics will be taken into consideration. The rationale is that the dynamic model of complex robotic structures is often unknown or computationally heavy. Moreover, updating the robot internal model on the basis of the dynamical changes of the environment could be a suitable solution to improve robot reactivity in variable environment and adaptability in contact/non-contact transitions.

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