Advancement of Robots With Double Encoders for Industrial and Collaborative Applications

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Abstract—**The paper deals with the control strategies advancement for robots with double encoders for industrial applications and human-robot collaboration. It addresses both external force/torque detection, classification the nature of the force applied to the manipulator as well as selection of an appropriate reaction strategy for either human-robot collaboration and technological process execution. In contrast to previous works, the external force is estimated based on the stiffness model and double encoders technology. To estimate the validity of the implemented compliance error estimation and compensation techniques based on the reduces stiffness model additional analyses were done. It showed that a widely used reduced stiffness model for the compliance error compensation is able to compensate about 90% of the end-effector errors caused by the external loading. Proposed control algorithms and reaction strategies were validated by a simulation study and experimental study with a collaborative robot with torque sensors Kuka IIWA LBR 14.**

I. INTRODUCTION

The efficient interaction between robot and environment requires getting information about external world. Such information can be obtained by means of different kind of sensors. In the case of distance sensors, an unwanted collision can be predicted and completely avoided. However, these sensors do not cover the whole robot space and their efficiency depending on the working conditions like illumination or presence of chips and sparks during the technological process. To avoid the impact of environmental factors it is possible to use contact sensors. Knowledge of joint torques allows localization of collision point and estimation of external force [1].

On the other hand, robot manipulators are usually considered as rigid multi-body mechanical systems, which simplifies dynamic analysis and control design, but may lead to performance degradation. Deformations and vibrations caused by these external forces decrease the robot accuracy and should be taken into account in order to achieve high positioning accuracy.

By placing encoders on both motor and load sides (Fig. 1) it is possible to detect the displacement caused by the joint elasticity. This additional information on the joint can be used at least in three possible ways: identification, control, and external torque sensing. The identification procedure provides information about compliance characteristic of the elastic joint. Advanced robot control algorithms use this data to eliminate compliance errors and vibrations in the system. Double encoders supplemented by a stiffness model also can work as the force/torque sensors, allowing to develop robot behavior strategies which are based on collision with the dynamically changed environment.

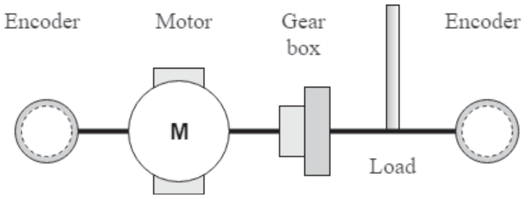

Fig. 1. Double encoders location

To control efficiently a compliant manipulator, corresponding model and its internal parameters must be known. In order to model robot stiffness behavior, Virtual Joint Modeling (VJM) could be used. VJM is a common technique for stiffness analysis and it provides good results with less computational effort than other techniques (see [3], [4], [2]). It is based on the extension of the traditional rigid model by adding virtual joints, which describe the elastic deformations of links and joints. Practical application of this methodology can be found in [6], [5]. A number of robot manufacturers try to integrate double encoders in the manipulator's joints and use them in the feedback control loop for compensation of the joint compliances ([7], [8]).

Simple and efficient dynamic model of a robot with elastic joints is required by the majority of control algorithms, in this work we use model proposed by [9]. As for control algorithms, several common techniques are available. Proportional-derivative (PD) control algorithm, based only on the motor side sensor data, was introduced by [10] with author-defined constraints for the controller which allow the system to be stabilized. More advanced control technique based on a singular perturbation can be found in [11], [12]. This approach is based on time scaling and separate control of fast and slow subprocesses. Sliding mode control is more robust to the accuracy of model parameters, its application to manipulators with elastic joints is described in [13], [14].

More specialized control technique, designed for the use of double encoders, is Self Resonance Cancellation (SRC). It allows to overcome the problem of anti-resonance restriction in the two-inertia system by introduction of a virtual angle [15]. This angle is calculated from motor and load side positions and provides the lack of resonance. Combination of SRC with traditional P-PI control technique can be found in [16]. Such combination allows to eliminate each other faults, as a result, poles can be arranged arbitrary, the vibration and disturbance suppression performances are improved and the control bandwidth becomes higher. While for single joint this technique demonstrates good results, our attempt to scale it for a system with several joints was failed.

By comparing data from the motor and load side encoders, double encoders can replace external torque sensors and be used in algorithms of collision driven interaction. Such interaction strategies can use an appropriate reaction based on information about the type of interaction, robot configuration, and final goals. [17] defined some base reactions like stopping or reflexing (go backward, become compliant). [19] presented an improved version of this approach with alternative collision reaction algorithms, using trajectory scaling. A unified framework for safe physical human-robot collaboration was described by [18], where the collision avoidance algorithm is based on the depth image and a collision reaction hierarchy. An approach based on the neural networks for collision detection has been proposed by [20], where the collision classification was introduced.

In this work, we discuss benefits that could be gained from equipping manipulators with double encoders. Three possible applications are considered such as compensation of the compliance errors, comparison of control techniques and the use of double encoders as torque sensors for reaction based interaction with the environment of the robot.

To address this issue, the remainder of the paper is organized as follows. Section 2 defines the methodology and approaches used in this paper. Section 3 describes an implementation for all three scenarios. In Section 4 results are given. Section 5 summarizes the main contributions of the paper.

II. METHODOLOGY

A. Stiffness identification

Compliance error compensation requires the stiffness matrix of the robot. The matrix can be found using the VJM method. This technique assumes that each elastic element could be replaced with its rigid analog and a virtual spring, which describes all possible elastic deformations (Fig. 2).

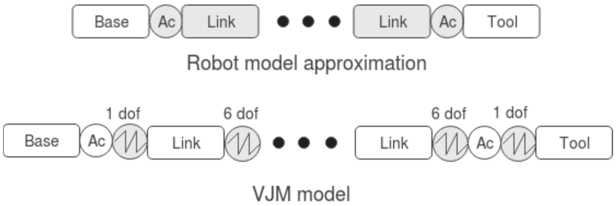

Fig. 2. VJM for serial manipulator (white elements are rigid, gray are elastic)

The total transform matrix T_{tot} of the robot with virtual joints could be found as

$$\boldsymbol{T}_{tot} = \boldsymbol{T}_{base} \prod_{i=1}^{N} \left[\boldsymbol{R}(q_i) \cdot \boldsymbol{R}(\theta^i_{Ac}) \cdot \boldsymbol{T}^i_{Link} \cdot \boldsymbol{T}_{3D}(\boldsymbol{\theta}^i_{3D}) \right] \boldsymbol{T}_{tool} \tag{1}$$

where $\boldsymbol{T}$ and $\boldsymbol{R}$ are homogeneous matrices of translation and rotation, q is a joint angle, θ_{Ac} and $\boldsymbol{\theta}_{3D}$ are virtual joint coordinates for active joint and link respectively. $\boldsymbol{T}_{3D}$ is the deflection in link, caused by translations and rotations of all the virtual joints in $\boldsymbol{\theta}_{3D}$:

$$\begin{aligned} \boldsymbol{T}_{3D}(\boldsymbol{\theta}_{3D}) = \boldsymbol{T}_x(\boldsymbol{\theta}_x) \cdot \boldsymbol{T}_y(\boldsymbol{\theta}_y) \cdot \boldsymbol{T}_z(\boldsymbol{\theta}_z) \times \\ \boldsymbol{R}_x(\boldsymbol{\theta}_{xx}) \cdot \boldsymbol{R}_y(\boldsymbol{\theta}_{yy}) \cdot R_z(\boldsymbol{\theta}_{zz}). \end{aligned}$$

Function $t(\boldsymbol{q}, \boldsymbol{\theta})$ could be obtained from the model (1) and defines position and orientation of the robot end-effector based on the current configuration and virtual joint state. It allows to find the Jacobian for virtual joints $\boldsymbol{J}_\theta = \partial t(\boldsymbol{q}, \boldsymbol{\theta}) / \partial \boldsymbol{\theta}$. In case of serial manipulator without passive joints, stiffness matrix in Cartesian space is equal to

$$\boldsymbol{K}_C = (\boldsymbol{J}_\theta \cdot \boldsymbol{K}_\theta^{-1} \cdot \boldsymbol{J}_\theta^T)^{-1}$$

where $\boldsymbol{K}_\theta$ is a stiffness matrix in joint space. Matrix $\boldsymbol{K}_\theta$ is diagonal, its elements are scalar values in case of joints and 6×6 matrices for links. Finally, end-effector deflection under the load $\boldsymbol{w}$ can be found as

$$\Delta \boldsymbol{t} = \boldsymbol{K}_C^{-1} \boldsymbol{w}. \tag{2}$$

Double encoders obtain information about joints only, therefore a reduced stiffness model should be introduced, which assumes that all elasticity is concentrated in joints. In order to find parameters of this model, equation (2) could be rewritten in the form

$$\begin{aligned} \Delta \boldsymbol{t} &= \boldsymbol{A} \cdot \boldsymbol{\pi} \\ \boldsymbol{A} &= (\boldsymbol{J}_1 \boldsymbol{J}_1^T \boldsymbol{w}, \boldsymbol{J}_2 \boldsymbol{J}_2^T \boldsymbol{w}, ... \boldsymbol{J}_m \boldsymbol{J}_m^T \boldsymbol{w}) \end{aligned}$$

where $\boldsymbol{\pi}$ is a vector of joint compliances, $\boldsymbol{A}$ is an observation matrix, which can be obtained from Jacobian $\boldsymbol{J}_\theta^j$ and applied force $\boldsymbol{w}$. Then elastostatic parameters of the model can be found with the help of least squares method:

$$\hat{\boldsymbol{\pi}} = \left(\sum_{j=1}^{m} \boldsymbol{A}_j^T \boldsymbol{\eta}^T \boldsymbol{\eta} \boldsymbol{A}_j \right)^{-1} \left(\sum_{j=1}^{m} \boldsymbol{A}_j^T \boldsymbol{\eta}^T \boldsymbol{\eta} \Delta \boldsymbol{t}_j \right)$$

where $\hat{\boldsymbol{\pi}}$ is a vector of estimated compliance values, m is a number of experiments, $\boldsymbol{\eta}$ is a matrix of weighting coefficients.

B. Compliance compensation strategy

There are following displacements which caused by the manipulator compliance:

- link deflection caused by robot mass;
- joint deflection caused by robot mass;
- link deflection caused by external loading;
- joint deflection caused by external loading.

The influence of each factor is different, but total end-effector position without compensation depends on a combination of them all.

In order to compensate compliance errors in both links and joints, the following steps could be applied. First, a difference of angles between primary and secondary encoders in combination with joint stiffness coefficients could be used to estimate the external loading. Further, the complete stiffness model is used to modify the actuator inputs and compensate both types of compliance errors. In this approach, the feedback relies on the primary encoder, while the secondary encoder is used to define the elastic deflection.

C. Control techniques

Information obtained from double encoders can be used to control manipulator in a more efficient way. Although there is a lot of control techniques for nonlinear systems, we consider only three of them.

The control techniques for elastic joint robot can be generalized in a form represented in the Fig. 3. It consists of two parts, the first one uses feedback based on the position, and the second uses information about motor and load rates. Depending on the particular technique, velocity feedback can use either difference in speed of the motor and load sides, or the motor speed only. Block ”Manipulator” has internal structure, represented on Fig. 1, and includes motor, gearbox, load, and two encoders.

Since we assume, that robot is equipped with encoders only, state observer is introduced in order to get information about velocities from the measured angles. As a state observer, for example, Extended Kalman Filter (EKF) can be used.

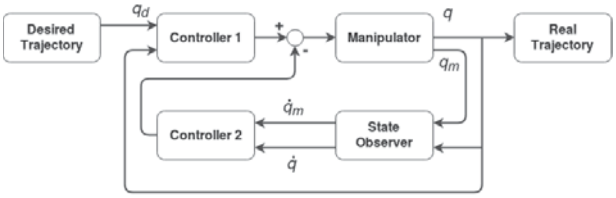

Fig. 3. Common control scheme

The dynamics of the robot with elastic joints can be modeled using equations proposed by [9]:

$$\begin{aligned} M(q)\ddot{q} + C(q,\dot{q}) + g(q) + K_\theta(q - rq_m) &= 0 \\ B\ddot{q}_m + rK_\theta(rq_m - q) &= \tau \end{aligned} \tag{3}$$

where $M(q)$ is an inertia matrix, B is an inertia of motors, $C(q,\dot{q})$ is a matrix of Coriolis and centrifugal terms, $g(q)$ is a vector of gravity terms, q is a load angle vector, q_m is a motor angle vector, B is a motor inertia, r is a gear ratio, τ is a torque value.

Proportional-derivative (PD) control is a widely used control technique based on the motor side information because of its simplicity. Typically Hooke’s law is used to estimate deflection on the load side. In the case of the robot with elastic joints and double encoders:

$$\tau = K_P(q_d - q) - K_D\dot{q}_m$$

where τ is a control torque, K_P and K_D are parameters of controllers, q_d is the desired load angle, q is an actual load angle, $\dot{q}_m$ is a motor velocity.

High stiffness values allows to divide the process parameters into fast and slow parts and control them separately. If K_θ is a joint stiffness matrix and $z = K_\theta(rq_m - q)$ is an elastic force in joints, then control law can be written as

$$\begin{aligned} \frac{\tau_s}{r} &= (M(q) + \frac{B}{r^2})\ddot{q} + C(q,\dot{q})\dot{q} + g(q) \\ \tau &= \tau_s(q,\dot{q},t) - \epsilon K_f\dot{z} \end{aligned}$$

where τ_s is a ”slow” torque value, ϵ is a rate between fast and slow time scales, K_f is a positive constant matrix.

The last technique is a sliding mode control. The advantage of this method is that it does not require the precise knowledge of the model parameters and can work even with roughly estimated values of the parameters. The classical approach used for rigid robots cannot be applied here because (3) does not allow to obtain the torque value explicitly. Second order sliding mode control solves this problem but requires higher order derivatives, which make control more complicated. In the case of high joint stiffness, additional term could be introduced to the equation in order to simplify the result. If the sliding surface s is defined in the form $s = \dot{e} + \Lambda_q e + \dot{z} + \Lambda_z z$, where $e = q - q_d$ is a joint error vector, Λ_q and Λ_z are positive matrices, then the control is

$$\begin{aligned} \tau = r^{-1}B(-D_s sign(s) - K_s s + \ddot{q}_d - \Lambda_e\dot{e}) \\ +rK_\theta z - r^{-1}B\Lambda_z\dot{z}. \end{aligned}$$

Parameters D_s and K_s are positive definite matrices, which define rate of error decrease.

D. External force identification

In general, the deflection angle of a joint is proportional to applied torque. For small deflections, we can assume that such dependence is linear and can be described with the help of the Hooke’s law. Since joint torques under the influence of applied external force F can be found with the help of kinematic Jacobian J as $J^T \cdot F$, the basic equation for the identification can be written as follows

$$K_\theta \Delta q = J^T F.$$

Thus, knowledge of manipulator configuration and value of deflections in joints allow us to find direction and amount of applied force. With the help of the robot dynamic model, external torque (part of total joint torque that corresponds to applied external force) also can be estimated. This opens up the possibility to use double encoders for interaction with the environment.

E. Interaction strategies

Efficient reaction strategy must take into account the type of interaction and collision location. Basic types of interaction are shown in Fig. 4. The collision classification starts with detecting the presence of an external force applied to the robot body. Next, by measuring collision duration, it is possible to distinguish single and continuous contact event. Events can be also divided into accidental and purposeful according to the current task. Accidental means that in this robot task stage physical interactions are not expected, for example, in the case of contactless operations. Purposeful assumes the possibility of contact. In general, collision expectation cannot be understood during the process of execution and should be predefined by the operator. Analyzing characteristics of collision it is possible to determine if the object is soft or not. Soft objects are expected to have a ”slower” change of the external torque rate than the hard ones.

The following reactions (extension from [21]) were chosen for the classification scheme, defined above.

- Touch reaction - stop/continue execution when operator touches the robot. Occurs in case of single short

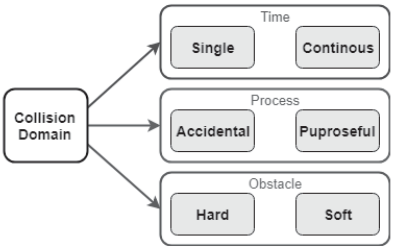

Fig. 4. Types of interaction

accidental collision with a soft object. Could be used to correct workpiece or remove an obstacle on the robot path.

- Wait - stop execution in case of unexpected collision and resume it later. Could be used in case of both hard and soft collisions in order to avoid any damage. Resume when external contact has disappeared. For example, if the obstacle is human who quickly moves out of workspace, there are no reasons to modify the robot trajectory or wait for more time.
- Elbow reaction - use kinematic redundancy to overcome the obstacle in case of collision with robot elbow. For sure, this reaction can be applied only to redundant manipulators but it allows to minimize time costs by continuing its programmed path without stopping.
- End-effector reaction - change trajectory to overcome the obstacle. This reaction occurs when the point of collision is located near the end-effector and kinematic redundancy cannot be used. In this case, the robot trajectory should be changed if it is acceptable. Attractive/repulsive fields approach is used to find a new path. Every time when manipulator finds an obstacle it marks such point as a source of repulsive fields and tries to get around in the future.
- Compliant mode - change robot configuration manually. This mode can be used by the operator in case of a complex environment and non-trivial task to move robot end-effector into the desired position. This scenario can also be used if the robot joints are close to limits or other scenarios does not have an effect.

III. IMPLEMENTATION

A. *Stiffness identification*

The process of calibration consists of two steps. The first step includes building of the robot stiffness model based on VJM approach. Such a model has been developed for a typical industrial manipulator with the help of Matlab computing environment. Kinematic scheme of the robot is represented in Fig. 5, geometrical parameters are shown in Table I.

TABLE I. LENGTH OF THE LINKS, m

l_0	l_1	l_2	l_3	l_4	l_5	l_6
0.67	0.35	1.15	1.2	0	0	0.24

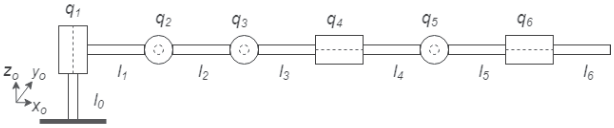

Fig. 5. Kinematic scheme of the manipulator

The second step consists of generating random configurations and forces with a value up to robot maximum load, calculation the end-effector displacement for the full stiffness model and estimation the joint compliances for reduced model. The process is iterative unless the error of intermediate values is higher than the predefined threshold.

In order to estimate the difference between the end-effector position for ideal and real (elastic) models deflection maps are used. These maps were built with the help of singular value decomposition (SVD) of the Cartesian stiffness matrix. This technique allows to obtain value and direction of maximal possible deflection for each robot configuration. Nevertheless, in order to compare deflection for the full and reduced stiffness models, we cannot just find the difference between them since the models are different and each one has its own directions of the maximal deflection. The more suitable results could be obtained when deflections for the reduced model are calculated for the directions, found for the full model since such directions correspond to the behavior of the real robot. More information about comparing full and reduced stiffness model can be found in [22].

B. *Robot control*

In order to compare different control strategies, a model of the manipulator was developed in Simulink. Each joint of the model was elastic with stiffness $10^6 Nm/rad$, which is close to the typical value of stiffness in an industrial robot.

The trajectory was defined using third-degree polynomial. Controllers parameters were optimized in such way to minimize the error between desired and actual joint angles.

C. *Interaction*

Reaction strategies were implemented in form of finite state machine (Fig. 6). Such architecture simplifies modification of robot behavior as it allows to easily add new states and transactions.

Practical improvement of the interaction strategies requires carrying out experiments using the robot, equipped with torque sensors. The redundant robot is preferable as it allows us to test the ”Elbow reaction” strategy as well.

In order to examine a multi-scenario collision avoidance algorithm in real time, the industrial robot KUKA LBR IIWA 14 was used. This robot implements some features that are important for collaborative work, such as:

- on-board force/torque sensors in each joint;
- 7 degrees of freedom that allow the robot to perform more complex tasks and use kinematic redundancy;
- real-time operating system offers a possibility for fast collision detection and reaction.

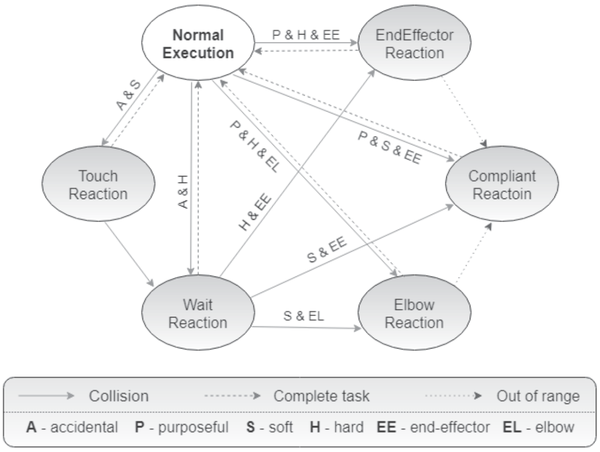

Fig. 6. Sequence of reactions

Robot Operating System (ROS) with a specific package which allows us to read some internal parameters like joint torque, external torque, current position, etc. was used to control the robot. The control program also was written as a ROS node and used the mechanism of topics and messages for communication. Contact point localization was implemented using two approaches: analytical and neural networks. The analytical approach is based on finding a point on the robot length and direction of applied external force where the equivalent torques will be the same as torques in a real robot. In the machine learning approach, feedforward neural network is used to solve a regression problem, where the robot torque values are used as input data and a point on the robot is an output.

In order to take into account redundancy, as well as angle and velocity constraints, Saturation in Null Space (SNS) algorithm was used (see [23]). Initial null-space velocity was calculated in such way to keep the robot far from it joint limits when it is possible.

IV. RESULTS AND DISCUSSION

A. Model improvement

Results of the stiffness identification are presented in Table II. As it can be seen, estimated joint stiffness values are not totally the same as original ones, because in the reduced model we try to compensate for link elasticity as well using joints only.

TABLE II. JOINT STIFFNESS, MNm/rad

	J1	J2	J3	J4	J5	J6
Model	2	2.3	3.5	1	1	1
Estimation	1.8	3.4	2.4	0.7	0.7	0.7

Deflection maps of the manipulator are represented in Fig. 7. The upper image corresponds to a full robot model, i.e. take into account elasticity of links and joints. Lower map is found as a difference between deflections in full and reduced models, and characterize the displacement after calibration. The biggest difference corresponds to straight horizontal manipulator position, but most of the working area has smaller error value, so the reduced stiffness model, which work only with elastic joints, should be in good accordance with the real robot. The calibrated robot could be used in order to compensate for the compliance error. With a correct model, the error should be minimized. So, it can improve the proposed technique of stiffness identification.

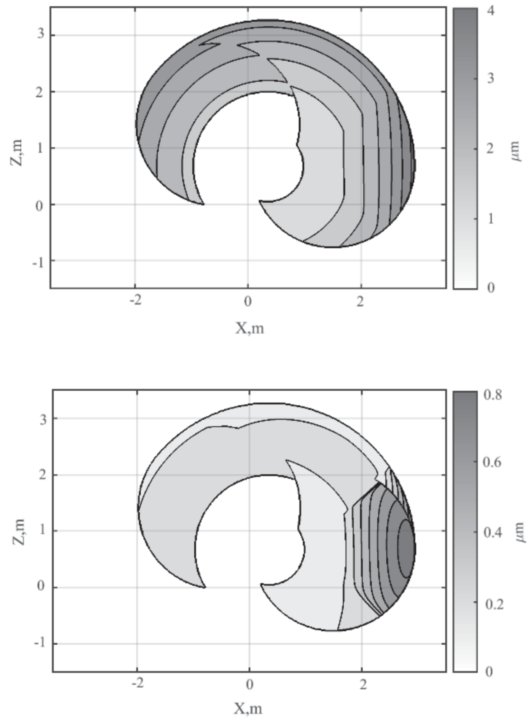

Fig. 7. Deflection maps of full (upper) and compensated (lower) models

For the purpose of calibration, the difference between the desired trajectory of the manipulator and its expected position due to elasticity should be found. This estimation can be performed on the reduced model. After that, the obtained deflection should be subtracted from the desired points in order to find new input trajectory.

In order to check the efficiency of reduced model, compensation was applied to test trajectory with load $F = (1000, 1000, 1000, 0, 0, 0)$. Results are represented on the Fig. 8, where the original trajectory is a hollow line, dotted curve corresponds to deflected position and dash point is the result of compensation.

For represented trajectories maximal deflection before compensation is 2.2 mm, after - 0.5 mm. Thus, the proposed technique provides a correct estimation of the joint stiffness. It demonstrates that knowledge of elastostatic model and value of joint deflections allows to compensate deformation in both joints and links and could be used in a system with double encoders.

The efficiency of compliance error compensation with the help of double encoders is also demonstrated with results, represented in Table III. It includes experimental results for compliance compensation using several algorithms [24]. The

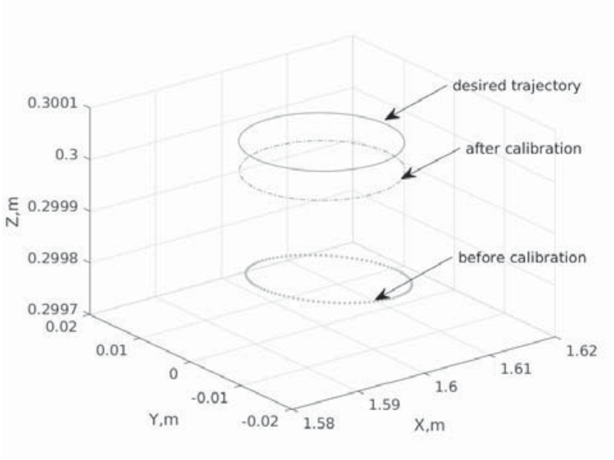

Fig. 8. Trajectory before and after compensation

TABLE III. COMPENSATION ALGORITHMS ERRORS, mm

	mean	std	max
Experimental set			
Primary encoder	4.03	2.17	9.52
Secondary encoder	1.74	0.93	3.36
Stiffness model	0.64	0.33	1.52
Entire robot workspace			
Primary encoder	4.03	2.28	9.17
Secondary encoder	1.81	0.79	4.63

base technique uses the information only from the primary encoders. In this case, the value of deflection could be estimated based on information about joint stiffness and gravitational forces. The results could be improved if the feedback from the second encoder is taken into account. In this case value of error becomes approximately twice lower. Such a technique is used in some industrial manipulators with double encoders.

The best results have been obtained for the case when information from double encoders is combined with stiffness model of the robot. The average error becomes 6 times lower in comparison with an algorithm based on primary encoders only, i.e. the proposed algorithm could increase the accuracy up to 80%.

The most time-consuming part of the proposed approach is elastostatic modeling and calibration. But the result is just a set of joint stiffness coefficients which are used during the robot manipulations. Thus, from real-time operability point of view, this method has the same complexity as a simple position calculation for a robot with elastic joints.

B. Control

Every tested technique was able to control the system, but errors were different. In the case of PD control, its peak was about $2.5 \cdot 10^{-3}$ rad, in case of proposed modification of sliding mode control amplitude was 10^{-6} rad. The lowest value obtained for time scaling, about 10^{-8} rad, moreover after 2 seconds its value reduced almost to zero. Error curves are shown in Fig. 9. Results are normalized to the maximum in order to combine different scales on the same figure.

All technique has pros and cons. PD control is simple, but the error is relatively high. Time scaling demonstrates good results but is sensitive to the estimation of the system parameters and the noise. Sliding mode control is more robust, but the error is higher. So, the choice of optimal technique will depend on the specific task at hand.

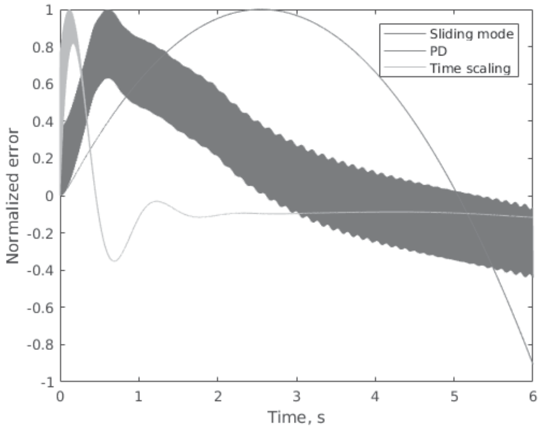

Fig. 9. Normalized control errors

C. Interaction

Developed scenarios of interaction with the dynamically changed environment are demonstrated in the video [25]. They are divided into four groups, corresponded to purposeful/accidental interaction with hard/soft obstacles in different combinations. While scenarios of interaction were tested on the robot without double encoders, the results do not depend on the type of torque sensors and could be applied to double encoders as well.

The main advantage of the developed method is its simplicity, it does not need complicated algorithms and powerful computer. On the other hand, the robot can only react, but not predict the collision, which restricts possible applications. The current system only considers a single collision event at a time. In future, multi-contact collision recognition will be implemented.

V. CONCLUSION

In this work, we discussed the advantages which could be gained by using double encoders in collaborative robots. First of all, this technique could be applied to the compensation of compliance errors. Within this task elastostatic model of the robot with typical for industry kinematic scheme was built, and demonstrated that because of proper calibration process reduced elastic joint model is enough for efficient compensation.

The second application is an improvement of the control quality. Three control techniques were adapted for double encoders. The results of the simulations were acceptable for all three approaches. Nevertheless, optimal solution was not found as each technique has its own advantages and disadvantages.

Finally, the ability of double encoders to be used as torque sensors in the collision-based strategies of interaction with the dynamical environment was investigated. These scenarios were tested on the manipulator, equipped with torque sensors and controlled from ROS. Type of collision and its location were defined using an analytical approach and feed-forward neural network techniques. A series of experiments confirm the advantages of the proposed solution.

In future work, we would like to test the possibilities and limitations of double encoders as force/torque sensors for interaction and implement the developed control algorithms in the prototype of robotic-manipulator, equipped with double encoders.

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REFERENCES

[1] S.Haddadin, A.De Luca and A.Albu-Schäffer, “Robot collisions: A survey on detection, isolation, and identification”, *IEEE Transactions on Robotics*, 2017, pp. 1292-1312.

[2] A.Pashkevich, A.Klimchik and D.Chablat, “Enhanced stiffness modeling of manipulators with passive joints”, *Mechanism and machine theory*, 2011, pp. 662-679.

[3] G.Alici and B.Shirinzadeh, “Enhanced stiffness modeling, identification and characterization for robot manipulators”, *IEEE transactions on robotics*, 2005, pp. 554-564.

[4] S.-F.Chen and I.Kao, “Conservative congruence transformation for joint and Cartesian stiffness matrices of robotic hands and fingers”, *The International Journal of Robotics Research*, 2000 , pp. 835-847.

[5] A.Klimchik, B. Furet, S.Caro and A.Pashkevich, “Identification of the manipulator stiffness model parameters in industrial environment”, *Mechanism and Machine Theory*, 2015, pp. 1-22.

[6] A.Klimchik, Y.Wu, A.Pashkevich, S.Caro and B.Furet, “Optimal Selection of Measurement Configurations for Stiffness Model Calibration of Anthropomorphic Manipulators”, *Applied Mechanics and Materials*, 2012, pp. 161-170.

[7] J.Tsai, E.Wong, J.Tao, H.D. McGee and H.Akeel, “Secondary position feedback control of a robot”, *Google Patents*, 2013

[8] T.Izumi and T.Matsuo, “Robot system and robot control apparatus”, *Google Patents*, 2014

[9] M.Spong, “Modeling and control of elastic joint robots”, *Journal of dynamic systems, measurement, and control*, 1987, pp. 310-319.

[10] P.Tomei, “A simple PD controller for robots with elastic joints”, *IEEE Transactions on automatic control*, 1991, pp. 1208-1213.

[11] B.Siciliano and W.Book, “A singular perturbation approach to control of lightweight flexible manipulators”, *The International Journal of Robotics Research*, 1988, pp.79-90.

[12] M.Spong, K.Khorasani and P.Kokotovic, “An integral manifold approach to the feedback control of flexible joint robots”, *IEEE Journal on Robotics and Automation*, 1987, pp. 291-300.

[13] G.Wilson and G.Irwin, “Robust tracking of elastic joint manipulators using sliding mode control”, *Transactions of the Institute of Measurement and Control*, 1994, pp. 99-107.

[14] R.Gorez and Y.-L.Hsu, “Sliding mode control for displacements of servomechanisms with elastic joints”, *IFAC Proceedings Volumes*, 1996, pp. 43-48.

[15] K.Sakata, H.Asaumi, K.Hirachi, K.Saiki and H.Fujimoto, “Self resonance cancellation techniques for a two-mass system and its application to a large-scale stage”, *IEEJ Journal of Industry Applications*, 2014, pp. 455-462

[16] A.Hasegawa, H.Fujimoto and T.Takahashi, “Robot joint angle control on self resonance cancellation using double encoders”, *Advanced Intelligent Mechatronics*, 2017, pp. 623-628

[17] A.De Luca, A.Albu-Schaffer, S.Haddadin and G.Hirzinger, “Collision detection and safe reaction with the DLR-III lightweight manipulator arm”, *Intelligent Robots and Systems*, 2006, pp. 1623-1630.

[18] A.De Luca and F.Flacco, “Integrated control for pHRI: Collision avoidance, detection, reaction and collaboration”, *Biomedical Robotics and Biomechatronics (BioRob)*, 2012, pp. 288-295.

[19] S.Haddadin, A.Albu-Schaffer, A.De Luca and G.Hirzinger, ‘Collision detection and reaction: A contribution to safe physical human-robot interaction‘”, *Intelligent Robots and Systems*, 2008, pp. 3356-3363.

[20] D.Popov, A.Klimchik and N.Mavridis, “Collision detection, localization & classification for industrial robots with joint torque sensors”, *Robot and Human Interactive Communication (RO-MAN)*, 2017, pp. 838-843.

[21] S.Mikhel, D.Popov and A.Klimchik, “Collision driven multi scenario approach for human collaboration with industrial robot”, *International Conference on Mechatronics and Robotics Engineering (ICMRE)*, 2018, pp. 78-84.

[22] S.Mamedov, D.Popov, S.Mikhel and A.Klimchik, “Compliance error compensation based on reduced model for industrial robots”, *International Conference on Informatics in Control, Automation and Robotics (ICINCO)*, 2018, pp. 180-191.

[23] F.Flacco, A.De Luca and O.Khatib, “Control of redundant robots under hard joint constraints: Saturation in the null space”, *IEEE Transactions on Robotics*, 2015, pp. 637-654.

[24] A.Klimchik and A.Pashkevich, “Robotic manipulators with double encoders: accuracy improvement based on advanced stiffness modeling and intelligent control”, *Symposium on Information Control Problems in Manufacturing (INCOM)*, 2018, pp. 740-745.

[25] YouTube, Collision driven multi scenario approach for human collaboration with industrial robot, Web: https://youtu.be/YpQXi36uTcA