Asymmetric Bimanual Control of Dual-arm Serial Manipulator for Robot-assisted Minimally Invasive Surgeries

Hang Su,[1] Yunus Schmirander,[1] Sarah Elena Valderrama-Hincapie,[1]
Jairo Pinedo,[1] Xuanyi Zhou,[1,2] Jiehao Li,[1,3] Longbin Zhang,[4]
Yingbai Hu,[5*] Giancarlo Ferrigno,[1] and Elena De Momi[1]

[1]Department of Electronics, Information and Bioengineering, Politecnico di Milano,
Via Giuseppe Colombo, 40, Milan 20133, Italy
[2]State Key Laboratory of High Performance Complex Manufacturing, Central South University,
Changsha 410083, China
[3]State Key Laboratory of Intelligent Control and Decision of Complex Systems, Beijing Institute of Technology,
Beijing 100081, China
[4]BioMEx Center & KTH Mechanics, KTH Royal Institute of Technology,
SE-100 44 Stockholm, Sweden
[5]Department of Informatics, Technical University of Munich,
Munich 85748, Germany

Robotic assistance is promising for improving minimally invasive surgery (MIS). This work presents asymmetric bimanual control of a dual-arm serial robot with two remote centers of motion (RCMs) constraints for MIS. In our previous works, general null space controllers to guarantee the fixed RCM constraint have been proposed. However, an incision on a patient's abdominal wall is not fixed owing to the respiration of the patient, which generates an uncertain disturbance at the joints of robotic manipulators. To improve accuracy, a radial basis function neural network is implemented to adapt to these disturbances and control the end-effector position. Finally, the adaptive bimanual control strategy is validated through simulations based on clinical data. The proposed control shows improved accuracy in the end effector position for all the designed surgical tasks. In future works, the algorithm will be validated on an actual dual-arm serial robot making use of a body phantom.

1. Introduction

Laparoscopy requires a small incision in the abdominal wall to allow the insertion of a trocar and surgical tools. Robotic implementation of such minimally invasive surgery (MIS) techniques is expected to improve the control and precision of the surgical tools used in interventions while reducing trauma to patients.[1–3] However, specialized surgical robots are expensive, which limits their acquisition and use in hospitals.

Industrial robots with redundancy have meanwhile been successfully adopted and further developed for precise automation processes in the last few decades. Their lower cost than specialized surgical robots has increased interest in their application in the medical field, particularly in MIS. Their redundancy, such as more DoFs than required for the executed task, provides benefits over nonredundant robots, including the facilitation of human-like behavior,[2,4] enhanced manipulability,[3] and obstacle avoidance.[5,6]

In robot-assisted MIS, the motion of the surgical tool is constrained to a point, referred to as the remote center of motion (RCM), where the surgical tool crosses the abdominal wall, allowing only translational movements around its axis. Whereas a mechanical implementation is generally considered safer but requires bulky, expensive structures and calibration procedures, a programmable RCM whose movement is restricted by the control algorithm is cheaper and more flexible and is therefore the preferable option.[7,8]

In our previous work, we achieved RCM control with a null space controller for a redundant serial robot.[9,10] In actual surgery, the RCM moves continuously owing to the respiration of the patient. To ensure accuracy, the controller has to compensate robustly for these movements to prevent bending of the surgical tool by the resulting forces.[11,12] Such deformation of the tool would not only directly distort its trajectory but also interfere with its readjustment since robotic systems generally obtain the position of the end effector (EE) from the positions of the manipulator's joints.

In this work, we simulate a moving RCM using clinical respiratory data.[13] Neural networks, particularly radial basis function neural networks (RBFNNs), have proven to be a powerful tool for robustly implementing model predictive control mechanisms, outperforming traditional controllers even for linear applications where proportional–integral–derivative (PID) controllers have been established as a benchmark.[14] With a Gaussian activation function, an RBFNN[11] can smoothly approximate any continuous function. Thus, it is suitable as an adaptive controller for compensating the uncertain disturbances caused by the respiratory motion, and therefore can be employed to improve the control of a surgical tool.

The aim of our research is to simulate a programmable RCM in a scenario close to the clinical scenario by implementing bimanual control[15,16] with two asymmetric KUKA LWR4+ robotic manipulators for MIS and utilizing an RBFNN to compensate for the disturbance from the respiratory movement. An evaluation is performed on surgically relevant trajectories for intraoperative suturing and knot tying.

The contributions of this paper are as follows. An RBFNN method is used to compensate for the disturbance from the respiratory movement under a constrained RCM. The experiment is verified on surgically relevant trajectories for intraoperative suturing and knot tying.

The paper is organized as follows. Section 2 describes the fundamentals and control methodology. In Sect. 3, the performance of the proposed control scheme is validated in a simulation with clinical data. Conclusions are drawn in Sect. 4.

2.   Methodology

In this section, we present the clinical workspace and the essential mathematical concepts used.

2.1　Clinical aspects

During the MIS of the torso, the breathing mechanism generates shifts in the abdominal wall, as shown in Fig. 1, and modifies the RCM position, causing disturbances in the system, which in turn lead to possible harm at the trocar. Furthermore, EE errors can result in insufficient accuracy of the suturing and knot-tying procedures.[12,17,18]

2.2　Null space control

The defined workspace and the RCM, EE, and wrist are depicted in Fig. 1. Our implementation is based on the programmable RCM introduced by Khatib[19] and controlled with two Jacobian matrices and an appropriate null matrix.[7,20]

The desired Cartesian velocity for the subsequent time step of the EE can be described as

$$\dot{x}_{EE} = \frac{x_{des} - x_{EE}}{T}, \tag{1}$$

where $\dot{x}_{EE}$ denotes the desired Cartesian velocity, x_{EE} denotes the current EE position, and x_{des} is the next time of the EE position. T is the duration of one-time step. Additionally, the desired velocity of the robot wrist $\dot{x}_{wrist}$ can be defined as

$$\dot{x}_{wrist} = \frac{(x_{des} - v_{tool}) - x_{wrist}}{T}, \tag{2}$$

subjected to

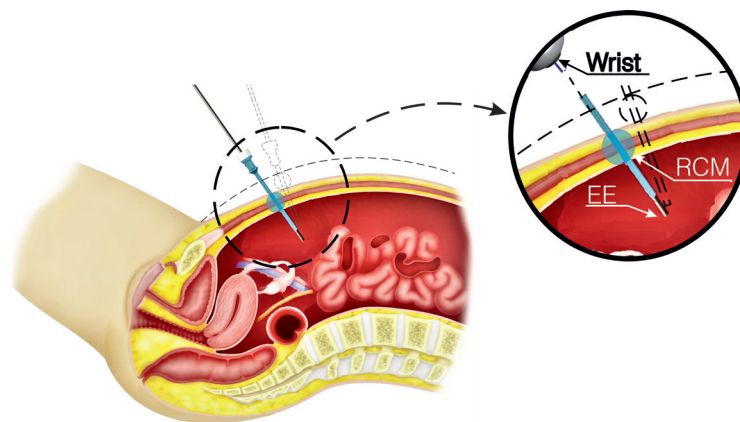$$v_{tool} = \frac{x_{des} - x_{RCM}}{\left\| x_{des} - x_{RCM} \right\|} L, \tag{3}$$

Fig. 1.　(Color online) Workspace representation of MIS of torso.

where x_{wrist} represents the current position of the wrist, v_{tool} denotes the vector describing the surgical tool position, x_{RCM} is the position of the RCM, and L is the length of the surgical tool.

To control the robotic manipulator, the desired joint velocities $\dot{q}_{EE}$ and wrist speed $\dot{q}_{wrist}$ at the EE can be presented as

$$\dot{q}_{EE} = J_{EE}^{-1} \cdot \dot{x}_{EE}, \tag{4}$$

$$\dot{q}_{wrist} = J_{wrist}^{-1} \cdot \dot{x}_{wrist}, \tag{5}$$

where J_{EE} and J_{wrist} are the corresponding 3×7 Jacobian matrices, respectively.

With the two matrices controlling the Cartesian positions of the EE and wrist, the rotational DoFs of the tool assume a configuration that makes the tool pass through the RCM.

The desired joint position $\dot{q}_{des}$ can be defined as

$$\dot{q}_{des} = \dot{q}_{EE} + N \cdot \dot{q}_{wrist}, \tag{6}$$

subjected to

$$N = I_7 - J_{wrist}^{+} \cdot J_{wrist}, \tag{7}$$

where I_7 denotes the seven-dimensional identity matrix, and J_{wrist} denotes the pseudoinverse.[5]

The desired overall joint velocity can be given by

$$q_{des} = \int_0^t \dot{q}_{des} dt. \tag{8}$$

All nonredundant components are removed from $\dot{q}_{wrist}$ to maintain the precise trajectory of the EE.

2.2 RBFNN

An RBFNN[21,22] is a type of feedforward neural network with an input layer, a hidden layer, and an output layer. The neurons of the hidden layer have Gaussian radial basis activation functions with adaptable center and width; hence, there are no weights of the hidden layer. The weights of the output layer are updated continuously with learning rate α. In the output layer, the weighted radial basis functions are summed to obtain one smooth continuous function, allowing it to adapt, and thus robustly compensate for unknown dynamics, nonlinearities, and disturbances.[23,24] The activation function h_i of the ith neuron in the hidden layer is given by

$$h_i = \exp \frac{-(x_{EE,v} - c_i)^{\mathrm{T}}(x_{EE,v} - c_i)}{2b_i^2}, \tag{9}$$

where $x_{EE,v}$ is the current Cartesian position of the EE, c is the vector containing the centers, and b is the vector of the widths of the Gaussian functions in the hidden layer.

The update of the weights Δw_{ij} of the output layer is given by

$$\Delta w_{ij} = \alpha \cdot e_j \cdot h_i + \beta \cdot \delta w_{ij} \,, \tag{11}$$

where e_j is the error between the desired and actual positions of the EE, $\alpha = 0.4$ is the learning rate, and $\beta = 0.02$ is the weighting of the previous update δw_{ij}.

The RBFNN control is implemented in the manner depicted in Fig. 2. An external disturbance simulating the respiratory movement is introduced, where clinical data is used. The RBFNN ensures that the EE of the surgical tool does not deviate significantly from its trajectory.

3. Experimental Validation

To evaluate the performance of the proposed control approach, simulations were conducted with the dual-arm robot shown in Fig. 3. The robot arms were set to autonomously follow surgical trajectories with five different shapes, a straight line, an angle, a sine curve, a semicircle, and a helix, to demonstrate and evaluate its versatility.[25,26] These shapes are directly related to the usual trajectory performed in MIS suturing and knot-tying techniques,[27–29] as shown in Fig. 4. The length or diameter of the trajectory, depending on the shape, was set to 5 mm.[30]

The respiratory movements were based on clinical data recorded by Shafiq and Veluvolu.[13] The registered movements of two markers in the abdominal region were picked as moving RCMs. Because of the low sampling frequency, spline interpolation was used to obtain the missing values.[31–33]

The control and robustness of the proposed system were evaluated considering the Euclidean norm tracking error of the EE,

$$E_{EE} = \left\| x_{des} - x_{EE} \right\|, \tag{11}$$

subjected to the Euclidean distance between the EE position x_{EE} and its desired trajectory x_{des} at
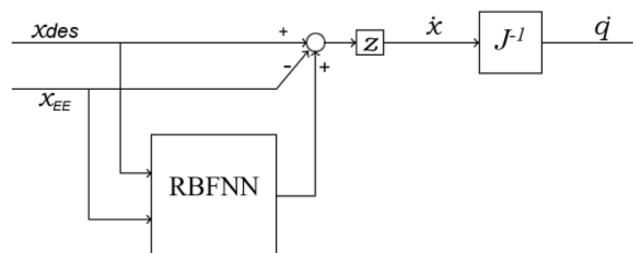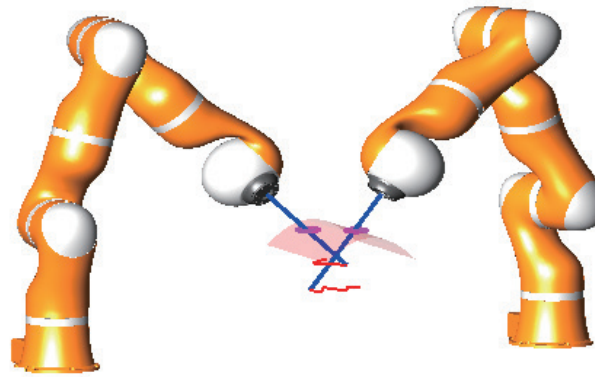

Fig. 2.   Block diagram of RBFNN control.

Fig. 3.   (Color online) Bimanual control of the dual-arm serial robot for MIS. Both robotic manipulators can perform independent tasks. The transparent red plane models the abdominal wall.
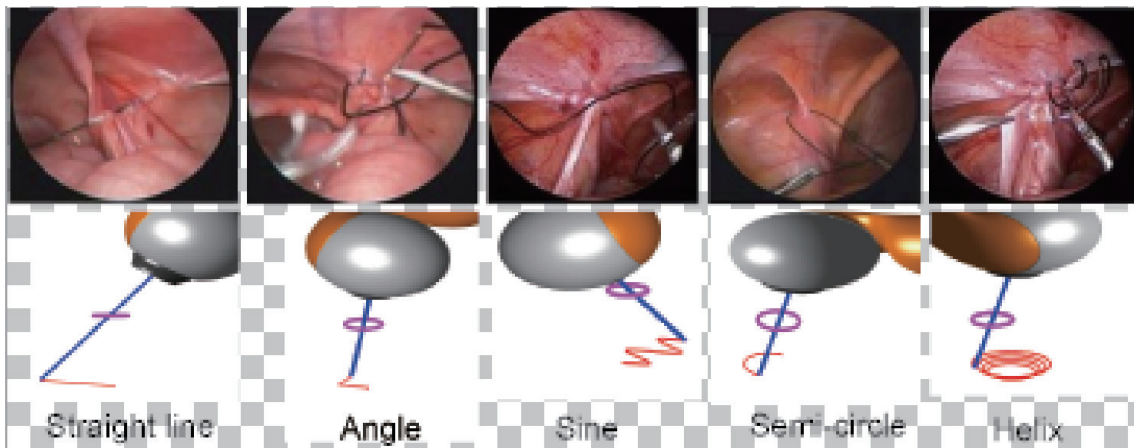

Fig. 4.   (Color online) MIS trajectories used for suturing and knot tying with corresponding simulated shapes.[5]

each time step. Then, the RCM error E_{RCM} can be represented as

$$E_{RCM} = \frac{\left\| v_{tool} \times (x_{EE} - x_{RCM}) \right\|}{\left\| v_{tool} \right\|}, \tag{12}$$

which measures the Euclidean distance between the optimal RCM position x_{RCM} at the incision and the surgical tool, where v_{tool} is the vector describing the surgical tool position.

From the EE error, depicted for the angle trajectory in Fig. 5(a), it was concluded that the RBFNN considerably improves the accuracy of the following trajectory, and at the same time, the RCM constraint by a small amount. The boxplots in Fig. 6 confirmed that the neural network control reduced the EE error for the other trajectories, decreasing the median of the error and shortening the whiskers. For more complex and nonlinear trajectories such as the helix, the errors of the implementations both without and with the RBFNN are larger than those for the simpler ones. However, the RCM error for the helix also decreased, suggesting that the proposed controller will enhance accuracy by compensating disturbances.
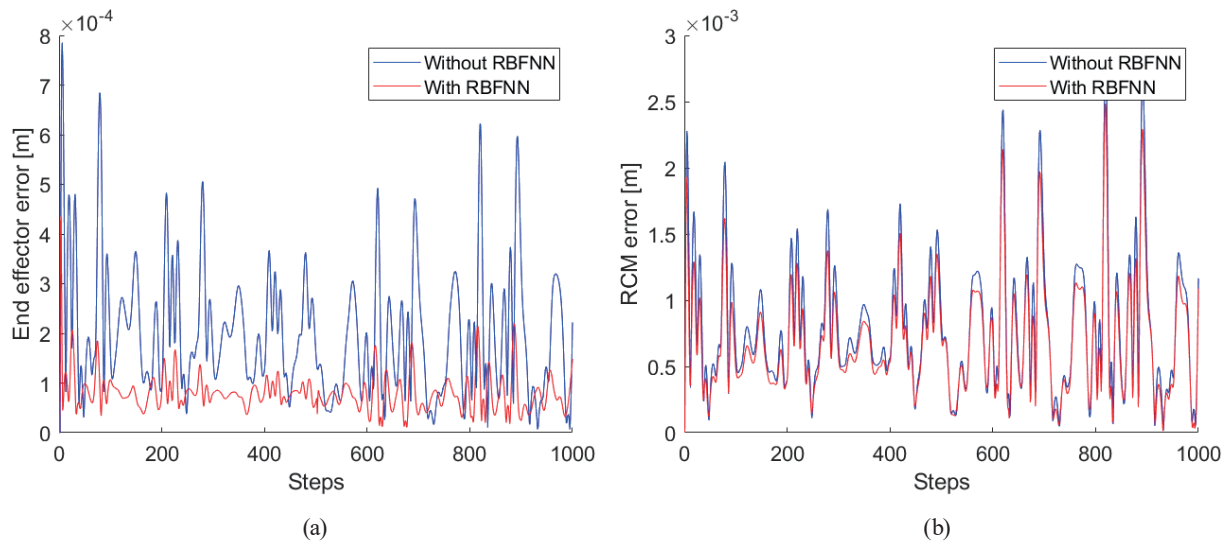
Fig. 5.   (Color online) Tracking performance of (a) EE in position error and (b) RCM error.
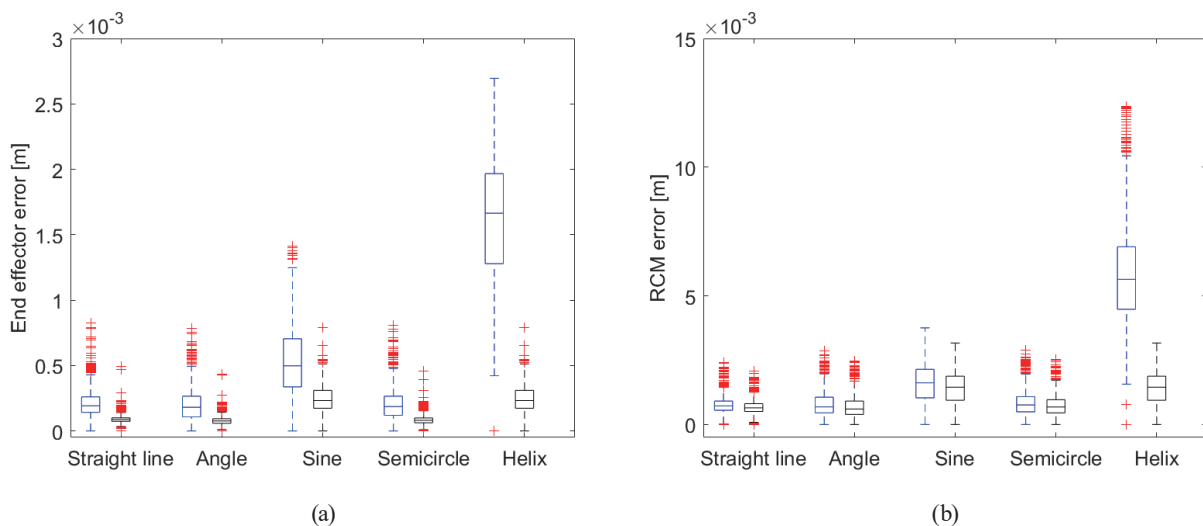

Fig. 6.   (Color online) Boxplots of (a) EE error and (b) RCM error. The errors without RBFNN are depicted with blue boxes while those with RBFNN control are black.

4.   Conclusions

This article mainly centers on the asymmetric bimanual control of a dual-arm serial robot with two RCM constraints for MIS. To evaluate the developed control scheme, some simulations are carried out, indicating that the proposed method can achieve advantageous performance for the accurate control mechanism of dual-arm serial robots. Even for a moving RCM, the RBFNN can robustly keep the EE error sufficiently small to meet the precision requirements of medical surgery with 1 mm at the EE. However, further improvements are required. Since our simulations did not consider physical effects such as inertia or force

feedback,[34] the next step should be to validate the performance of our implemented algorithm on actual KUKA LWR4+ robots and a phantom with force feedback. Furthermore, human–robot physical interaction in the surgical environment will be implemented to assist the motion of the surgeon.[35]

Acknowledgments

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About the Authors

Hang Su received his M.Sc. degree in control theory and control engineering from South China University of Technology, Guangzhou, China, in 2015. He obtained his Ph.D. degree in 2019 as a member of the Medical and Robotic Surgery Group (NEARLab) from Politecnico di Milano, Milan, Italy. He participated in an EU-funded project (SMARTsurg) in the field of surgical robotics. Dr. Su is currently a research fellow in the Department of Electronics, Information and Bioengineering (DEIB) of Politecnico di Milano. He is fostering an international research team composed of three Ph.D. students and a few Masters students in the field of medical robotics. He has served as a reviewer for over 30 scientific journals, such as IEEE Transactions on Biomedical Engineering, IEEE/ASME Transactions on Mechatronics, IEEE Transactions on Automation and Engineering, IEEE Transactions on Cybernetics, and IEEE Transactions on Systems, Man, and Cybernetics: Systems. He is currently Special Session Chair of the IEEE International Conference on Advanced Robotics and Mechatronics (ICARM 2020). He has published several papers in proceeding of international conferences and in journals and was awarded an ICRA 2019 travel grant. His main research interests include control and instrumentation in medical robotics, human–robot interaction, surgical robotics, deep learning, and bilateral teleoperation. (hang.su@polimi.it; hang.su@ieee.org)

Yunus Schmirander received his B.Sc. degree in biomedical engineering from the University of Stuttgart and the University of Tübingen, Germany, in 2017, which included a year abroad at Lund University, Sweden. He received his M.Sc. degree from Politecnico di Milano, Italy, in 2019 and is working there on research projects at the Neuroengineering and Medical Robotics Laboratory (NEARLab) and at the Department of Electronics, Information and Bioengineering (DEIB). (yunus.schmirander@mail.polimi.it)

Sarah Elena Valderrama-Hincapie received her bachelor's degree in bioengineering from the University of Antioquia, Colombia. Currently, she is an M.Sc. candidate in biomedical engineering, focusing on electronic technologies, at Politecnico di Milano. She is also conducting research at the Biorobotics Institute of Sant' Anna School of Advanced Studies. Her main interests are biorobotics, control in robotics, and neuroengineering. (sarahelena.valdrrama@mail.polimi.it)

Jairo Pinedo received his bachelor's degree in fluid mechanics engineering from San Marcos University, Peru. He has experience in supervising the development of electromechanical projects as a project engineer. He has recently finished his master's degree in biomedical engineering at Politecnico di Milano. His research mainly focuses on biomechanics and cardiovascular issues. (Jairo.pinedo@mail.polimi.it)

Xuanyi Zhou received his bachelor's degree from Hunan University, Changsha, China. He is currently pursuing his Ph.D. degree at Central South University. He is also working on research projects at the Neuroengineering and Medical Robotics Laboratory (NEARLab) and at the Department of Electronics, Information and Bioengineering (DEIB), Politecnico di Milano. His research interests include intelligent control and its application in robot-assisted minimally invasive surgery. (xuanyi.zhou@mail.polimi.it)

Jiehao Li received his M.Sc. degree in control engineering from South China University of Technology, Guangzhou, China, in 2017. He is pursuing a Ph.D. degree as a member of the State Key Laboratory of Intelligent Control and Decision of Complex Systems, Beijing Institute of Technology, China, and as a visiting research fellow of the Medical and Robotic Surgery Group (NEARLab) and the Department of Electronics, Information and Bioengineering (DEIB) in Politecnico di Milano, Milan, Italy, where he is working on the intelligent control and practical application of medical robots. (jiehao.li@bit.edu.cn)

Longbin Zhang received her M.Sc. degree in control engineering from South China University of Technology, Guangzhou, China, in 2017. She is currently pursuing a Ph.D. degree at the Department of Mechanics, KTH Royal Institute of Technology, Stockholm, Sweden, working on robotic exoskeletons for patients with motor disorders. Her main research interests include human movement simulation, strategies, consequences, assistance for patients with motor disorders, and adaptive control. (longbin@kth.se)

Yingbai Hu received his M.S. degree in control engineering from South China University of Technology, Guangzhou, China, in 2017. He is currently working toward a Ph.D. degree in computer science from the Faculty of Informatics, Technical University of Munich, Munich, Germany. His research interests include robot control, motion planning, neural network optimization, and robot learning. (yingbai.hu@tum.de)

Giancarlo Ferrigno received his M.Sc. degree in electrical engineering and his Ph.D. degree in bioengineering from Politecnico di Milano, Milan, Italy. He founded the Neuroengineering and Medical Robotics Laboratory with the Department of Electronics, Information and Bioengineering, Politecnico di Milano, in 2008, and is a lecturer of medical robotics. He is a full professor with Politecnico di Milano. (giancarlo.ferrigno@polimi.it)

Elena De Momi received her M.Sc. and Ph.D. degrees in biomedical engineering from Politecnico di Milano, Milan, Italy, in 2002 and 2006, respectively. She is an associate professor with the Department of Electronics, Information and Bioengineering, Politecnico di Milano. As an IEEE Senior Member, she is currently an associate editor of the Journal of Medical Robotics Research, International Journal of Advanced Robotic Systems, Frontiers in Robotics, and AI. (elena.demomi@polimi.it)