This paper appears in at - Automatisierungstechnik, Methoden und Anwendungen der Steuerungs-, Regelungs- und Informationstechnik, 2017
DOI: 10.1515/auto-2017-0062

Bita Fallahi*, Ron S. Sloboda, and Mahdi Tavakoli

Applications of Observers in Medical Robotics

Abstract: This paper presents the applications of observers in robot-assisted medical procedures, in which robotic manipulators act in collaboration with surgeons or therapists to improve the efficiency and accuracy of the interventions. Observers can be considered as replacements for sensors to provide the surgeon and/or the robots with information about the tissue, surgical tools, and their interaction. This paper provides an overview of the observation methods for estimating the tool pose, tissue motion, and the interaction forces. Having a good model for the system and guaranteeing the safety and efficiency of the methods are the challenges involved in using the observers in medical procedures. However, the application-driven nature of the medical robotics provides a thriving field of study for using the observers.

Keywords: Robot-assisted, Estimation, Observer

1 Introduction

Robots have influenced the human's life in different domains such as manufacturing, medicine, transportation, and entertainment. The main advantage of employing robotic systems is the higher degree of accuracy, efficiency, reliability, repeatability and higher power/force that they provide. In recent years, robotic systems have been widely used in medical applications. According to [1], the medical robots can be classified as surgical computer-aided design/manufacturing (CAD/CAM) systems and surgical assistants. CAD/CAM systems are used for planning, registration and assessment of the procedures whereas surgical assistants are special tools that are operated directly by the surgeon to make the surgery collaborative by keeping the surgeon in the operation loop to take advantage of both the surgeon's and the robot's abilities and also to increase the safety of the operation [2]. In other applications in which the assistant robots are fully automated, the manipulators are usually programmed to precisely follow the desired pre-planned trajectories.

***Corresponding author: Bita Fallahi, Mahdi Tavakoli,** Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, Canada, T6G 1H9. E-mail: {fallahi, mahdi.tavakoli}@ualberta.ca
Ron S. Sloboda, Cross Cancer Institute and the Department of Oncology, University of Alberta, Edmonton, AB, Canada, T6G 1Z2. E-mail: ron.sloboda@albertahealthservices.ca.

The application of robotic-assisted systems spans different procedures such as radiotherapy, minimally invasive surgery (MIS) and tele-surgery [3]. Radiotherapy is a treatment mostly against cancer, in which high energy rays are used for destroying the cancerous tissue. In this case, the radiation should be targeted toward the cancerous tissue. Minimally invasive surgery is becoming very popular due to its less patient pain, recovery time and discomfort. In these procedures less trauma is imposed to the tissue as unlike conventional surgeries, several small incisions are made in the skin, through which the surgeon can perform the operation on the target organ using long and slender surgical tools. The surgeon is provided with a real-time view of the surgical area using endoscopes or ultrasound images. Remote surgery or tele-surgery is an example of directly using telerobotic systems in medicine. In telesurgery, the surgeon and the patient are not physically in the same location. In this case, the operation is performed through master and slave robots. The surgeon interacts with the master robot. The slave robot, which is controlled to exactly follow the master's motion, performs the operation on the patient at a remote location. Using haptics, the surgeon will be able to have a feeling of the surgical site, i.e., tele-presence.

Other than surgeries, robotic manipulators can be used in post-disability rehabilitation training to improve the sensorimotor functions of the patient. Demonstrating a high degree of repeatability and providing objective measurements of patient performance, rehabilitation robots are employed for assisting therapeutic procedures and for performance assessment.

From control perspective, there are different challenges in controlling robot-assisted procedures. The manipulator kinematics and dynamics should be taken into account in the design procedure. Besides, the measurement tools and sensors need to be clinically approved and should meet the sterilization and dimension issues [4]. Imaging modalities are very important components in medical procedures. Real-time images not only provide the surgeon with a view of the surgical site, can be combined with image processing techniques [5] to convert the visual information into numerical values, which can be used by computers. This is useful mainly for position tracking of an organ or a surgical tool during the operation. When, due to occlusion, the desired object might not be visible in all imaging frames, there is motivation for using estimators and predictive schemes to estimate the position. Furthermore, in any application where the robot/human and/or robot-tissue interactions are involved, measuring the interaction forces becomes very important to both the safety and the performance of the control system.

These examples show the importance of the measurements in feedback control of the medical robots. Observers can be considered as a replacement for sensors. Observers are special sort of estimators which use mathematical models describing the behavior of the system, and require some measurements of the system states to estimate non-measurable states. As the name shows, an observer, "observes" the value of the non-measurable states using the measured ones. This requires to have some specific relation between the measured and non-measured states, called the observability condition [6]. Observers are also capable of estimating the measured states, which can be used to remove the noise and smoothen the signals. A general estimator acts as a filter and does not necessarily use a model. Also, the estimated variable can be the same as the measured value. For example, measuring the motion of an organ based on images without using any models can be done by an estimator. Though the application of observers and estimators seems to be similar, they have different characteristics and in many applications, they are used together.

The application of the robotics in medical procedures is very task dependent. According to the application, observers can be used as a replacement for sensors or can be used in situations where sensors are not applicable. In rehabilitation applications replacing sensors with observers provides a way to reduce the cost and the weight of the devices. In these applications where the rehabilitation devices (such as exoskeleton devices) are used by the patient for a long duration, reducing the cost and the weight of the devices is very advantageous. Moreover, due to the limited space in some devices such as hand exoskeleton [7], force sensors should be replaced by other measurement or estimation methods. In MIS procedures, where the fine tools are inserted into the body through small incisions, placing measurement devices at the tip of the surgical tools to be inserted into the body is not practical. Besides, one of the important issues in surgical procedures is the sterilization of the equipment, as well as the sensors. Replacing sensors with observers relaxes this issue. There are also different challenges in designing and using the observers. In medical procedures, safety is a very important issue, which should also be considered in designing observers. The performance of the observer (convergence to the real values) should be guaranteed to provide the surgeon/assistant robot with realistic values to ensure the safety of the patient and the efficiency of the method. Especially, when the observers are used to control the assistant robots, the stability of the observer/controller should be guaranteed. Besides, effective observers require a good model describing the system's behavior. In some applications, finding such a model is not a trivial task.

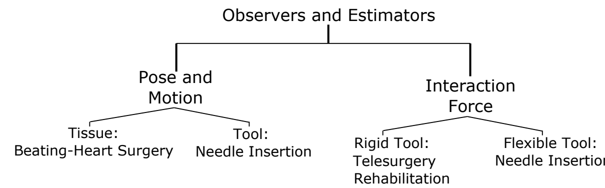

Fig. 1: Applications of estimators considered in this paper

This paper provides a review of the applications of the observers in medical procedures. As shown in Fig .1, this survey is performed for two main areas: 1) pose and motion estimation 2) force estimation. The paper is organized as follows: In Section 2, the mainly used methods for motion estimation in beating-heart surgeries and radiotherapy as well as position and orientation estimation in needle insertion procedures are presented. In Section 3, the problem of force estimation in surgeries, rehabilitation training, and needle insertion therapies are discussed for two cases of rigid and flexible tools. The concluding remarks are presented in Section 4.

2 Pose and Motion Estimation

In medical applications, preoperative imaging provides valuable information for diagnosis and performing plannings of the operations. In minimally invasive surgeries, intraoperative imaging using endoscopes and ultrasound images, enable the surgeon to track the surgical instruments as well as the organ's motion. In robot-assisted interventions, this visual information can be translated into numerical values using image processing techniques and used as feedback in the robot control loop. There have been different methods proposed in the literature for pose and motion tracking of the targeted organ and the surgical tools. These two applications are represented in the sequel.

2.1 Physiological Motion Estimation

To avoid inaccuracy during surgical interventions, it is desired to remove any unwanted motions or disturbances.

Even if the patient is still, there may be physiological organ motion. There are two types of physiological motions: periodic motion such as the heartbeat and respiration, and the non-periodic motions. The examples of non-periodic motions, which are very relevant in surgical interventions, are the organ motion after opening the body such as brain [8] and abdominal cavity during MIS [9]. Using the imaging modalities, all these motions can be captured from images processing techniques. If no model of the motion is available, the motion can only be retrieved from the images following a point of interest (POI) on the target organ. There have been different methods proposed in the literature for estimating the physiological motion using images and calculating the POI using image registration. Image registration is a technique for finding a transformation between the reference image and current image to align all images in one coordinate [10]. Rigid registration involves finding a rotation and translation to describe the motion. On the other hand, non-rigid registration consists of defining a set of geometric features in both coordinates and finding a transformation that minimizes some distance function. Mani et al. provide a survey on different methods in medical image registration [10].

In the work done by Pennec et al., 3D intra-operative ultrasound images are used to track the brain deformation to assist a neuro-surgical operation manipulator arm [11]. The brain shift can also be found using non-rigid surface registration and combined with finite element methods to estimate the 3D volumetric displacement [12]. Letteboer et al. acquire the brain shift before and after opening the dura using 3D ultrasound data and use as a basis for intra-operative planning [13]. Hagemann et al. propose a non-rigid finite element model for head to estimate the brain deformations during the image-guided neuro-surgery [8]. Vijayan et al. use a non-rigid registration method based on minimization of the image intensity changes over time to estimate the organ movements using ultrasound images in liver radiotherapy [14]. Hu et al. present a framework for reconstructing the 3D surface of an organ using endoscopic images in MIS [9]. Maier et al. provide a survey of the optical 3D reconstruction of the soft tissue surface geometry in laparoscopic surgery [15]. These non-periodic motions can be captured using CAD/CAM systems during the pre- and intra-operative planning and are used by the surgeon and/or the surgical assistants.

The imaging techniques are also used in estimating the periodic motions. The two main sources of periodic physiological motions are the respiration and the heartbeat. Respiration causes low-frequency, large-amplitude cyclic motions while heartbeat produces high-frequency, small-amplitude semi-periodic motion in the heart. In radiation therapy, in which the goal is to focus the high energy beams on cancerous tissue, the motion caused by respiration reduces the concentration of the dosage on the targeted tissue. In cardiac surgery, the surgeon's motion can be disturbed by heartbeat motions. To overcome the heart beat motion, one possible way is to stop the heart and use a heart-lung machine. However, by using a heart-lung machine, the risk of stroke and long-term cognitive loss is higher [16]. Another solution is the use of stabilizers, which can only be used for the exterior surface of the heart [17]. physiological motion can also be dealt with by actively compensating for it in the controller of the surgical robot. Regardless of radiotherapy or beating-heart surgery, in active motion compensation, it is desired to remove the relative motion between the surgical/therapeutic tool and the targeted organ so that they seem stationary with respect to each other [18]. This can be performed by moving the patient, which may be uncomfortable for the patient, or by moving the tool in synchrony with the physiological motion. For these fast periodic physiological motions, in order to have an effective compensation, the motion of the POI should be retrieved in real-time. However, a big challenge in measuring the POI motion using imaging modalities such as Computer Tomography (CT), endoscopes and ultrasound is the low update rate of the images. In these imaging methods, since the update rate is much lower than the high-frequency motion of the POI, the data loss is not negligible.

There have been different methods proposed in the literature for estimating the heart motion using images and calculating the POI motion based on the transformation defined between the reference image and current image. Sauv et al. consider two approaches based on landmark and texture tracking for 3D heart surface tracking [19]. Richa et al. employ a thin-plate spline warping model (TPS) for 3D tracking of beating heart using endoscopic images [20]. TPS is a mapping function between the pixel coordinates of a reference image and the current image, minimizing the bending energy using a set of control points. Yang et al. propose a robust 3D tracking scheme based on two methods [21]. Using spatial-color space and by defining a probabilistic similarity measure, the region of interest can be tracked in a new image. The second method is based on TPS model, for which the optimal model parameters are found using an iterative method. These two processes are computed in parallel to form a 3D tracking scheme of the heart motion. To predict the heart motion, there are non-model based methods proposed in the literature which use a long embedding vector of past measurements of the heart motion and predict the motion by finding a previous embedding vector similar to the current vector [17].

However, these methods lack the required robustness and accuracy, since they are only based on the images and no information about the dynamics of the heart motion and the respiratory system are taken into account. Also, imaging methods fail to predict the motion in case of any occlusions such as surgical instrument, blood, and smoke. Another issue in retrieving the heart motion only based on images is data acquisition delay. The delay in the position data is caused by image update rate, which depends on the utilized sensor, and the processing time. Using the delayed position data in the robot feedback loop may cause the control loop become unstable, leading to undesirable performance. In this case, predictive strategies can be used to compensate for the data acquisition and processing delay.

According to the nature of the physiological motion, a quasi-periodic model can be used to estimate the heart and respiratory motion, which can be further updated to predict the POI motion. The quasi-periodic motion is defined as a time-varying Fourier series, for which the coefficients can be estimated using different methods [22] [23]. Extended Kalman filter (EKF) is an estimation method in which the current measurements and the mathematical model are simultaneously used to estimate the unknown variables, which also overcomes the low update rate of the images and can be used to predict the motion in case of any occlusions. Consider the following state space model that evolves through a random walk:

$$x(t+\Delta t) = A(\Delta t)x(t) + \mu \tag{1a}$$

$$z(t) = y(x(t)) + v \tag{1b}$$

$$y(x(t)) = c + \sum_{l=1}^{m} r_l \sin\theta_l(t) \tag{1c}$$

$$A(\Delta t) = \left[\begin{array}{c|ccccc} \mathbf{I}_{m+1} & & & \mathbf{0} & & \\ \hline & 1 & & & & \\ & \Delta t & 1 & & & \\ \mathbf{0} & 2\Delta t & 0 & 1 & & \\ & \vdots & & & \ddots & \\ & m\Delta t & & & & 1 \end{array}\right] \tag{1d}$$

in which μ and v are independent Gaussian noise terms. The vector $x = \left[c(t), r_l(t), \omega(t), \theta_l(t)\right]^T$ and z represent the state vector and the noisy measurements, respectively and $y(x(t))$ is the output function defining the quasi-periodic motion of the heart. In this equation, $\theta_l(t) = l\int_0^t \omega(\tau)d\tau + \phi_l(t)$, where $\omega(t)$ and $\phi_l(t)$ represent the heart rate and the harmonic phases, respectively

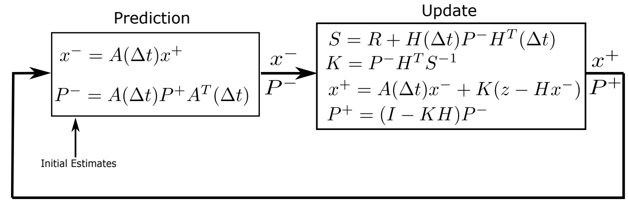

Fig. 2: The block diagram of Extended Kalman Filter. The equations for x, z and H are given in (1) and (2), respectively.

and m is the number of the harmonics. The estimation process can be then divided into prediction and update stages as shown in Fig. 2.

In prediction stage, in the first iteration, the initial guess values for x^+ and P^+ are used to make the first prediction x^- and P^- to be used in the next stage. In the update stage, the values of x^+ and P^+ are updated and fed back to the prediction stage for the next iteration. In this figure, Q is the process noise covariance matrix, R is the observation noise covariance matrix and H can be found as

$$H = \left.\frac{\partial y}{\partial x}\right|_{x^-} \tag{2}$$

Bowthorpe and Tavakoli have considered the quasi-periodic model for the heart motion and found the coefficients using the Extended Kalman filter [24]. Similarly, in the work done by Yuen et al., the heart motion is estimated and is used to predict the future heart motion [25]. To model both the breathing and heart beat motions, Richa et al. [26] and Yang et al. [27] propose the summation of two Fourier series and use Extended Kalman filtering method for estimating the parameters.

2.2 Tool Pose Estimation

In robotic-assisted surgeries, where the surgical tool is manipulated by a robotic system, the position and orientation of the surgical tool are valuable information for controlling the robotic manipulator. Some of that information can be obtained from imaging modalities. Ultrasound imaging is a cost-effective and widely used imaging modality, which has been employed in many applications. There have been different methods proposed in the literature for localization (position estimation) of the surgical instruments and needles inside the body using ultrasound images. In this paper, the focus is on the localization of needles in needle insertion procedures such as brachytherapy, biopsy and neurosurgery. In these methods, long hollow beveled tip needles are inserted into the human body for diagnosis, drug delivery or sample removal. As the

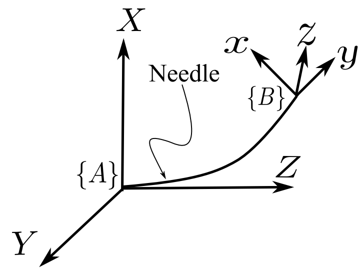

Fig. 3: Needle in 3D space. The position and orientation of the needle is defined as the position and orientation of the moving frame $\{B\}$ with respect to fixed frame $\{A\}$.

needle is inserted into the tissue, the needle/tissue interaction forces cause the needle to bend toward the bevel orientation and move on a curved path in 3D space.

The desired needle path is task dependent. In biopsy, it is desired to reach a final point regardless of the traveled path. In brachytherapy, which is a type of radiotherapy, it is desired to move the needle on a straight path and deliver some radioactive seeds on the needle track during the retraction. If there are any obstacles on the needle path, such as bones or nerves, the needle should follow a curved path to avoid any collisions with the obstacles. The steering problem can be addressed using motion planning or control algorithms. In motion planning methods, the necessary actions for steering the needle at the current and future times are determined offline using mathematical models, while the desired trajectory can be updated during the insertion to compensate for unanticipated tracking errors. Control algorithms use a feedback loop structure, in which the controller determines the required actions online. Different issues in needle steering can be found in the work done by Rossa et al. [28].

The motion of the needle can be described by the position of the origin of the moving frame $\{B\}$ attached to the needle tip with respect to a fixed frame $\{A\}$ as shown in Fig. 3. The orientation of the needle tip can also be defined as the rotation matrix, relating the moving frame to the fixed frame. To find the position of the needle during the insertion, the needle can be tracked in the images. To this end, there are different researches done in the literature which are based on parallel projections and are relatively computationally expensive [29] [30]. A more robust algorithm, random sample consensus (RANSAC), is proposed for finding polynomial curves in a 3D environment [31]. RANSAC is an iterative algorithm for estimating the model parameters using a set of observed data with outliers. This method can also be used to fit the polynomial curve and combined with Kalman filters to reduce the search area [32] [33]. Waine et al. employ this algorithm to estimate the needle tip position using 2D transverse ultrasound images [34]. To improve the accuracy, Malekian et al. combine a denoising method with RANSAC [35]. These methods are able to localize and track the needle position in real time during the insertion. Asadian et al. design a high gain observer for estimating needle tip velocity from noisy position signals [36].

According to needle kinematics [37], the three fixed angles of roll, yaw, and pitch, representing the needle tip orientation, are highly involved in the system motion and having knowledge of them is very beneficial for controlling the needle tip position. However, due to the small diameter of the needle and the low resolution of the ultrasound images, it is not possible to measure the needle tip orientation from ultrasound images. This motivates the idea of designing state observers for estimating the needle tip orientation using the needle tip position obtained from ultrasound images. There are a few researches on estimating the needle tip orientation using observation methods. In the sliding mode controller proposed by Rucker et al., the needle tip orientation is required for calculation of the control action [38]. In this work, a 5 DOF magnetic tracking sensor is used which is combined with a Kalman filter to find the full information about the needle tip position and orientation. This may work in a lab setting but is not clinically feasible due to sterilization issues.

Considering the planar case, in which the needle is inserted in the z direction and deflects in the x direction, the needle's kinematic equations can be written as

$$\dot{x} = v \sin\beta, \tag{3a}$$
$$\dot{\beta} = kv \sin\gamma, \tag{3b}$$
$$\dot{\gamma} = -kv \cos\gamma \tan\beta + u \tag{3c}$$

where x is the Cartesian needle tip position along the x axis, which is perpendicular to the insertion direction, and β and γ represent the pitch and roll angels, respectively. v is the insertion velocity and k is the needle path curvature, which is constant. While x can be measured from ultrasound images, β cannot be measured in that way and needs to be observed using the equations in (3). Using the nonlinear transformation $s = \begin{bmatrix} x & \sin\beta & -\cos\beta\sin\gamma \end{bmatrix}^T$, (3) can be written in state space, comprising a linear and a nonlinear part with state vector s and output y as

$$\dot{s} = As + B\phi \tag{4a}$$
$$y = Cs \tag{4b}$$

with

$$A = \begin{bmatrix} 0 & v & 0 \\ 0 & 0 & -vk \\ 0 & 0 & 0 \end{bmatrix}, \ B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \ C = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \tag{5a}$$

$$\phi = kvs_2 \mp u\sqrt{1-(s_2^2+s_3^2)} \tag{5b}$$

Assuming ϕ is fully known, Kallem and Cowan design a linear state observer as $\dot{\hat{s}} = A\hat{s} + B\phi + L(y - \hat{y})$, where L is the observer gain to make $A + LC$ Hurwitz and $\hat{}$ represents the estimated values [37]. This observer is then combined with a state feedback controller. However, due to the singularities of the nonlinear system, the designed observer-controller is only capable to stabilize the needle in one plane. In other words, the closed-loop equations are only convergent in a neighborhood of zero. Motaharifar et al. combine the same observer with other controllers [39]. In the work done by Fallahi et al. [40], the nonlinear terms are also considered in the observer design and the observer is given by $\dot{\hat{s}} = A\hat{s}+\hat{\phi}+\Delta_\theta L(\hat{y}-y)$ with $\Delta_\theta = diag\{\theta, \theta^2, \theta^3\}$ and $\theta > 1$. However, since the nonlinearities do not satisfy the Lipschitz continuity condition, the observer is convergent under certain assumptions to keep the system states bounded. Since there are only a few researches done in the literature for using observers in estimating the needle tip orientation, this problem still remains open for further studies.

3 Force Estimation

When it comes to human-robot interaction, using force control methods become crucial to providing a safe and effective environment for the human and prevent any excessive damage or trauma to patient's body [41]. In robot-assisted surgeries or telesurgeries, the robot is in direct contact with the soft tissue. In this case, it is important to detect the contact and measure the force applied by the robot on the soft tissue. In rehabilitation tasks, in which the goal is to rehabilitate the musculoskeletal system, the robot is also in interaction with the patient.

In the case of the direct contact, the motion control of the robotic manipulator will be effective only if the exact model of the robot, tissue and all their parameters are known and incorporated in the controller design. In most of the cases, the contact surface is the non-homogeneous body soft tissue, for which the exact model and the parameters are unknown and any modelling encounter some degrees of uncertainty. Contact motion control in the presence of such uncertainties finally leads to actuator saturation or tissue damage, which both are equivalent to the failure of the process. In such cases, force control strategies provide better solutions for controlling the robotic manipulators [3].

In teleoperation tasks, where the surgeon is performing the operation remotely by manipulating a master robot, displaying the contact force information to the surgeon can provide him/her with a more realistic situation. The contact force information can be transferred to the surgeon's hand through the master robot in the form of haptic feedback. Incorporating the force feedback in the control loop improves the performance by giving the surgeon the feeling of the remote site [42]. Obviously, in these control schemes, first, the contact force should be measured. However, in most of the medical applications, robot-mounted force sensors are not practical as they need to be clinically approved [3].

In addition to robot-assisted surgeries, there have been different types of wearable exoskeleton robots developed for rehabilitation of upper and lower limbs [43], spine [44], knee [45], hand [46], etc. These robots are designed to improve the functionality of body joints and limbs after stroke or other disability events [47] [48] [49]. These devices are designed to measure the joint position and orientation as well as the forces applied by the patient and drive the exoskeleton device and train the targeted limb. Unmodeled dynamics, friction and external forces which act as disturbances on these devices make the device control very challenging, compared to the situation where no uncertainty is present. Due to safety issues, these devices should be controlled precisely to prevent any further damage to the affected limb. These devices demonstrate another example of direct interaction between a robot and human, in which measuring the interaction forces is imperative. In some applications, due to the limited space on the device (e.g. hand exoskeleton [7]), narrow bandwidth of the force sensors and cost issues, it is desired to move from using force sensors to force estimation methods.

In both of aforementioned applications, using sensorless methods would be beneficial to decrease the costs and increase the applicability of the designed devices; however, the difficulty arises in terms of designing observers and estimators and analysis of the effects of the estimation error on combined observer/control strategies, and guaranteeing stability, safety and efficiency. In the following, the force estimation problem in medical applications is divided into two main groups. First, the interaction forces in rehabilitation devices and the forces between rigid surgical tools and tissue are discussed and next, the interaction forces in the presence of flexible tools such as needles are studied. These applications benefit from using disturbance observers and Kalman filtering methods.

3.1 Rigid Tool

Due to the nonlinear dynamics of rigid robots, nonlinear disturbance observer (NDOB) are used. The main task of a disturbance observer (DOB) is to estimate the disturbances and modelling uncertainties [50]. To design an NDOB, the robot's unmodeled dynamics are considered as additive uncertainties. All these uncertainties and external forces are lumped into one disturbance vector. Consider the dynamics of a robotic manipulator as [51]

$$\hat{M}(q)\ddot{q} + \hat{N}(q,\dot{q}) = \tau + \tau_d \tag{6}$$

where q and $\dot{q}$ represent the manipulator joint angle and velocity vectors, respectively. $\hat{M}$ is the nominal inertia matrix and $\hat{N}$ is the nominal value of the summation of Coriolis, centrifugal and gravity vectors. τ and τ_d represent the control torque and the lumped external force and disturbance, respectively. In the conventional NDOB, where it is assumed that the joint accelerations are measured, the NDOB equations can be written as [52]

$$\dot{\hat{\tau}}_d = -L\hat{\tau}_d + L\{\hat{M}(q)\ddot{q} + \hat{N}(q,\dot{q}) - \tau\} \tag{7}$$

in which L is the observer gain and should be designed properly. However, in most of the cases, there are no acceleration sensors available and it is not also practical to derive the acceleration signals by taking time derivative of noisy velocity measurements. In such cases, an advanced NDOB [53] provides a suitable structure, in which no acceleration measurement is required. To this end, an auxiliary variable is defined, whose derivative cancels the acceleration term in the observer equations. Using this technique, the observer equations are found as

$$\dot{z} = -L(q,\dot{q})z + L(q,\dot{q})\{\hat{N}(q,\dot{q}) - \tau - p(q,\dot{q})\} \tag{8a}$$

$$\hat{\tau}_d = z + p(q,\dot{q}) \tag{8b}$$

where

$$\frac{d}{dt}p(q,\dot{q}) = L(q,\dot{q})\hat{M}(q)\ddot{q} \tag{9}$$

The above has the same estimation error dynamics as (7). A systematic method for designing the nonlinear observer and finding the observer gain for robotic manipulators can be found in the work done by Mohammadi et al. [50]. This strategy has been used for estimating the robot-environment contact forces. Li et al. use a NDOB at slave side to estimate the external forces at the forceps tip [54]. Liang et al. utilize a DOB for estimating the contact force in an ear surgery and for detecting sensor failure [55]. Emre and Kouhei propose a force control strategy based on a DOB for estimating the disturbance forces [56]. The estimated disturbance forces are then canceled in an inner loop and the effects of the dynamics of the DOB on the performance is analyzed. The work done by Amini et al. is a bilateral teleoperation study, in which DOBs are used both at master and slave sides to estimate the human and the environment forces [57]. The proposed structure provides bounded estimation errors, for which a sliding mode controller is designed.

Disturbance observers have also been employed in estimating the external forces in rehabilitation applications [58] [59]. Mohammed et al. use a DOB for estimating the patient muscular torque and combine it with a siding-mode controller to improve the bandwidth and tracking precision for controlling a knee joint orthosis [58]. Popescu et al. employ three observers for estimating velocity, external forces and, disturbances [7]. Two disturbance observers are used for estimating the human finger force and the external disturbances. In order to estimate the interaction forces between the user and the rehabilitation device, Chen et al. use the conventional form of a DOB [60]. In this work, the controller is an impedance-based controller combined with a passive velocity controller to moderately assist the patient and guarantee the safety of the system. Ugurlu et al. propose an upper body exoskeleton for shoulder and elbow rehabilitation, in which the human force is estimated and cancelled to improve the position control performance [59].

Kalman filters also provide another approach for estimating the interaction forces. Mitsantisuk et al. use a Kalman-filter based state observer for estimating the hand and wrist forces of the patient in robot-assisted rehabilitation [61]. Pehlivan et al. employ a Kalman filter and Lyapunov analysis to provide a stable and fast force estimation in upper limb rehabilitation [62]. Fakoorian et al. use extended Kalman filter as well as unscented Kalman filter (UKF) for estimating robot states and the ground reaction forces in a prosthetic leg [63]. Mitsantisuk et al. propose a method that takes the advantage of both DOB and Kalman filter [64]. In this work, a disturbance observer is combined with a Kalman filter to estimate the system states and the interaction forces in human stiffness estimation application. The mentioned works represent examples of the application of DOB and EKF in estimating the human/robot interaction forces. In the following, the application of observation methods for estimating the needle/tissue interaction forces are presented.

Table 1: Summary of the discussed methods

Observers	**Motion/Pose**	**Beating-Heart Surgery**	**EKF**	**[24]-[27]**
		Needle Insertion	**Linear/Nonlinear**	**[37],[39],[40]**
	Force	**Tele-surgery**	**DOB**	**[54]-[57]**
		Rehabilitation	**DOB/EKF**	**[58]-[64]**
		Needle Insertion	**DOB/EKF**	**[65],[66]-[67]**

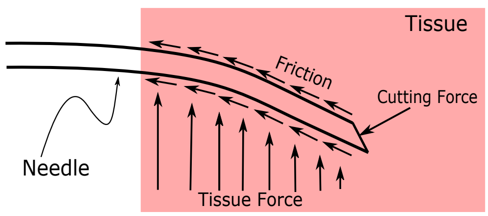

Fig. 4: Needle/tissue interaction forces. The cutting force is at the needle tip, friction forces act along the needle shaft and tissue forces depends on tissue stiffness.

3.2 Flexible Tool

As stated before, in order to increase the efficiency of needle insertion procedures, accurate steering algorithms are required. Since the needle bends as a result of forces acting on the needle, any information about the needle/tissue interaction will be helpful for steering the needle. The needle/tissue interaction forces are composed of cutting, stiffness and friction forces [68] as shown in Fig. 4. The cutting force is the force at the needle tip causing the needle to slice the tissue and move through it, which is a constant value. The friction force acts along the needle shaft during the insertion and the stiffness force depends on the tissue properties. Since there are no clinically approved needle mounted sensors available, it is not possible to measure the needle/tissue interaction forces. However, a needle-based-mounted force sensor provides a practical way for measuring the total forces acting on the needle at its base.

The force estimation methods in needle insertion procedures are mainly the techniques described in the previous sections. In these methods, the force data is found using the deflection information and the forces measured at needle base. Asadian et al. model the interaction forces base on LuGre [69] model and estimate the parameters online using multiple EKFs [65]. Fukushima et al. employ a DOB and the recursive least squares (RLS) technique to find the tip and friction force acting on the needle [66]. Maghsoudi et al. propose two methods for estimating the forces; a DOB and a model-based method [70]. The two methods are then compared in a needle insertion control loop and the results show the robustness of DOB to uncertainties. Having the total force acting on the needle, Suzuki et al. combine a reaction force observer [67] with the RLS method to find the stiffness force of the tissue in a stiffness assessment task in liver teleoperation biopsy [71].

4 Concluding Remarks

In this work, a classification and applications of observers and estimation methods in medical robotics are presented. To this end, the most relevant and used techniques are introduced and their applications in motion and force estimation in beating-heart surgeries, needle insertion procedures, telesurgeries and rehabilitation interventions are studied as summarized in Table. 1. Different formats of Kalman filters have been used in robot-assisted procedures for motion and force estimation. Disturbance observers (DOB) also provides an effective approach for estimating the disturbance and external forces. The advanced form of the DOB has more application in robot-assisted applications since in this method there is no requirement for acceleration measurements.

This study shows that employing observers in robotic-assisted procedures can be helpful to simplify the procedures, relax the size constraint and reduce the costs of the equipment. However, the application of observers in medical robotics is very task-dependent and varies based on the procedure and equipment. It should also be noted that not all the mentioned methods are clinically approved as there are still challenges in guaranteeing the safety and the performance of such system. However, the application-driven and multi-disciplinary nature of this field open a wide research area for using the observers in medical robotics.

Acknowledgment: This work was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada under grant CHRP 446520, the Canadian Institutes of Health Research (CIHR) under grant CPG 127768 and the Alberta Innovates - Health Solutions (AIHS) under grant CRIO 201201232.

References

[1] R. Taylor and D. Stoianovici, "Medical robotics in computer-integrated surgery," *IEEE Transactions on Robotics and Automation*, vol. 19, no. 5, pp. 765 – 781, 2003.

[2] P. Dario, B. Hannaford, and A. Menciassi, "Smart surgical tools and augmenting devices," *IEEE transactions on robotics and automation*, vol. 19, no. 5, pp. 782–792, 2003.

[3] B. Siciliano and O. Khatib, *Springer handbook of robotics.* Springer, 2016.

[4] P. Puangmali, K. Althoefer, L. D. Seneviratne, D. Murphy, and P. Dasgupta, "State-of-the-art in force and tactile sensing for minimally invasive surgery," *IEEE Sensors Journal*, vol. 8, no. 4, pp. 371–381, 2008.

[5] I. Bankman, *Handbook of medical image processing and analysis.* academic press, 2008.

[6] R. C. Dorf and R. H. Bishop, *Modern control systems.* Pearson, 2011.

[7] N. Popescu, D. Popescu, M. Ivanescu, D. Popescu, C. Vladu, and I. Vladu, "Force observer-based control for a rehabilitation hand exoskeleton system," in *9th Asian Control Conference (ASCC).* IEEE, 2013, pp. 1–6.

[8] A. Hagemann, K. Rohr, H. S. Stiehl, U. Spetzger, and J. M. Gilsbach, "Biomechanical modeling of the human head for physically based, nonrigid image registration," *IEEE transactions on medical imaging*, vol. 18, no. 10, pp. 875–884, 1999.

[9] M. Hu, G. Penney, M. Figl, P. Edwards, F. Bello, R. Casula, D. Rueckert, and D. Hawkes, "Reconstruction of a 3d surface from video that is robust to missing data and outliers: Application to minimally invasive surgery using stereo and mono endoscopes," *Medical image analysis*, vol. 16, no. 3, pp. 597–611, 2012.

[10] V. Mani *et al.*, "Survey of medical image registration," *Journal of Biomedical Engineering and Technology*, vol. 1, no. 2, pp. 8–25, 2013.

[11] X. Pennec, P. Cachier, and N. Ayache, "Tracking brain deformations in time sequences of 3d us images," *Pattern Recognition Letters*, vol. 24, no. 4, pp. 801–813, 2003.

[12] M. A. Audette, K. Siddiqi, F. P. Ferrie, and T. M. Peters, "An integrated range-sensing, segmentation and registration framework for the characterization of intra-surgical brain deformations in image-guided surgery," *Computer Vision and Image Understanding*, vol. 89, no. 2, pp. 226–251, 2003.

[13] M. M. J. Letteboer, P. W. Willems, M. A. Viergever, and W. J. Niessen, "Brain shift estimation in image-guided neurosurgery using 3-d ultrasound," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 2, pp. 268–276, 2005.

[14] S. Vijayan, S. Klein, E. F. Hofstad, F. Lindseth, B. Ystgaard, and T. Langø, "Motion tracking in the liver: Validation of a method based on 4d ultrasound using a nonrigid registration technique," *Medical physics*, vol. 41, no. 8, 2014.

[15] L. Maier-Hein, P. Mountney, A. Bartoli, H. Elhawary, D. Elson, A. Groch, A. Kolb, M. Rodrigues, J. Sorger, S. Speidel *et al.*, "Optical techniques for 3d surface reconstruction in computer-assisted laparoscopic surgery," *Medical image analysis*, vol. 17, no. 8, pp. 974–996, 2013.

[16] G. L. Reed III, D. E. Singer, E. H. Picard, and R. W. DeSanctis, "Stroke following coronary-artery bypass surgery," *New England Journal of Medicine*, vol. 319, no. 19, pp. 1246–1250, 1988.

[17] T. Ortmaier, M. Groger, D. H. Boehm, V. Falk, and G. Hirzinger, "Motion estimation in beating heart surgery," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 10, pp. 1729–1740, 2005.

[18] A. Trejos, S. Salcudean, F. Sassani, and S. Lichtenstein, "On the feasibility of a moving support for surgery on the beating heart," in *Medical Image Computing and Computer-Assisted Intervention–MICCAI'99.* Springer, 1999, pp. 1088–1097.

[19] M. Sauvée, A. Noce, P. Poignet, J. Triboulet, and E. Dombre, "Three-dimensional heart motion estimation using endoscopic monocular vision system: From artificial landmarks to texture analysis," *Biomedical Signal Processing and Control*, vol. 2, no. 3, pp. 199–207, 2007.

[20] R. Richa, P. Poignet, and C. Liu, "Three-dimensional motion tracking for beating heart surgery using a thin-plate spline deformable model," *The International Journal of Robotics Research*, vol. 29, no. 2-3, pp. 218–230, 2010.

[21] B. Yang, W.-K. Wong, C. Liu, and P. Poignet, "3d soft-tissue tracking using spatial-color joint probability distribution and thin-plate spline model," *Pattern recognition*, vol. 47, no. 9, pp. 2962–2973, 2014.

[22] A. Thakral, J. Wallace, D. Tomlin, N. Seth, and N. Thakor, "Surgical motion adaptive robotic tech-

nology (smart): Taking the motion out of physiological motion," in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2001*. Springer, 2001, pp. 317–325.

[23] S. G. Yuen, P. M. Novotny, and R. D. Howe, "Quasiperiodic predictive filtering for robot-assisted beating heart surgery," in *IEEE International Conference on Robotics and Automation, ICRA*, 2008, pp. 3875–3880.

[24] M. Bowthorpe and M. Tavakoli, "Physiological organ motion prediction and compensation based on multirate, delayed, and unregistered measurements in robot-assisted surgery and therapy," *IEEE/ASME Transactions on Mechatronics*, vol. 21, no. 2, pp. 900–911, 2016.

[25] S. Yuen, S. Kesner, N. Vasilyev, P. Del Nido, and R. Howe, "3d ultrasound-guided motion compensation system for beating heart mitral valve repair," *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2008*, pp. 711–719, 2008.

[26] R. Richa, A. P. Bó, and P. Poignet, "Towards robust 3d visual tracking for motion compensation in beating heart surgery," *Medical Image Analysis*, vol. 15, no. 3, pp. 302–315, 2011.

[27] B. Yang, C. Liu, W. Zheng, and S. Liu, "Motion prediction via online instantaneous frequency estimation for vision-based beating heart tracking," *Information Fusion*, vol. 35, pp. 58–67, 2017.

[28] C. Rossa and M. Tavakoli, "Issues in closed-loop needle steering," *Control Engineering Practice*, vol. 62, pp. 55–69, 2017.

[29] J.-S. Hong, T. Dohi, M. Hasizume, K. Konishi, and N. Hata, "A motion adaptable needle placement instrument based on tumor specific ultrasonic image segmentation," *Medical Image Computing and Computer-Assisted Intervention, MICCAI*, pp. 122–129, 2002.

[30] M. Aboofazeli, P. Abolmaesumi, P. Mousavi, and G. Fichtinger, "A new scheme for curved needle segmentation in three-dimensional ultrasound images," in *IEEE International Symposium on Biomedical Imaging: From Nano to Macro, ISBI'09*. IEEE, 2009, pp. 1067–1070.

[31] M. Uherčík, H. Liebgott, J. Kybic, and C. Cachard, "Needle localization methods in 3d ultrasound data," in *International congress on ultrasonics*, 2009, pp. 11–17.

[32] Y. Zhao, C. Cachard, and H. Liebgott, "Automatic needle detection and tracking in 3d ultrasound using an roi-based ransac and kalman method," *Ultrasonic imaging*, vol. 35, no. 4, pp. 283–306, 2013.

[33] Y. Zhao, H. Liebgott, and C. Cachard, "Tracking micro tool in a dynamic 3d ultrasound situation using kalman filter and ransac algorithm," in *9th IEEE International Symposium on Biomedical Imaging (ISBI)*. IEEE, 2012, pp. 1076–1079.

[34] M. Waine, C. Rossa, R. Sloboda, N. Usmani, and M. Tavakoli, "Three-dimensional needle shape estimation in trus-guided prostate brachytherapy using 2-d ultrasound images," *IEEE journal of biomedical and health informatics*, vol. 20, no. 6, pp. 1621–1631, 2016.

[35] L. Malekian, H. A. Talebi, and F. Towhidkhah, "Needle detection in 3d ultrasound images using anisotropic diffusion and robust fitting," in *International Symposium on Artificial Intelligence and Signal Processing*. Springer, 2013, pp. 111–120.

[36] A. Asadian, R. V. Patel, and M. R. Kermani, "A distributed model for needle-tissue friction in percutaneous interventions," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2011, pp. 1896–1901.

[37] V. Kallem and N. J. Cowan, "Image guidance of flexible tip-steerable needles," *IEEE Transactions on Robotics*, vol. 25, no. 1, pp. 191–196, 2009.

[38] D. C. Rucker, J. Das, H. B. Gilbert, P. J. Swaney, M. I. Miga, N. Sarkar, and R. J. Webster, "Sliding mode control of steerable needles," *IEEE Transactions on Robotics*, vol. 29, no. 5, pp. 1289–1299, 2013.

[39] M. Motaharifar, H. A. Talebi, A. Afshar, and F. Abdollahi, "Adaptive observer-based controller design for a class of nonlinear systems with application to image guided control of steerable needles," in *American Control Conference (ACC)*. IEEE, 2012, pp. 4849–4854.

[40] B. Fallahi, C. Rossa, R. Sloboda, N. Usmani, and M. Tavakoli, "Partial estimation of needle tip orientation in generalized coordinates in ultrasound image-guided needle insertion," in *IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, 2016, pp. 1604–1609.

[41] T. Haidegger, B. Benyó, L. Kovács, and Z. Benyó, "Force sensing and force control for surgical robots," *IFAC Proceedings Volumes*, vol. 42, no. 12, pp. 401–406, 2009.

[42] G. Tholey, J. P. Desai, and A. E. Castellanos, "Force feedback plays a significant role in minimally invasive surgery: results and analysis," *Annals of surgery*, vol. 241, no. 1, p. 102, 2005.

[43] S. Viteckova, P. Kutilek, and M. Jirina, "Wearable lower limb robotics: A review," *Biocybernetics and*

Biomedical Engineering, vol. 33, no. 2, pp. 96–105, 2013.

[44] S. A. Kolakowsky-Hayner, J. Crew, S. Moran, and A. Shah, "Safety and feasibility of using the ekso™ bionic exoskeleton to aid ambulation after spinal cord injury," *J Spine*, vol. 4, p. 003, 2013.

[45] P. Beyl, K. Knaepen, S. Duerinck, M. Van Damme, B. Vanderborght, R. Meeusen, and D. Lefeber, "Safe and compliant guidance by a powered knee exoskeleton for robot-assisted rehabilitation of gait," *Advanced Robotics*, vol. 25, no. 5, pp. 513–535, 2011.

[46] P. Heo, G. M. Gu, S.-j. Lee, K. Rhee, and J. Kim, "Current hand exoskeleton technologies for rehabilitation and assistive engineering," *International Journal of Precision Engineering and Manufacturing*, vol. 13, no. 5, pp. 807–824, 2012.

[47] B. Chen, H. Ma, L.-Y. Qin, F. Gao, K.-M. Chan, S.-W. Law, L. Qin, and W.-H. Liao, "Recent developments and challenges of lower extremity exoskeletons," *Journal of Orthopaedic Translation*, vol. 5, pp. 26–37, 2016.

[48] I. Díaz, J. J. Gil, and E. Sánchez, "Lower-limb robotic rehabilitation: literature review and challenges," *Journal of Robotics*, vol. 2011, 2011.

[49] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, and S. Leonhardt, "A survey on robotic devices for upper limb rehabilitation," *Journal of neuroengineering and rehabilitation*, vol. 11, no. 1, p. 3, 2014.

[50] A. Mohammadi, M. Tavakoli, H. Marquez, and F. Hashemzadeh, "Nonlinear disturbance observer design for robotic manipulators," *Control Engineering Practice*, vol. 21, no. 3, pp. 253–267, 2013.

[51] J. J. Craig, *Introduction to robotics: mechanics and control.* Pearson Prentice Hall Upper Saddle River, 2005, vol. 3.

[52] W.-H. Chen, "Disturbance observer based control for nonlinear systems," *IEEE/ASME transactions on mechatronics*, vol. 9, no. 4, pp. 706–710, 2004.

[53] W.-H. Chen, D. J. Ballance, P. J. Gawthrop, and J. O'Reilly, "A nonlinear disturbance observer for robotic manipulators," *IEEE Transactions on industrial Electronics*, vol. 47, no. 4, pp. 932–938, 2000.

[54] H. Li, K. Kawashima, K. Tadano, S. Ganguly, and S. Nakano, "Achieving haptic perception in forceps' manipulator using pneumatic artificial muscle," *IEEE/ASME Transactions on Mechatronics*, vol. 18, no. 1, pp. 74–85, 2013.

[55] W. Liang, S. Huang, S. Chen, and K. K. Tan, "Force estimation and failure detection based on disturbance observer for an ear surgical device," *ISA transactions*, vol. 66, pp. 476–484, 2017.

[56] S. Emre and O. Kouhei, "On the explicit robust force control via disturbance observer," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 3, pp. 1581–1589, 2015.

[57] H. Amini, S. Rezaei, M. Zareinejad, and H. Ghafarirad, "Enhanced time delayed linear bilateral teleoperation system by external force estimation," *Transactions of the Institute of Measurement and Control*, vol. 35, no. 5, pp. 637–647, 2013.

[58] S. Mohammed, W. Huo, J. Huang, H. Rifaï, and Y. Amirat, "Nonlinear disturbance observer based sliding mode control of a human-driven knee joint orthosis," *Robotics and Autonomous Systems*, vol. 75, pp. 41–49, 2016.

[59] B. Ugurlu, M. Nishimura, K. Hyodo, M. Kawanishi, and T. Narikiyo, "Proof of concept for robot-aided upper limb rehabilitation using disturbance observers," *IEEE Transactions on Human-Machine Systems*, vol. 45, no. 1, pp. 110–118, 2015.

[60] C.-J. Chen, M.-Y. Cheng, and K.-H. Su, "Observer-based impedance control and passive velocity control of power assisting devices for exercise and rehabilitation," in *39th Annual Conference of the IEEE Industrial Electronics Society, IECON.* IEEE, 2013, pp. 6502–6507.

[61] C. Mitsantisuk and K. Ohishi, "Robotics-assisted rehabilitation therapy for the hands and wrists using force sensorless bilateral control with shadow and mirror mode," in *IEEE International Conference on Mechatronics (ICM).* IEEE, 2015, pp. 541–546.

[62] A. U. Pehlivan, D. P. Losey, and M. K. O'Malley, "Minimal assist-as-needed controller for upper limb robotic rehabilitation," *IEEE Transactions on Robotics*, vol. 32, no. 1, pp. 113–124, 2016.

[63] S. A. Fakoorian, V. Azimi, M. Moosavi, H. Richter, and D. Simon, "Ground reaction force estimation in prosthetic legs with nonlinear kalman filtering methods," *Journal of Dynamic Systems, Measurement, and Control*, 2017.

[64] C. Mitsantisuk, S. Katsura, and K. Ohishi, "Kalman-filter-based sensor integration of variable power assist control based on human stiffness estimation," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 10, pp. 3897–3905, 2009.

[65] A. Asadian, M. R. Kermani, and R. V. Patel, "A novel force modeling scheme for needle insertion using multiple kalman filters," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 2, pp. 429–438, 2012.

[66] Y. Fukushima and K. Naemura, "Estimation of the friction force during the needle insertion using the disturbance observer and the recursive least square," *ROBOMECH Journal*, vol. 1, no. 1, pp. 1–8, 2014.

[67] T. Murakami, F. Yu, and K. Ohnishi, "Torque sensorless control in multidegree-of-freedom manipulator," *IEEE Transactions on Industrial Electronics*, vol. 40, no. 2, pp. 259–265, 1993.

[68] A. M. Okamura, C. Simone, and M. D. O'leary, "Force modeling for needle insertion into soft tissue," *IEEE transactions on biomedical engineering*, vol. 51, no. 10, pp. 1707–1716, 2004.

[69] M. R. Kermani, R. V. Patel, and M. Moallem, "Friction identification and compensation in robotic manipulators," *IEEE Transactions on Instrumentation and Measurement*, vol. 56, no. 6, pp. 2346–2353, 2007.

[70] A. Maghsoudi and M. Jahed, "A comparison between disturbance observer-based and model-based control of needle in percutaneous applications," in *38th Annual Conference on IEEE Industrial Electronics Society, IECON.* IEEE, 2012, pp. 2104–2108.

[71] D. Suzuki, K. Yu, and K. Ohnishi, "A quantitative stiffness assessment method in liver biopsy teleoperations," in *39th Annual Conference of the IEEE Industrial Electronics Society, IECON.* IEEE, 2013, pp. 3281–3286.

Bita Fallahi received her BSc and MSc degrees in electrical engineering from K.N. Toosi University of Technology, Iran, in 2007 and 2011, respectively. She is currently working towards the Doctoral degree in Electrical and Computer Engineering at the University of Alberta and is working on control of robot-assisted minimally invasive surgery. Her current research interests include medical robotics and image-guided surgery.

Ron S. Sloboda received the B.Sc. degree in physics from the University of Manitoba, Winnipeg, MB, Canada, in 1974, and the Ph.D. degree in physics, nuclear theory, from the University of Alberta, Edmonton, AB, Canada, in 1979. He is currently a Professor in the Department of Oncology, University of Alberta. His research interests include dosimetry and treatment planning for brachytherapy, including the design of clinical studies to obtain patient data and model based dose calculation.

Mahdi Tavakoli is a Professor in the Department of Electrical and Computer Engineering, University of Alberta, Canada. He received his BSc and MSc degrees in Electrical Engineering from Ferdowsi University and K.N. Toosi University, Iran, in 1996 and 1999, respectively. He received his PhD degree in Electrical and Computer Engineering from the University of Western Ontario, Canada, in 2005. In 2006, he was a post-doctoral researcher at Canadian Surgical Technologies and Advanced Robotics (CSTAR), Canada. In 2007-2008, he was an NSERC Post-Doctoral Fellow at Harvard University, USA. Dr. Tavakoli's research interests broadly involve the areas of robotics and systems control. Specifically, his research focuses on haptics and teleoperation control, medical robotics, and image-guided surgery. Dr. Tavakoli is the lead author of Haptics for Teleoperated Surgical Robotic Systems (World Scientific, 2008). He is an Associate Editor for IEEE/ASME Transactions on Mechatronics, Journal of Medical Robotics Research, Control Engineering Practice, and Mechatronics.