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Physiological Motion Compensation in Robotized Surgery using Force Feedback Control

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Abstract— **This paper presents a force feedback control scheme for the compensation of periodic motions of organs induced by respiration or heartbeat in minimally invasive robotized surgery. It applies surgical tasks involving a contact between an instrument and a moving organ.**
It is well known that conventional force control allows for compensating the motion of the environment thanks to its natural disturbance rejection capabilities. However, as experimentally evidenced in the first part of this paper, bandwidth limitations do not allow for exact disturbance rejection.
Therefore, in addition to a conventional inner force feedback control loop, an outer control loop based on Iterative Learning Control (ILC) is implemented. It is aimed at compensating the physiological motions, based on the hypothesis that the disturbance is periodic. The transient performances of this ILC controller are improved thanks to a wavelet transform-based approach and conclusive experiments are finally presented, evidencing that the tracking performance under cyclic disturbances is significantly improved.

I. INTRODUCTION

During a surgical operation, the physiological motions of the patient's organs, induced by respiration and by heartbeat, can be very disturbing for the surgeon. Indeed, the gesture accuracy strongly depends on his/her ability of compensating these motions. There may be a strong difficulty in performing such a manual compensation, as breath induces large displacements while heart beating motions involve high accelerations.

As far as cardiac surgery is concerned, a currently used solution exploits mechanical passive stabilizers. However, whatever kind of stabilizer is used, there is still a remaining residual motion which can be disturbing for the surgeon. An alternative solution to stabilizers is the heart-lung machine. This machine ensures the circulation and the filtration of the blood while the heart is stopped. However, the use of a heart-lung machine implies more risks and a longer recovery time for the patient.

In order to overcome these difficulties, robotic solutions that actively compensate for physiological motions are being developed. Many contributions use the repetitive property of physiological motions to predict and anticipate these motions.

In [1], the compensation of respiratory motion using robotic radiosurgery is proposed in order to allow for an accurate treatment of tumors. In [2], Riviere *et al.* have investigated the prediction of bodily motion due to respiration in order to actively compensate for these motions in a robot-assisted system for percutaneous kidney surgery. Nakamura *et al.* [3] have performed experiments to synchronize the slave arm of a teleoperation system with heart beat motions by visual feedback.

Ginhoux *et al.* [4] have proposed an approach to compensate for cardiac motions using a robotic arm controlled by visual servoing. In order to localize the instrument with respect to the heart, the instrument tip is equipped with a laser source. It projects a beam parallel to the axis of the instrument yielding a spot on the surface of the heart. Moreover, optical markers are placed on the heart surface. According to the authors, conventional visual servoing control schemes proved unable to reject the perturbation due to heart beating motion due to the limited bandwidth of surgical robots. This is why they propose to use Generalized Predictive Control with an adaptive disturbance predictor (GCP+A). This control scheme anticipates future motion of the heart yielding a much better rejection. This adaptive predictor involves the measure of the disturbance signal. This is realized by placing artificial marks on the heart surface and by measuring their displacement thanks to a high-speed fixed camera. Note that it is always possible to avoid the need of markers, e. g. in [6], visual tracking of natural landmarks on the heart surface is proposed.

In a recent work, presented in [7], the authors have taken into account biological signals such as Electrocardiogram in a Model Predictive Control (MPC) algorithm in order to achieve an accurate and more robust compensation of heart motions. However, the proposed controller is hard to tune and sensitive to noises.

In this paper, we investigate physiological motion compensation for surgical tasks involving a contact between the instrument and a moving organ thanks to force feedback. Force sensors are expected make possible a more accurate motion compensation thanks to their better resolution and high bandwidth.

Performing force feedback in Minimally Invasive Surgery (MIS) rises the problem of force measurement and the problem of taking into account, in the control law, the kinematic constraint induced by the trocar. In previous papers, *e.g.* [8], [9], we have presented an original robot and an associated passive force feedback controller that are both briefly presented in section II. However, the proposed system, with a conventional compensator, proved unable to totally reject the perturbation induced by physiological motions. In order, to overcome this problem, one could try to increase the control gains, but it is not possible because of the limited bandwidth of surgical robots. This is why, in order to provide a high performance perturbation rejection, we propose in section III to exploit the repetitive nature of physiological motions to anticipate for the disturbance. Practically, this is achieved by modifying the reference signal of the control law proposed in section II, *i.e.* by adding an external loop. Control algorithms such as MPC or GPC are not suitable for this purpose because they require a fine model of the system while here, the contact between the tool and the organ can hardly be modelled. Iterative Learning Control (ILC, see Section III) has been preferred because this kind of control does not require any accurate prediction of the disturbance nor any accurate model of the system. However, it may lead to bad transients during the learning process and thus may not be applicable in practice. To cope with this problem, section IV proposes an advanced implementation of ILC based on [10]. It exploits a low-pass filter which cutoff frequency is deduced from discrete wavelet transform. The approach is experimentally proven to be efficient and robust in section V.

II. A robot for minimally invasive surgery

A. Description of the robot

The robot MC^2E (French acronym for *compact manipulator for endoscopic surgery*) is a Kinematically Defective Manipulator (KDM) which means that it has fewer joints than the dimension of the space in which its end-effector evolves. It is specially suited for minimally invasive robotic surgery applications [8]. With $n = 4$ joints and a spherical structure, this robot provides 4 degrees of freedom (DoFs) at the instrument tip.

More precisely, the robot consists of two parts, as shown in 1. The lower part is a compact spherical 2 DoFs mechanism (Θ_1 and Θ_2) which center of rotation coincide with the fulcrum point. The base of this lower subsystem is easily installed on the patient's skin and clipped to the trocar. The upper part of the robot is mounted on the trocar. It provides the two remaining DoFs : the rotation about the instrument axis (Θ_3) and translation along the instrument axis (d_4). Apart from its compactness, the main feature of this robot is that it offers a new possibility for force measurement in MIS. Namely, MC^2E can measure the distal organ-instrument interaction with a 6-axis force-torque sensor placed outside the patien. Thus, it is subject to much

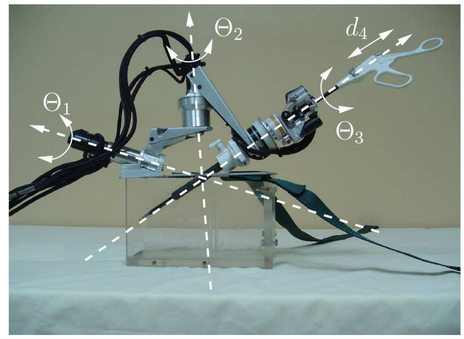


Fig. 1. Picture of MC^2E with joint parameters.

less sterilization constraints. Remarkably, due to the special mounting of the force sensor, these measurements are not affected by the disturbance forces and torques arising from the interaction between the trocar and the instrument.

B. Force control scheme

The force control scheme used to control MC^2E exploits a classical PI joint torque compensator with a feedforward action.

It is detailed on Figure 2 where the following notations are used :

$\mathbf{C}_\tau(\mathbf{z})$: the PI joint torque compensator for the inner loop

$\mathbf{J}(\mathbf{q})$: the Jacobian matrix of the robot

$\mathbf{w_d}$, $\tau_\mathbf{d}$: desired wrench, desired joint torques

$\mathbf{w_e}$: measured wrench

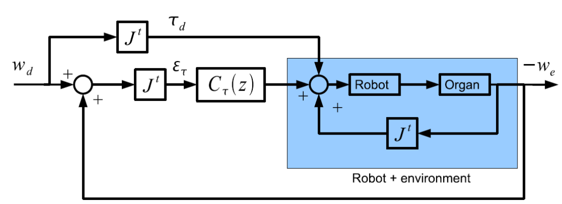


Fig. 2. Control scheme of MC^2E

In previous work, [9], we have shown that when the PI gains are correctly selected, this scheme guarantees the system passivity and consequently the stability of the system. The controller is particularly robust to changes in the nature and geometry of contacts. This represents a significant advantage in the context of robotic surgery where large uncertainties do occur on both contact geometry and dynamics.

Nevertheless, the bandwidth of this controller is limited because the tuning of the gains depends on the robot dynamics. In the presence of a periodic disturbance acting on the output, with a large magnitude, there is absolutely no way to obtain a zero-tracking error.

To illustrate the unability of the controller to finely reject the disturbances, during in-vivo experiments, we applied a force of 0.5N on a liver affected by movements due to breath, see Figure 3. Results of this experiment are plotted in Figure 4.

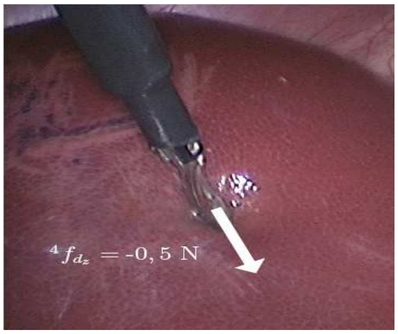


Fig. 3. Instrument in constant contact with liver

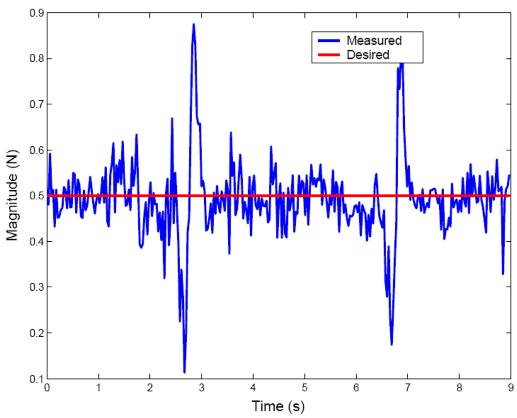


Fig. 4. Forces applied on the liver

It can be seen that a disturbance, due to the expiration, creates an error peak every 4 seconds. This 4 second period corresponds exactly to the period of the artificial breather.
To overcome this problem, we chose to use a control scheme based on Iterative Learning Control (ILC), which was implemented as an outer loop of the controller. The aim of this controller is to reject periodic disturbances. It is important to keep in mind that no direct knowledge on the perturbation (except for its period) is presumed and no specific model is necessary, neither for the contact nor the robot.

III. An ILC controller for the compensation of physiological motions

A. Motivations and hypothesis

As illustrated in Figure 4, the force feedback controller of Figure 2 is not able to reject the perturbation induced by physiological motions. Doing high gain control, in order to overcome this problem, is not possible because of the limited bandwidth of surgical robots. In addition, surgical tools used for MIS are long instruments introduced through small incisions. So the robot grasps this instrument at a long distance from its tip. This induces delays in the force transmission that make high gain control exciting so-called non collocated modes.

In this paper, physiological motions are supposed to be periodic. Since respiration is controlled by an external ventilator, this hypothesis is not very restrictive as far as respiratory motions are concerned. Thanks to this hypothesis the perturbation induced by the motions of the organ may be predicted by assuming that it will be almost the same in the next perturbance cycle than in the previous one. Therefore, the prediction allows this perturbation to be anticipated.

The control scheme presented in this paper is composed of an inner control loop presented in section II and of an outer loop based on ILC. The inner loop allows to take into account the kinematic constraint induced by the trocar and the outer loop aims at rejecting the cyclic disturbance induced by physiological motions. The ILC control algorithm is presented hereafter.

B. Considered ILC control scheme

As shown in Figure 5, an ILC controller is used for the regulation of the wrench describing the interaction between the instrument tip and the organ (forces and moments in the 3 directions of the space). The desired wrench $\tilde{w}_d$ provided to the inner loop is the concatenation of the outputs of six ILC controllers. This subsection presents the ILC control law implemented for the regulation of one component of force along the instrument axis d_4. The principle of ILC controllers which regulate the other wrench components is similar. The sampling period is noted T_e. The desired and measured values of the force applied by the instrument to the organ, along the axis d_4, at time step k are respectively noted $F_{zd}(k)$ and $F_{ze}(k)$. The error at time step k is $e_z(k) = F_{zd}(k) - F_{ze}(k)$. The output of the ILC controller, $\widetilde{F}_{zd}(k)$, is the desired force provided to the inner force loop. We made the assumption that the disturbance induced by physiological motion is periodic and that its period is a multiple of the sampling period. So, we assume that one disturbance cycle is p steps long.

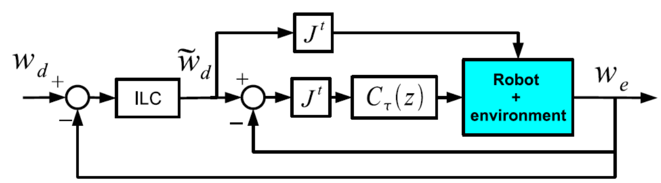


Fig. 5. Considered control scheme.

Under the hypothesis that the disturbance is periodic, if $\widetilde{F}_{zd}(.)$ is the same for each disturbance cycle, the error, $e_z(.)$, will be repeated as well. Consequently, ILC theory suggests to use information from the previous disturbance cycle to produce a new output $\widetilde{F}_{zd}(.)$ so that the error $e_z(.)$ will decrease as the number of disturbance cycles increase. Experience from previous disturbance cycles is used such that the ILC controller will gradually learn the output $\widetilde{F}_{zd}(.)$ that will result in minimal error. The current output $\widetilde{F}_{zd}(k)$ is computed by correcting the output at the previous disturbance cycle, $\widetilde{F}_{zd}(k-p)$, linearly with respect to the previous values of the error signal :

$$\widetilde{F}_{zd}(k) = \widetilde{F}_{zd}(k-p) + \sum_{i=0}^{i_f} \Phi(i)\, e_z(k-p+\gamma+i) \quad (1)$$

where $\Phi(i)$ are constant learning gains. The terms $e_z(k+p+\gamma+i)$ with $\gamma+i>1$ allows to anticipate the organ's motion.

The summation in (1) is a convolution sum. Thus, the z transform of equation (1) gives :

$$\widetilde{\boldsymbol{F}}_{\boldsymbol{zd}}(z) = \frac{z^{\gamma}\boldsymbol{\Phi}(z)}{z^p-1}\, \boldsymbol{e}_{\boldsymbol{z}}(z) \quad (2)$$

In [10], the author derives stability conditions for linear systems controlled by ILC control laws such as equation (1). A coarse linear model of the closed loop system presented in section II may be identified. Applying the stability conditions derived in [10] to this model may help tuning the controller given by equation (1).

As mentioned in [10], the control law equation (1) may lead to bad transients. Thus, it may not be applicable in practice even if the closed loop is proven stable. Indeed, the error may decrease during the first disturbance cycles, then start to increase to high values prejudicial for the hardware and decrease to zero after a prohibitive time. Such a phenomenon has been noticed during the experimentations that we have conducted (see Section V). Therefore, the considered ILC control scheme's performances have to be improved in order to ensure satisfactory transients. The proposed improvements are presented in the following section.

IV. Wavelet transform based ILC

As mentioned above, the ILC which has been described in the previous section could lead to bad transients during learning process. To overcome this problem, experimentations have shown that it is interesting to filter the error signal with a low-pass filter (see [11]). However, a constant cut-off frequency may not lead to good enough performances. Therefore, better performances may be expected from a varying cut-off frequency at each time step.

Indeed, at time steps where the tracking error falls into low frequency range, the cut-off frequency may be chosen low enough in order to reduce the influence of noise. At time steps where the tracking error presents high-frequency components, the cut-off frequency may be chosen high enough to fasten the learning process.

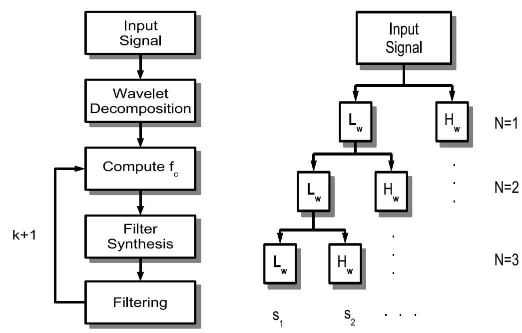
The Wavelet Packet Decomposition (WPD) preserves signal properties for both time and frequency domains. It is possible to perform a frequency analysis of the error signal $\epsilon_{\mathbf{w}}$ for each time step k.

Here, we consider the wrench error, during one perturbation cycle (p samples), as the input signal. It is defined such that :

$$\epsilon_{\mathbf{w}} = \mathbf{w_d} - \mathbf{w_e} \quad (3)$$

To perform such analysis of $\epsilon_{\mathbf{w}}$, the control scheme depicted on Figure 5 is modified as follow. A low-pass filter ($\mathbf{G_i}, \forall\, i \in [1..6]$) is associated to each ILC controller. The particularity of $\mathbf{G_i}$ resides in a varying cut-off frequency $f_{c_i}(k)$ which is deduced from WPD of the tracking error. In the sequel of this paper, the WPD will be relative to a given wrench error component. Thus, subscript i will be omitted.

For any time step k, we use the algorithm represented on Figure 6(a). At the beginning of each perturbation



(a) Algorithm for wavelet packet decomposition

(b) Signal Processing

Fig. 6. Wavelet Packet Decomposition

cycle, the signal is analyzed. The input signal is filtered successively with a low-pass filter ($\mathbf{L_w}$) and a high-pass filter ($\mathbf{H_w}$) as it appears on Figure 6(b). The two resulting signals are also filtered with the same filters and so on. To perform this operation, we used the two following filters deduced from wavelet theory (see [12]) :

$$\begin{cases} \mathbf{H_w}(z) = \frac{1-z}{2} \\ \mathbf{L_w}(z) = \frac{1+z}{2} \end{cases} \quad (4)$$

Afterward, we obtain 2^N signals ($\mathbf{s_j}, \forall\, j \in [1..2^N]$), where N denotes the level of decomposition.

Hence, one can rearrange these signals to obtain a matrix $\mathbf{S}$ which describes both time and frequencies components of the signal :

$$\mathbf{S} = \begin{bmatrix} a_{1,1} & \dots & a_{1,p} \\ \vdots & \vdots & \vdots \\ a_{2^N,1} & \dots & a_{2^N,p} \end{bmatrix} \quad (5)$$

with a_{ft} such that f denotes increasing frequencies and t denotes increasing time steps.

For each column of $\mathbf{S}$, corresponding to a given time step k, we define $M(k)$ as :

$$M(k) = \arg\max_j |a_{j,k}|,\ j = [1, ..., 2^N] \quad (6)$$

For example, if $M(k) = 1$ then $f_c(k)$ is such that it belongs to the lowest frequency range, $[0; f_0]$, to reduce noise effects. f_0 is the cut-off frequency of a low-pass filter used to eliminate noises on measurements. More precisely, the upper bound f_0 is chosen to prevent high frequencies effects. Therefore, $f_c(k)$ can be obtained for each time step with respect to Equation 7 :

$$f_c(k) = \frac{M(k)}{2^N} f_0 \tag{7}$$

The results that we present in the section V have been obtained by choosing a Hamming window to design a non-causal filter used for preprocessing. The advantage of using a WPD appears with experiments that we have conducted.

V. Experimental results

This section describes the results obtained from putting the ILC into practice. After describing the experimental setup, the results are presented. The first series of results reflects the use of a classical ILC without any low-pass filter, while the second reflects the use of wavelet decomposition to tune a low-pass filter with varying cut-off frequencies.

A. Experimental setup

Two robots were used to conduct these experiments :

1) MC^2E (see section II for details) is controlled using the control scheme depicted in Figure 5.
2) a planar 2R robot which allows us to generate a periodic disturbance, with a known period. It is controlled in position with a PID and its end-effector is in contact with the end-point of the MC^2E's instrument.

Both robots are controlled with a real-time operating system. Periodic main threads are the same and periods are equal to 1.5ms.

The movements of the planar 2R robot create a periodic error in the force measurements. The aim of this experiment is to compensate for this error with an ILC.

B. Classical ILC controller

The desired force created along the axis of the instrument is such that :

$$F_{zd}(t) = 0.7 + 0.4\ \sin(2\pi \times 1.2\ t)$$

A periodic disturbance with a frequency of 1.2Hz is created with the planar 2R robot. The corresponding desired trajectory is such that :

$$q_d(t) = 2\sin(2\pi \times 1.2\ t)$$

As shown in Figure 7, there is a periodic error in the force measurements. The parameters for ILC controller are such that $i_f = 0$, $\gamma = 40$ and $\Phi(0) = 0.5$ to obtain a constant anticipation.

To evaluate the ILC performance, the Mean Square (MS) error is examined. At time k it is calculated as the following :

$$E = \sum_{l=0}^{l=p} (F_{zd}(l) - F_{ze}(l))^2 \tag{8}$$

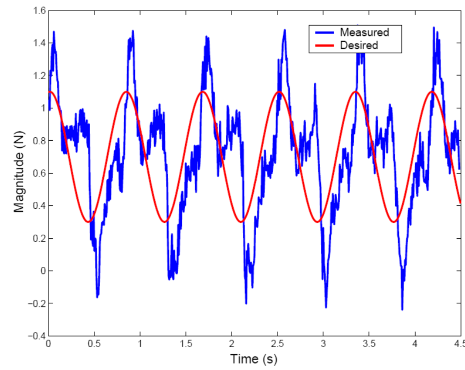


Fig. 7. Response of the system with a conventional force control (no learning)

A zero-tracking error is obtained if : $E = 0$.

The Figure 8 shows the evolution of the MS error,

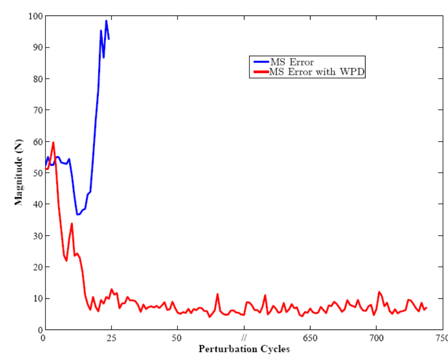


Fig. 8. MS Error

calculated at the start of each perturbation cycle.

The MS error reaches a minimum value after 12 cycles. However, this minimum is unstable and the error increases quickly afterward. This phenomena, which is described in [10] and [11] is a consequence of high frequencies in the system, which tend to destabilize the system. To preserve system safety, the controller was turned off when instability was observed.

A WPD was then used to solve this problem.

C. ILC controller with WPD

Here the desired forces and the disturbance are exactly the same as in the previous experiment. At the beginning of each cycle, the error signal is analyzed with a wavelet decomposition. We are thereby able to design a low-pass filter with a variable cut-off frequency for the subsequent cycle.

The parameters are chosen for the wavelet decomposition such that $N = 4$. Since the frequency of the controller is higher than 600Hz, this level allows an acceptable compromise between time and frequency resolutions.

Results plotted in Figure 8 show that the minimal level of MS error remains stable.

The Figure 9 shows how ILC has improved the response of the system. Disturbances appearing in Figure 7 have been rejected.

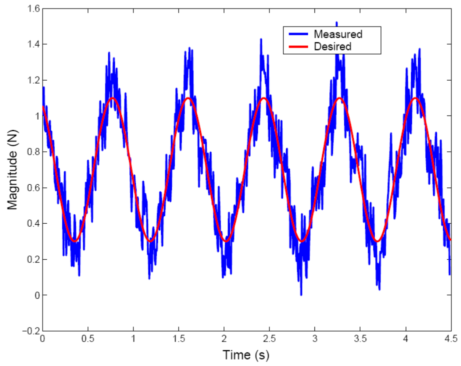


Fig. 9. Response of the system with wavelets decomposition

VI. Overview and conclusions

This paper has presented first results for physiological motions compensation by force feedback in order to allow accurate surgical tasks involving a contact between the surgical instrument and a moving organ.

A first proposition involving conventional ILC leads to bad transients during the learning period which makes it not applicable in practice. This problem has been mainly solved by filtering the tracking error with a low-pass filter which cut-off frequency is deduced from discrete wavelets transform. Experimental results showed that this algorithm leads to a significant decrease of the tracking error. The next step of the research will focus on the tuning of the algorithm in order to prevent bad transients. This tuning could be performed by using a coarse model of the system in order to satisfy the monotonic decay conditions presented in [10]. The satisfaction of these conditions would also ensure the stability of the control scheme.

The proposed algorithm supposes that the perturbation is periodic. Since respiration is controlled by an external ventilator, the motions induced by respiration may be considered as periodic. However, this hypothesis may be too restrictive concerning the motions induced by heartbeat. Thus future work will focus on the robustness of the proposed algorithm with respect to disturbances in the periodicity of physiological motions.

References

[1] A. Schweikard, G. Glosser, M. Bodduluri, M.J. Murphy and J.R. Adler, “Robotic motion compensation for respiratory movement during radiosurgery”, *Computer Aided Surgery*, vol. 5, no. 4, pp. 263-277, 2000

[2] C. Riviere, A. Thakral, I.I. Iordachita, G. Mitroi and D. Stoianovici, “Predicting respiratory motion for active canceling during percutaneous needle insertion” *Proc. 23rd Annual Int. Conf. IEEE Engineering in Medicine and Biology Society*, vol. 4, pp 3477-3480, 2001

[3] Y. Nakamura, K. Kishi and H. Kawakami, “Heartbeat synchronisation for robotic cardiac surgery” *Proc. of IEEE International Conference on Robotic and Automation, ICRA'01*, vol.2, pp 2014-2019, 2001

[4] J. Gangloff, R. Ginhoux, M. de Mathelin, L. Soler and J. Mares, ”Model Predictive Control for Compensation of Cyclic Organ Motions in Teleoperated Laparoscopic Surgery”, *IEEE Trans. on Control Systems Technology*, vol. 14, no. 2, pp 235-246, March 2006

[5] A. Krupa, J. Gangloff, C. Doignon, M. de Mathelin, G. Morel, J. Leroy, L. Soler and J. Marescaux, ”Autonomous 3D positionning of surgical instruments in rototized laparoscopic surgery using visual servoing” *IEEE Transactions on Robotics and Automation, Special Issue on Medical Robotics*, Vol. 19, no. 5, pp 842-853, 2003

[6] T. Ortmaier. Motion Compensation in Minimally Invasive Robotic Surgery. PhD thesis, Technische Universität München, March 2003.

[7] O. Bebek and M.C. Cavusoglu, “Predictive Control Algorithms Using Biological Signals for Actve Relative Motion Canceling in Robotic Assisted Heart Surgery”, *Proceedings of the IEEE International Conference on Robotics and Automation*, Orlando (Florida), pp 237-244, May 2006

[8] N. Zemiti, T. Ortmaier, M. Vitrani and G. Morel, ”A Force Controlled Laparoscopic Surgical Robot without Distal Force Sensing”, *Proc. of ISER'04 : 9th International Symposium on Experimental Robotics*, Singapore, 2004

[9] N. Zemiti, G. Morel, A. Micaelli, B. Cagneau and D. Bellot, ”A Passive Formulation of Force Control for Kinematically Constrained Manipulators”, *Proceedings of the IEEE International Conference on Robotics and Automation*, Orlando (Florida), pp 2238-2243, May 2006

[10] R. W. Longman, ”Iterative Learning Control and Repetitive Control for Engineering Practice”, *Int. J. Control*, vol. 73, no. 10, pp 930-954, 2000

[11] B. Zhang, D. Wang and Y. Ye, ”Experimental Study of Time-Frequency Based ILC”, *8th Int. Conference on Control, Automation, Robotics and Vision*, Kunming (China), vol. 1, pp 619-624, December 2004

[12] S. Mallat, ”A Wavelet Tour of Signal Processing”, 2nd Edition, Academic Press,1999