ACTIVE MECHANICAL FILTERING OF BREATHING-INDUCED MOTION IN ROBOTIZED LAPAROSCOPY

R. GINHOUX, A. KRUPA, J. GANGLOFF,
M. DE MATHELIN, C. DOIGNON, L. SOLER*

LSIIT (UMR CNRS 7005) - Strasbourg I University - Bd Sébastien Brant, 67400 Illkirch, France
*IRCAD - Hôpitaux universitaires de Strasbourg - 1, place de l'hôpital, Strasbourg, France

This work presents a predictive visual control system for laparoscopic robotized surgery. The aim is to cancel the motion of organs due to breathing movements by keeping constant the distance measured in endoscopic images along the instrument, from its tip to the viewed organ's surface. The period of the observed movement is estimated by use of a recursive algorithm. Experimental results are shown on an endo-training box that prove the efficiency of this active mechanical filtering method.

INTRODUCTION

Robotic systems appeared recently in the field of laparoscopic surgery. Several commercial systems are already in use, e.g., ZEUS (Computer Motion, Inc.) or DaVinci (Intuitive Surgical, Inc.). In these systems, robot arms are used to manipulate the surgical instruments as well as the endoscope. The surgeon tele-operates the robot through master arms using the visual feedback from the endoscope (see Fig. 1). Such systems have a lot of advantages: the surgeon's tiredness is reduced as he can comfortably seat during the operation; natural tremor is eliminated by translating the surgeon's hand motions to robotic movements; the use of a high master/slave motion ratio can increase the surgeon's motion accuracy. Furthermore, teleoperation allows long distance surgical procedures to be performed (see, e.g., the Lindberg Operation [7]).

In a typical surgical procedure, the surgeon first drives the laparoscope into a region of interest (for example by voice, with the AESOP system of Computer Motion Inc.). Then, he or she drives the surgical instruments at the operating position. Several works have been conducted in this context to develop visual servoing techniques to control the robotic arms in order to assist the surgeon or even to realize semi-autonomous tasks. Systems appeared that use patterned (Casals et al. [2]) or coloured (Wei et al. [10]) marks to make the endoscope track instrument's motions. The system proposed by Krupa et al. [5] can automatically bring the instrument at the center of the endoscopic image. This helps the surgeon when he or she has to blindly move its instruments when they are not in the endoscope's field of view, thereby avoiding possible undesirable contacts with internal organs. This system includes a specially designed instrument holder. It is equipped with tiny laser pointers which project laser spots in the laparoscopic image even if the surgical instrument is not in the field of view. The image of the projected laser spots is used to automatically guide the instrument towards the endoscopic field of view.

This system is combined in [4] with optical markers mounted on the tip of the instrument (see Fig. 1, right) to provide a robust measurement of the distance between the organ and the instrument's tip. This measurement is then fed back in a servo loop that regulates the distance at a specified value. The advantage of this system is that it allows the surgeon to automatically move the instrument at a chosen 3-D location, by means of, e.g., a mouse-like device.

Nevertheless, these systems do not explicitly consider the motion of the organs in tele-operated laparoscopic surgery; organs' motions induced by the patient's breathing or heart beating have to be manually compensated for by the surgeon through the manipulation interface while he or she is doing precise tasks. In [8], authors consider the non-rigid motion of the heart during cardiac surgery and show a visual synchronization technique to cancel the motion of a target point in the image. A high-speed camera and a special robotic device are used, and their system requires that an artificial reference point be put on the beating heart. In our work, we use the active vision system described above (see [5,4] for more details) and develop a predictive control scheme in order to accurately compensate the periodic motion of the organs induced by the breathing during laparoscopic surgery. We address the problem of keeping constant the distance from the instrument to the organ under the influence of breathing movements.

Fig. 1: left: robot tele-operation; right: laser pointing instrument holder during an in-vivo test at IRCAD [5,4].

The paper is organized as follows: The first section presents the laparoscopic robotic setup used in our experiment with the visual servoing loop. The second section introduces the basics for generalized predictive control (GPC) and show how repetitive perturbations can be rejected by the predictive controller. The third section briefly explains the recursive algorithm used to estimate the breathing period and to adaptively update the controller. The last section presents experimental results obtained on an endo-trainer box with simulated breathing motion and a laparoscopic surgery robotic arm.

LAPAROSCOPIC ROBOTIC SETUP

The system configuration is shown in Fig. 4: A monochrome PAL camera is mounted on a fixed rigid support and provides images of the scene through an endoscopic lens and a trocard. Images are updated every Te = 40 ms and are made of two interlaced frames showing laser pointers and optical marks mounted on the instrument. Distance from the tip of the instrument to the observed scene is estimated using the technique described in [5,4]. This measure is fed into the generalized predictive controller, which, in turn, returns the optimal command to apply as the desired speed along the instrument's axis (see Fig. 2). The model used in the GPC predictor is the identified transfer function of the translational joint of an AESOP arm.

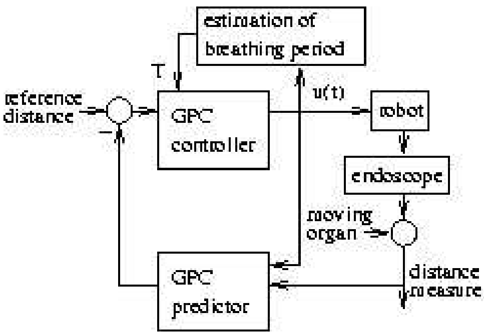

Fig. 2: block-diagram of the GPC-controlled system.

The GPC control thread and the vision thread are hosted by a 800 MHz bi-processor PC computer that communicates via a serial link with the AESOP robot. The GPC computations are synchronized with the image acquisition and made within a single control period (Te). A supplementary device is shown in Fig. 4 that is used to simulate repetitive organs' motions under the influence of breathing (see experimental results in the last section). The motion period is estimated using the corresponding block in Fig. 2 (see next section).

PREDICTIVE CONTROL

1. Generalized Predictive Control

The Generalized Predictive Control was originally introduced by Clarke et al. [3]. It is based on the minimization of a cost function J over a finite receding horizon:

$$J(u,t) = \sum_{j=N_1}^{N_2} \left\| \hat{y}(t+j) - r(t+j) \right\|^2 +$$

$$\lambda \sum_{j=1}^{N_u} \left\| \Delta u(t+j-1) \right\|^2$$

with $N_u < N_2$ and $\Delta u(t + j - 1) = 0$ for $j > N_u$, N_1 is the minimum costing horizon, N_2 is the maximum costing horizon and N_u is the control costing horizon; λ weights the relative importance of the control energy. This controller is predictive because it takes into account the future reference signals r. The arguments of the minimization are the N_u future steps of the control input. The computation of the output predictions $\hat{y}$ requires the knowledge of a system model expressed in the ARIMAX form:

$$A(q^{-1})y(t) = B(q^{-1})u(t - T_e) + \frac{C(q^{-1})}{\Delta(q^{-1})}\xi(t)$$

where q^{-1} is the discrete backward operator, A and B are two polynomials (or matrix polynomials in the multidimensional case) modelling the system dynamics (B may also include pure delays), ξ represents a zero mean white noise, and polynomial C is used to color it. Polynomial Δ can be used to make noise ξ / Δ be non-stationary, which is suitable to model any perturbation in a control loop. Polynomial C can also be selected to have a filtering effect on non-modelled noise [1]. For our experiments, we use the identified model of the translational joint of the AESOP robotic arm as the system model in the GPC control scheme.

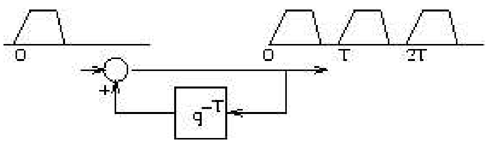

Fig. 3: periodic signal generator.

Classical GPC schemes [3,1] consider $\Delta = 1 - q^{-1}$, which allows the rejection of step perturbations and, therefore, is equivalent to the introduction of an integrator in the controller. In order to reject a periodic perturbation, one can use $\Delta = 1 - q^{-T}$, where T is the number of sampling periods in one perturbation period. Indeed, the perturbation model ξ / Δ is made periodic, as shown in Fig. 3. In this paper, we propose the use of

$$\Delta = (1 - q^{-1})(1 - \alpha q^{-T})$$

where $\alpha \in$]0; 1] is a forgetting factor, that acts as an additive low-pass filter.

2. Recursive estimation of an unknown period

For effective cancelling of the breathing disturbance, the actual disturbance frequency is required to be known. We will further suppose that a disturbance period always contains an integer number of sampling periods so that the T parameter in the GPC controller can be precisely adjusted. This is not a limitation since the robot control system is run with a period of Te = 40 ms which is largely less than typical breathing periods (see in-vivo measurements in Fig. 5). Even if the frequency could be measured directly (e.g., by use of external monitoring systems), the effect of the disturbance in the feedback loop will be seen in the control signal. We use the recursive algorithm that was proposed by Tsao et al. [9,6] in the context of repetitive control, considering a periodic signal u(t) that is not identically zero with period T*. The identification algorithm is based on the gradient minimization of a quadratic energy function:

$$J(T) = \frac{1}{2} \int_{t-T_{\max}}^{t} [u(s) - u(s-T)]^2 \, ds$$

where $T_{max} > T^*$. One can note that the cost function J(T) is periodic and has local minima at integer multiples of the base period T. For the gradient iterations to converge to T*, the initial condition must therefore lie within the concave region containing T*. This technique only requires the knowledge of the T_{max} parameter.

The GPC control strategy is modified to account for changes in the disturbance signal's period. This is used to estimate the true period T* of the motion perturbation when it is not known, or to track its temporal variations (see fig. 2). Note that we apply the gradient descent algorithm of [9,6] to filtered values of the control signal. Typical values of breathing disturbance frequency in the endobox trainer are 0.3-0.4 Hz (see experimental measurements in Fig. 5) and the elliptic low-pass filter used for the identification is designed with a stop-band of 1 Hz.

EXPERIMENTAL RESULTS

This section gives results of the predictive controller obtained with an endo-trainer box. A periodic motion of the organ is simulated through the use of an additive platform mounted on a semi-rotating motor (see fig. 4). The platform exhibits an oscillating motion and is put in the laser pointers' field-of-view. The laser-pointing instrument is held by an AESOP arm, as explained in the first section. Figure 6 shows the error observed on the endo-trainer box, with a depth-servoing algorithm running a proportional controller and a constant reference signal. The curve of Fig. 5 shows the perturbations obtained with the same controller during in-vivo tests at the operating room of IRCAD.

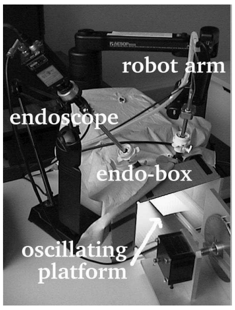

Fig 4: system setup

In Figure 6, the perturbation period was set to 2.4 s and the sampling period is 0.04 s. The reference signal was to keep a constant distance of 20 mm between the instrument and the oscillating platform. The amplitude of the oscillations were about 25 mm.

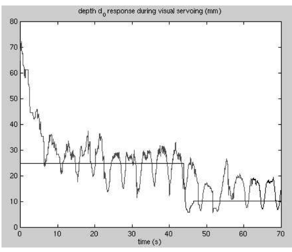

Fig. 5: original breathing perturbations during depth servoing during in-vivo tests with a proportional controller.

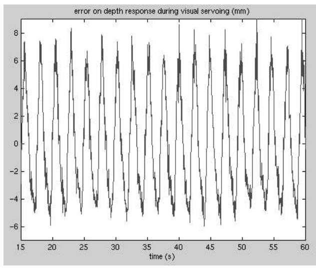

Fig. 6: error during depth servoing in a endo-trainer box.

Fig. 7 shows the error obtained with the repetitive GPC controller that was set with T=2.4 s and α=0.98. Variance of the error is divided by a factor 30.

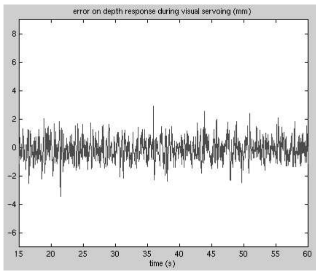

Fig. 7: error during depth servoing with a repetitive GPC controller.

Figure 8 shows the evolution of the error when the GPC switches from T=1.8 s to T=2.4 s after the period estimation is recovered by the gradient descent algorithm.

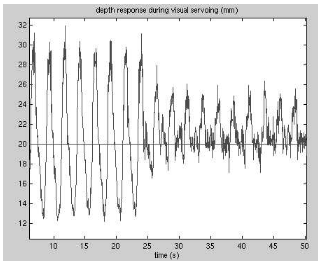

Fig. 8: period switching in GPC controller.

Fig. 9 depicts the gradient descent and the evolution of the period estimation before the GPC switches in Fig.8.

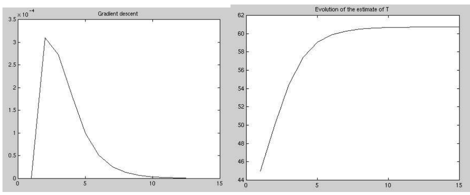

Fig. 9: gradient descent (left) and evolution of the period estimation (right) when the initial period of the GPC is set to 1.8 s and the true period is 2.4 s.

CONCLUSION

This paper presented a repetitive predictive controller approach for an active mechanical filtering of periodic motions (induced by respiration or even heart beating) in laparoscopic robotized operations. The control scheme uses the periodic property of the perturbation to anticipate the motion of the tool in order to increase the accuracy. The GPC is made adaptive against the perturbation period by use of a recursive estimation algorithm. We have shown successful experimental results on an endo-training box and an AESOP surgical robotic arm. In-vivo tests are planned in the coming months in the training room of IRCAD. Application of such a filtering is for thermal ablation of liver tumors with RF probe. Currently, the surgeon has to manually compensate for the breathing movements, whereas the probe penetration depth could be filtered by the robot, yielding to a better accuracy.

ACKNOWLEDGEMENTS

The authors thank Computer Motion Inc. that has graciously provided the AESOP medical robot.

BIBLIOGRAPHY

[1] E. F. CAMACHO, C. BORDONS
Model Predictive Control. Springer-Verlag, London, 1999.

[2] A. CASALS, J. AMAT ET AL.
Vision-guided robotic system for laparoscopic surgery. Proc. Of the 1995 IFAC International Congress on Advanced Robotics, pp. 33-36, Barcelona, Spain, 1995.

[3] D. W. CLARKE, C. MOHTADI, P. S. TUFFS
Generalized predictive control - part 1. The basic algorithm. Automatica, vol. 23, pp. 137-160, 1987.

[4] A. KRUPA, C. DOIGNON, J. GANGLOFF, M. DE MATHELIN
Combined image-based and depth visual servoing applied to robotized laparoscopic surgery. To appear in Proc. Of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems, Lausanne, Switzerland, October 2002.

[5] A. KRUPA, J. GANGLOFF, M. DE MATHELIN ET AL.
Autonomous retrieval and positioning of surgical instruments in robotized laparoscopic surgery using visual servoing and laser pointers. Proc. Of the 2002 IEEE International Conference on Robotics and Automation, Washington, D.C., May 2002.

[6] T. J. MANAYATHARA, T.-C. TSAO, J. BENTSMAN, D. ROSS
Rejection of Unknown Periodic Load Disturbances in Continuous Steel Casting Process Using Learning Repetitive Control Approach. IEEE Transactions on control systems technology, vol. 4, no. 3, pp. 259-265, May 1996.

[7] J. MARESCAUX, J.. LEROY, M. GAGNER
Transatlantic robot-assisted telesurgery. Nature, 413, pp. 379-380, 2001.

[8] Y. NAKAMURA, K. KISHI, H. KAWAKAMI
Hearbeat Synchronization for Robotic Cardiac Surgery. Proc. Of the 2001 IEEE International Conference on Robotics and Automation, Seoul, Korea, May 2001.

[9] T.-C. TSAO, Y.-X. QIAN
An Adaptive Repetitive Control Scheme for Tracking Periodic Signals with Unknown Period. In Proc. Of the American Control Conference, pp. 1736-1740, San Francisco, California, June, 1993.

[10] G.-Q. WEI, K. ARBTER, G. HIRZINGER
Real-time visual-servoing for laparoscopic surgery. IEEE Engineering in Medicine and Biology, vol. 16, no. 1, pp.40-45, 1999.