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Predictive Control Algorithms Using Biological Signals for Active Relative Motion Canceling in Robotic Assisted Heart Surgery

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***Abstract*— Robotics technology promises an enhanced way of performing off-pump coronary artery bypass graft (CABG) surgery. In the robotic-assisted CABG surgery, surgeon performs the operation with intelligent robotic instruments controlled through teleoperation in place of conventional surgical tools. The robotic tools actively cancel the relative motion between the surgical instruments and the point-of-interest on the beating heart, in contrast to traditional off-pump CABG where the heart is passively constrained to dampen the beating motion. As a result, the surgeon operates on the heart as if it were stationary. This algorithm is called Active Relative Motion Canceling (ARMC). In this paper, the use of biological signals, such as electrocardiogram (ECG), to achieve better motion canceling in the model-based intelligent ARMC algorithm is proposed. An ECG contains records for the electrical activity of the heart, which forms a series of waves and complexes. Real time identification of these waves and complexes will improve the estimation of the future heart motion and improve the performance of the ARMC algorithm. Finally, the experimental results of the algorithm implemented on a 3-DOF robotic test-bed system are reported.**

I. Introduction

Off-pump coronary artery bypass graft (CABG) surgery is performed while the heart is still beating instead of using a cardiopulmonary bypass machine and stopping the heart to perform the surgery. Although off-pump CABG surgery is in a nascent stage and only applicable to limited cases, it is preferred over on-pump CABG because of the significant complications due to the use of bypass machine, which include long term cognitive loss [1], and increased hospitalization time and cost [2]. Off-pump operations constitute only a small part of CABG surgeries. Robotic assisted teleoperation technology promises an enhanced way of performing off-pump CABG surgery. With the help of developed telerobotic tools and algorithms it is aimed to attain the perfection of the traditional on-pump operations, in the off-pump operations by actively tracking and canceling the relative motion between the surgical instruments and the heart [3]–[5]. Towards this direction, the study in this paper proposes the use of biological signals, such as Electrocardiogram (ECG), to achieve better motion canceling in the model-based intelligent Active Relative Motion Canceling (ARMC) algorithm (Figure 1).

The earlier studies in the literature on canceling biological motion in robotic assisted medical interventions are focused on cancelation of respiratory motion. Sharma *et al.* and

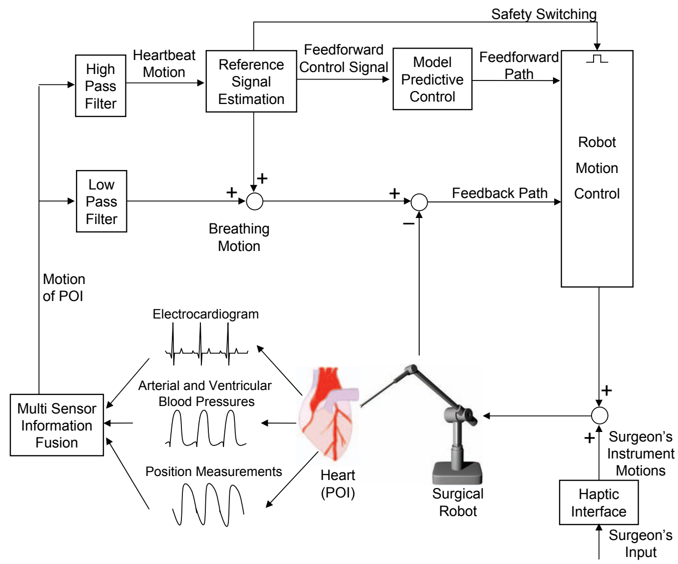

Fig. 1. Proposed control architecture for designing Intelligent Control Algorithms for Active Relative Motion Canceling on the beating heart surgery.

Schweikard *et al.* studied the compensation of the breathing motion in order to reduce the applied radiation dose to irradiate tumors [6], [7]. Both studies concluded that motion compensation was achievable. In [8], Riviere *et al.* looked at the cancelation of respiratory motion during percutaneous needle insertion. Results showed that an adaptive controller was able to model and predict the breathing motion. Trejos *et al.* conducted a feasibility study on the ability to perform tasks on motion-canceled targets [9], and demonstrated that tasks could be performed better using motion canceling. In [10], Nakamura *et al.* performed experiments to track the heart motion with a 4-DOF robot using a vision system to measure heart motion. The tracking error due to the camera feedback system was relatively large to perform beating heart surgery. Thakral *et al.* used a laser range finder system to measure one-dimensional motion of a rat's heart [11]. Ortmaier *et al.* [12] utilized ECG as biological signal in visual measurement of heart motion using a camera system. ECG was employed in estimation of the motion when the surgical tools occluded the view. Heart motion estimation was not based on a heart motion model and completely depended on the early recorded heart position data. Actual tracking of the heart motion using a robotic system was presented as a future work. More recently, in a pair of independent parallel studies [13] and [5], motion canceling through prediction of future signals was demonstrated. In both studies, model predictive controllers were used to get higher precision tracking. In the former, a high-speed camera was used to measure heart motion. Although it yielded better results than earlier studies using vision systems, the error was still very large to perform heart surgery, as operation targets to be manipulated using the robotic systems in a CABG surgery are blood vessels with 2-mm or less diameter. Although in [5] the desired error specifications for heart surgery were achieved on a 1-DOF test bed system, they concluded that there still was a need for better signal prediction.

This paper discusses the use of biological signals in the model-based intelligent ARMC algorithm to achieve better motion canceling. In the next section our research objectives and an outline of the proposed intelligent control algorithm is given. Section III describes the ECG and its importance to ARMC algorithm. Section IV discuses and analyzes the Experimental Heart Motion Data. Section V outlines the method used in ECG wave form detection. In section VI, the control algorithms used for tracking problem are described. The simulation and experimental results are given in section VII and finally the conclusions are presented and future directions are proposed.

II. Intelligent Control Algorithms for Model Based ARMC

The goal of our research is the development of intelligent control algorithms that utilize the biological signals in a model-based predictive control fashion. The control architecture we are proposing in this research project is shown in Figure 1. In this architecture, the control algorithms need to fuse information from multiple sources: mechanical motion sensors which measure the heart motion and sensors measuring biological signals. The control algorithm needs to identify the salient features of the biological signals and merge these information to predict the feedforward reference signal. This will improve the performance of the system since these signals are results of physiological processes which causally precede the heart motion.

The control algorithm also needs to be able to handle changes in the heart motion, including adapting to slow variations in heart rhythm during the course of the surgery, as well as handling occasional arrhythmias which may have natural causes or may be due to the manipulation of the heart during surgery.

Motion of the point of interest (POI) has two dominant modes of motion (Details on the heart motion data is described in Section IV). In order to gain a better understanding of these two modes, they are separated by using proper filters as shown in the algorithm architecture. This paper mainly concentrates on the upper part of the Figure 1, where the feedforward path for tracking of the heart beat component of the motion is followed. This part has significantly more demanding requirements on the high bandwidth motion that needs to be tracked (see Section IV). Breathing motion has significantly lower frequency, it can be canceled by a purely feedback based controller if the high frequency heart motion component is canceled by a model based predictive controller.

In the architecture proposed (Figure 1), the robot motion control signal will be computed by combining the feedforward signal provided by the heart motion model and the feedback signal measured from direct heart motion measurements. The confidence level reported by the heart motion model will be used to adaptively weigh the amount of feedforward and feedback components used in the final control signal. This confidence level will also be used as a safety switching signal to turn off the feedforward component of the controller if an arrhythmia is detected, and switch to a further fail-safe mode if necessary. These safety features will be an important component of our research. Therefore, the best design strategies for developing feedforward motion control was aimed. The feedforward controller was designed using the model predictive control [15] and optimal control [16], [17] methodology of modern control theory, as described in Section VI.

Although, some of the system concepts in literature are similar to ours at the most basic level, there are significant differences including the lack of intelligent model based predictive control using biological signals, and multi sensor fusion with complementary and redundant sensors, which form the core of our proposed architecture.

The system by Nakamura *et al.* [10] used purely position feedback obtained from a two-camera computer vision system. Neither biological signals were used in the system, nor a feedforward control component was present. The system by Ginhoux *et al.* [13], [14] utilized a feedforward control algorithm, based on model predictive control and adaptive observers, however, it did not utilize any biological signals. Ortmaier *et al.* [12] utilized ECG but their research lacked the use of any heart model in the process.

With the architecture proposed in this paper, system's awareness will be increased by utilizing a heart motion model in reference signal prediction. Inclusion of biological signals in a model-based predictive control algorithm will increase the estimation quality, and such a scheme will provide better safety with more precise detection of anomalies and switching to a safer mode of tracking.

III. Electrocardiogram as the biological signal

The human body acts as a giant conductor of electrical currents. Connecting electrical 'leads' to any two points on the body may be used to register an ECG. Thus ECG contains records for the electrical activity of the heart. The ECG of heart forms a series of waves and complexes that have been labeled in alphabetical order, the P wave, the QRS complex, the T wave and the U wave (Figure 2) [18]. Depolarization of the atria produces the P wave; depolarization

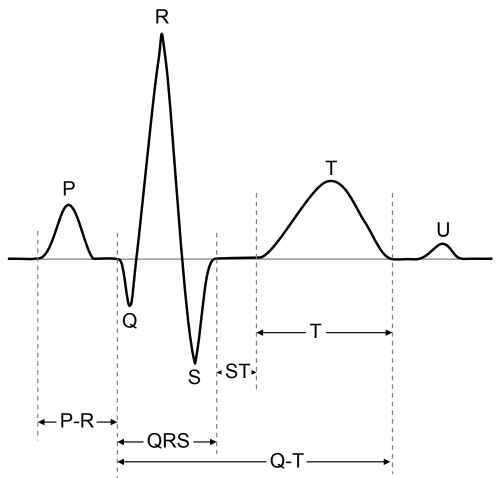

Fig. 2. A typical scalar electrocardiogram, showing significant deflection points.

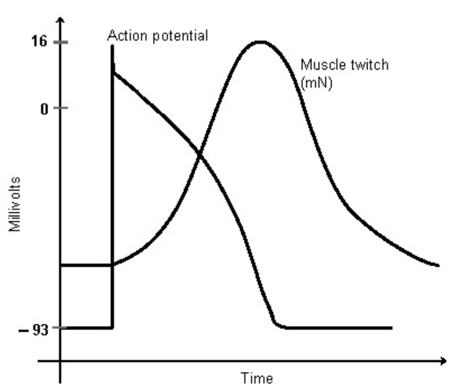

Fig. 3. Time relationship between action potentials and mechanical force developed by ventricular muscle. Rapid depolarization of a cardiac muscle fiber is followed by force development in the muscle. The lag between the excitation and the peak force is about 200 ms long (Redrawn from [20]).

of the ventricles produces the QRS complex. Repolarization of the ventricles causes the T wave. The significance of the U wave is uncertain [19]. Each of these electrical stimulations results in a mechanical muscle twitch. This is called the electrical excitation-mechanical contraction coupling of the heart. Thus, the identification of such waves and complexes would help determine the electromechanical coupling of the heart. Using ECG in the control algorithm would improve the performance of the system since these wave forms are results of physiological processes which causally precede the heart motion. Time relationship between action potentials and mechanical force developed by ventricular muscle is shown in Figure 3 [20], [21]. Rapid depolarization of a cardiac muscle fiber is followed by force development in the muscle. The completion of repolarization coincides approximately with the peak force, and the duration of contraction parallels the duration of the action potential, which are about 150 to 200 ms long. The lag between these two formations enables the prediction of future heart activity. Although this time lag is about 150 ms, it is sufficient for real time detection of the waves and complexes of the ECG.

ECG signal is very suitable for period-to-period synchronization with sufficient lead time for feedforward control, and identification of arrhythmias. Biological signals other than ECG that can be used to track heart motion are arterial and ventricular blood pressures. Similar to ECG signal, the aortic, atrial and ventricular blood pressures are significant indicatives of the heart motion as they can be used to predict when the heart valves will be opening and closing, identifying the distinct phases of the heart cycle. These distinct phases correspond to qualitatively different mechanical properties of the heart tissue, changing the local deformation model. The blood pressure signals also give additional independent information, which can be used in conjunction with ECG signal to improve noise robustness and to reliably detect unexpected rhythm abnormalities and arrhythmias.

IV. Experimental Heart Motion Data

A. Heart Motion Data Collection

A sonomicrometry system was used to collect the heart motion data used in this study. Sonomicrometer measures the distances within soft tissue by using ultrasound signals. A set of small piezoelectric crystals embedded, sutured, or otherwise fixed to the tissue are used to transmit and receive short pulses of ultrasound signal, and the "time of flight" of the sound wave as it travels between the transmitting and receiving crystals are measured. Using these data, the 3-D configuration of all the crystals is calculated [22]. The sonomicrometry system is more advantageous than using a vision system, which is the sensor of choice in the earlier works in the literature, for measuring heart motion for robotic ARMC. A vision system is not suitable for use during surgical manipulation because the surgical instruments (including the robotic tools) may occlude the point-of-interest (POI) making the vision system practically useless. The sonomicrometry system does not have this inadequacy.

The heart motion data were collected from an adult pig. In the experimental set-up one crystal of the sonomicrometric system was sutured next to the Left Anterior Descending Artery (LAD), which is on the front surface of the left ventricle, at a point one third of the way from the starting point of the LAD. Six other crystals were asymmetrically mounted on a rigid base, in a circle of 50 mm diameter forming a reference coordinate frame. This rigid plastic sensor base was inserted behind the heart, inside the pericardial sack, and the motion of the POI on the LAD was measured relative to this coordinate frame. The pericardial sack had been filled with a saline solution, completely immersing the sensor base, which enabled the continuous contact of sonomicrometric sensor system with the heart and proper operation. Data were collected at a sampling rate of 257 Hz, and were processed offline using the proprietary software provided with the system to calculate the 3D motion of the POI. Filtering performed on the raw data was only to remove the ultrasound echoing effects.

B. Analysis of Heart Motion Data

A detailed analysis of the data was presented in [3]. Here we will describe several critical properties of the heart motion that is relevant for the rest of the paper. The average heart rate of the animal model was 120 beats-per-minute during the 60 seconds duration of data collection. The peak displacement of the POI from its mean location was 12.1 mm, with a root-mean-square (RMS) value of 5.1 mm. The Power Spectral Density (PSD) of the motion of the POI is shown at Figure 4. Two observable dominant modes of motion can be seen in this figure. The first mode is at 0.37 Hz and corresponds to the breathing motion. The second dominant mode is at 2.0 Hz and corresponds to the main mode of motion due to heart beating. This reveals the specifications for the robotic mechanism and ARMC control algorithm design. The control algorithm proposed is based on the premise that the heart motion is quasiperiodic and the motion during the previous beats can be used, to some extent, as a feedforward signal during the control of the robotic tool for ARMC. Here, our main concern is with the moderate to high frequency components of the motion since they are the most demanding for the mechanism and the ARMC control algorithm. The low frequency components of motion typically results from breathing with bandwidth of 0.8 Hz including the first harmonic of the breathing frequency, and can easily be canceled using a feedback controller. The feedforward controller is needed to cancel the high frequency components of motion. In order to gain a better understanding of the heart motion itself, the breathing motion was filtered out using a high pass filter with stop band frequency equal to 1.1 Hz. Filtered data was used in the heartbeat signal tracking experiments that is described in Section VII. After the breathing motion was filtered out the PSD of the motion signal is composed of very narrow peaks at the harmonics of the heart beat frequency. This supports the feasibility of the ARMC algorithm by showing that the moderate-to-high frequency component of the motion signal is quasiperiodic, with fundamental frequency equal to heart beat rate.

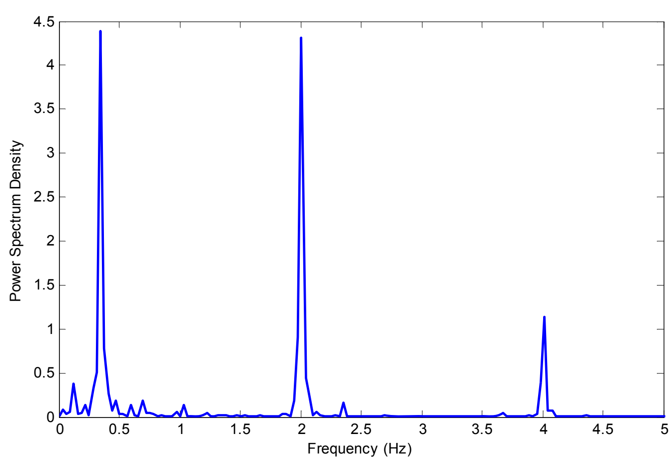

Fig. 4. The Power Spectral Density (PSD) of the motion of the point-of-interest (POI).

V. ECG Wave Forms Detection

Several algorithms were proposed and used to detect the ECG characteristic points with high detection accuracies [23]–[26]. However most of them are desined for offline processing of ECG signals and only a few of them are for real time detection of ECG signal complexes and points [27], [28]. The difficulty in detection arises from the diversity of complex wave forms and the noise and artifacts accompanying the ECG signals. In this work, the significant ECG wave forms and points, such as P, QRS and T, were detected using wavelet transform analysis using the method described in [28].

A short description of the ECG wave forms detection is as follows. At the sampling frequency of the ECG data, 257 Hz, Wavelet Transform of the ECG was calculated at scales 2^j, j=1...5. These energy levels cover the power spectra of ECG signal. The energy of the QRS complex is typically placed in the levels 2^3 and 2^4. The energies of P and T waves are located at levels 2^4 and 2^5. To detect peaks, threshold filters and decision making rules were used in each energy level. First, QRS complexes were detected by locating any peak pairs on the wavelet transforms. After the possible QRS complexes were marked, unmarked peaks on levels 2^4 and 2^5 were marked as T waves, since both QRS and T peak pairs appear on the same energy levels. P wave detection was done similarly by detecting peak pairs at the energy scale 2^4 which corresponded to neither a QRS complex nor a T wave. With this method, QRS-T-P waves were detected in real time. Detected signals were fed to the model predictive controller as shown in Figure 1.

VI. Control Algorithms

The control algorithm is the core of the robotic tools for tracking heart motion during CABG surgery. The robotic tools that track and manipulate should have high precision. During free beating, individual points on the heart move as much as 7-10 mm. Although the dominant mode of heart motion is in the order of 1-2 Hz, if we look at measured motion of individual points on the heart during normal beating, there is significant energy in the motion to frequencies up to 20 Hz. The coronary arteries that are operated on during CABG surgery range from 2 mm in diameter down to smaller than 0.5 mm, which means the system needs to have a tracking precision in the order of 100 μm. This corresponds to a less than 1% dynamic tracking error up to a bandwidth of 20 Hz. It is hard to satisfy these specifications with traditional controllers which only rely on the feedback from the sensors that measure heart position and they do not use any model of the heart motion. This was verified by comparing traditional and MPC controllers in [5]. The control algorithm needs to be able to handle changes in the heart motion, including adapting to slow variations in heart rhythm during the course of the surgery, as well as handling occasional arrhythmias which may have natural causes or may be due to the manipulation of the heart during surgery. In order to detect these changes, information from multiple sensors should be fused: motion sensors and sensors measuring biological signals. Within this framework, three different variations of the MPC algorithm were studied for tracking: MPC, Signal Estimated MPC and Biological Signal added MPC. The basic MPC algorithm uses the actual heart motion for the future desired trajectory, therefore it has the maximum achievable tracking performance in the linear controllers. Therefore, the results of the MPC algorithm were used to crate a basis for the performance index. Other algorithms were designed to increase the performance of predictive tracking.

A. Model Predictive Control

Model Predictive Control (MPC) is an acausal algorithm used for trajectory tracking. MPC algorithm uses system model to predict future outputs. The future outputs are compared to a desired reference signal and used to calculate gains. In MPC generally there is a knowledge of the future reference signal. A typical MPC algorithm contains three characteristics. A model is used to find the future outputs; the control output sequence are calculated by minimizing a cost function; and the gains are calculated by solving the linear quadratic optimal controller with a receding horizon where furthermost point ahead considered to be moving one step ahead for every control cycle [16], [17]. In MPC, as the horizon value increases, the error decreases. Using this algorithm, horizon values starting from 5 to 200 were tested. As the horizon was increased linearly, an exponential decay in the position error was observed. A trade off between computational effort (long horizon) and large error (short horizon) was done. An optimum value of 100 was selected and used in all three algorithms.

Knowing the future reference signal for the MPC algorithm is close to perfect tracking. However using the future signal in heart tracking is not feasible as this makes the algorithm acasual. In this case it was used to show the base line performance.

B. Signal Estimated Model Predictive Control

In the MPC algorithm the future signal is assumed to be known a *priori*. If the MPC algorithm has high enough precision to perform the necessary tracking then the tracking problem can be reduced to predicting the desired future signal effectively. In design, there are not any explicit specifications on estimation error. The main specification is for the tracking error, as described earlier.

Heartbeat is a quasiperiodic motion with small variations in every beating cycle. If the past heartbeat motion cycle is known, it can be used as an estimate reference signal for the future cycle. Using an averaged heartbeat period that was calculated offline, the last beating signal was buffered. The stored beating cycle was used as the approximate future reference beating signal in MPC algorithm. In Signal Estimated MPC, one cycle of heart motion ahead is more then enough information to perform tracking with the MPC algorithm, since it needs only a future signal with the length of horizon.

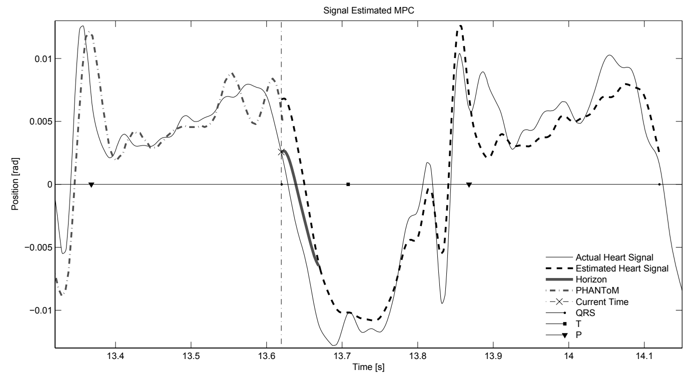

Fig. 5. Future Signal Estimation during control action. Observe the horizon signal where the offset between the current position and estimated signal is added gradually starting from current time to horizon steps ahead.

Using the last cycle as an exact future reference would result in large errors due to the quasiperiodic characteristics of the heart motion and other irregularities of the signal. Instead of using the past beating cycle in the gain iterations directly, the reference beating signal was processed online to meet requirements. Any position offset between the past cycle's starting point and future cycle's starting point, that is current position, were lined up by subtracting the difference. The added offset was gradually decreased using a second order error correction function. So, only some percentage of the current error were added to the future signals, and no error was added to horizon steps ahead (Figure 5). This maintained the continuity of the signal estimate and converges it onto the actual signal within the horizon ahead.

C. Model Predictive Control with Reference Estimation Using Biological Signal

Although the position offset between the last and future beating cycles was eliminated in Signal Estimated MPC algorithm, the error due to changes in heartbeat period remained. Because heartbeat is a quasiperiodic motion with small period variations in every beating cycle, these period changes could result in large offsets in the estimated signal. Although the offset between cycles were removed gradually, it still could have caused jumps during the tracking.

As described earlier in the Section III, ECG signal is very suitable for period-to-period synchronization. In this algorithm QRS, P, and T waves were used as check points for detecting current heart beating period.

The current heart beat period was calculated by averaging the periods of these three wave forms. The period was updated continuously as new wave forms were detected. Due to the reading noises in the ECG signal, ECG wave forms could be missed. This is understood when the next ECG wave form is detected. Note that wave forms are always lined up in the same order (QRS-T-P). So, if any ECG wave forms are missed by ECG detection algorithm, the missed signal's period is doubled. Some upper and lower period boundaries are put to eliminate any misses by the detection algorithm. In Figure 6 the estimated signals just before and after the detection of a

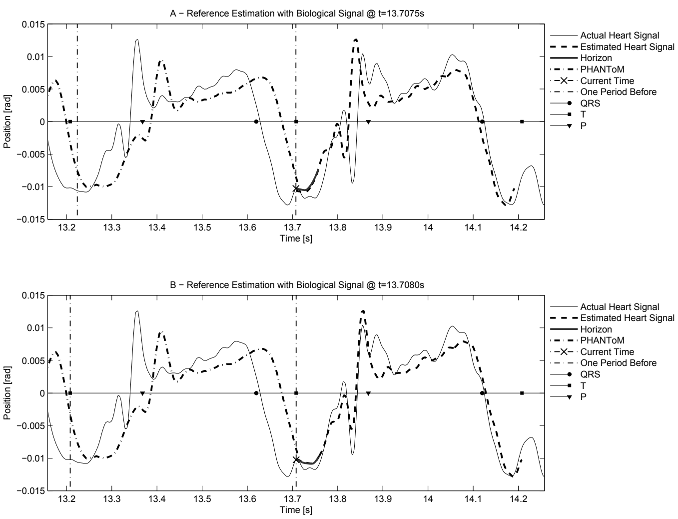

Fig. 6. Reference Estimation with Biological Signal. **A** - *Just before T Wave was detected:* Estimated Heart Signal did not fit well with the Actual Heart Signal. **B** - *T Wave has been detected:* Heart Period and Estimated Signal were adjusted. Observe that the beginning of the previous heartbeat period marker (·–·–) was shifted back in time as a result of the increase in the heartbeat period. Accordingly, Estimated Heart Signal was changed to adjust with the new period. RMS estimation error was decreased from 0.8871 mm to 0.4561 mm with the shift.

new wave form are shown. In Figure 6-B, observe that after the T wave was detected, the past heartbeat period time mark was shifted back in time as a result of the increase in the heartbeat period. In the example shown with Figures 6-A and 6-B, RMS estimation error for one heartbeat period ahead decreased from 0.8871 mm to 0.4561 mm after the shift. With the use of ECG in ARMC algorithm, heart beating period can be adjusted online.

VII. Simulation and Experimental Results

A. Test Bed System

In order to develop and test the algorithms, a hardware test bed system, PHANToM® Premium v1.5, was selected and modeled. For detailed information on the mathematical modeling of the PHANToM robot, see [29]. The PHANToM robot possesses similar characteristics of an actual surgery robot. Its lightweight links, low inertial axes and drive system allows sufficient motion and speed abilities for tracking the heart beat signal (Figure 7).

Experiments were executed on a 2.6 MHz Intel® Pentium® 4 PC running MATLAB® xPC Target v2.6.1 real-time kernel with a sampling time of 0.5 ms. PHANToM does not come with a built-in homing option. In order to improve the accuracy of the experiments, before every experiment, the robot was brought to a home position where the tracking was started. In the experiments prerecorded heart motion signal-with filtered out breathing motion-and ECG signal were used. Raw Heart Position data was re-sampled in order to use in the control algorithms and experiments with PHANToM from 257 Hz to 2 kHz by cubic interpolation. In MPC algorithm, heart position data was used as future signal. A buffer of length horizon was used to store the future heart signal and passed to the model predictive control algorithm. In signal estimation algorithms, the buffers that were used in heart motion signal were 1300 elements long. Only the recently stored part of the buffer, in the length of current heartbeat period, was used for estimation.

B. Experimental Results

In both simulation and experiment, same methods and position data were used. Some slight differences in parameters were observed due to the modeling of the robot. Matrix weighting parameters of the optimal index were tuned to minimize error. Parameters were selected in order to accentuate the states and hence regulate more quickly, with the loss of higher control efforts.

In MPC, the feedback gains were calculated offline, before the control loop, on the other hand, the feedforward portion was iteratively calculated during the control. The feedback and feedforward portions both used the same parameters in their calculations. The most intense calculation was occurred during the backwards iteration calculation of feedforward gains. With the addition of the *heart motion signal buffers* for reference signal estimation, task execution times were peaked up to %90 of the sampling time.

For each algorithm, experiments on PHANToM robot were repeated 10 times. Among these results, the maximum values for the *End-effector Position Error* and *Control Effort* are summarized in Table I to project the worst case. Tabulated values are the RMS position error of the end effector in 3D and sum of the RMS control action values of all three axes. A more detailed listing for all three axes are given in Table II. Similarly the worst cases were presented here. We noted that the deviation between the trials are relatively small. MPC tracking results of the 3-axes of the PHANToM are shown in Figure 8. Biological signal added reference signal estimation results for axis 3 only are shown in Figure 9.

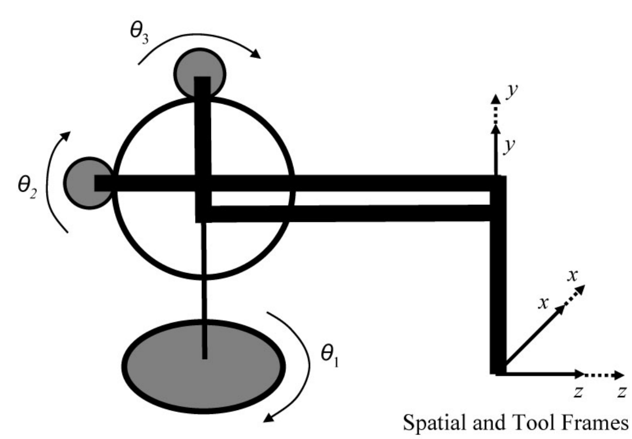

Fig. 7. Zero Configuration of the PHANToM manipulator, also showing the axes movements and spatial and tool frames.

TABLE II

3 AXES SIMULATION AND EXPERIMENTAL RESULTS : *Summary of the maximum end-effector RMS position error and RMS control effort values for the control algorithms used. Position values correspond to the end point of each axis' link.*

Tracking Results	*Simulation*						*PHANToM*					
For All 3 Axes	RMS Error			RMS Control			RMS Error			RMS Control		
Units	mm			Nm			mm			Nm		
Axes No	Axis 1	Axis 2	Axis 3	Axis 1	Axis 2	Axis 3	Axis 1	Axis 2	Axis 3	Axis 1	Axis 2	Axis 3
MPC	0.2485	0.2131	0.1539	0.0266	0.0089	0.0084	0.1832	0.2201	0.1663	0.0860	0.0469	0.0296
Signal Estimated MPC	0.4037	0.3395	0.2796	0.0341	0.0103	0.0090	0.3922	0.4574	0.4117	0.0933	0.0435	0.0349
SE MPC with Bio Signal	0.3468	0.3148	0.2454	0.0330	0.0117	0.0108	0.3440	0.4568	0.3939	0.1107	0.0431	0.0385

C. Discussion of the Results

As predicted, *the MPC with ECG added signal estimation algorithm* outperformed *the signal estimated MPC algorithm*. Results proved that by using ECG signal in the motion estimation, heart position tracking was not only improved but also became more robust. Our tracking results are 2.5 times much better than the reported in the literature [14]. Comparing the results with the baseline performance, results of the MPC, there is still room for improving the estimation algorithm.

High jumps in the position error are due to the noisy data collected by sonometric signal. Although high frequency parts of the raw data are filtered out, relatively low "high frequency" components are intact. It is unlikely that POI on the heart is capable of moving 5 mm in milliseconds time. Heavy filtering would have been performed to delete the high frequency motions, but they were kept in order to measure the performance of the system.

CONCLUSIONS AND FUTURE WORK

In this paper, the use of biological signals in the model-based intelligent ARMC algorithm to achieve better motion canceling was presented. Tracking problem was reduced to

TABLE I

END-EFFECTOR SIMULATION AND EXPERIMENTAL RESULTS: *Summary of the maximum end-effector RMS position error and RMS control effort values for the control algorithms used.*

End-effector	*Simulation*		*PHANToM*	
Tracking Results	Error	Control	Error	Control
Units	mm	Nm	mm	Nm
MPC	0.3612	0.0146	0.3285	0.0539
Signal Estimated MPC	0.5962	0.0178	0.7270	0.0566
MPC with Bio Signal	0.5280	0.0185	0.6930	0.0638

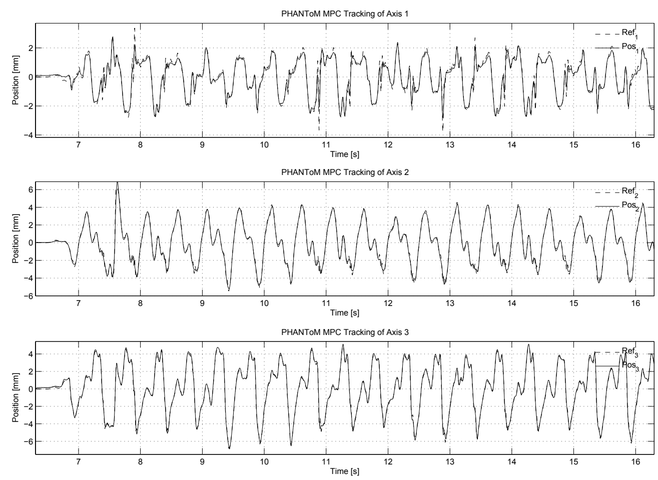

Fig. 8. PHANToM 3D - MPC Tracking Results. Reference and Position signals of all three axes are shown.

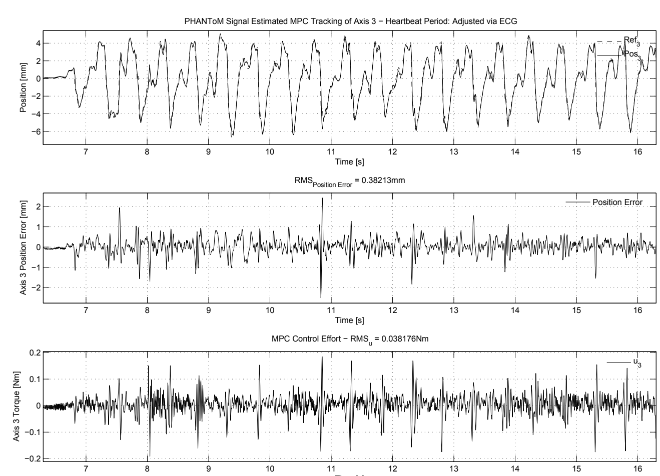

Fig. 9. PHANToM 3D - MPC with ECG Added Signal Estimation Tracking Results. Reference & Position, Position Error and Control Effort signals are shown for the 3^{rd} axis.

reference signal estimation problem with the help of model predictive controller. Estimated signal was created by using the last heart beat cycle with cancelation of the position offset. Due to the quasiperiodic nature of the heart motion, heartbeat period could change in time. In order to reduce the error ECG wave forms were detected and used to adjust heart beating period during the tracking. Experimental results showed that using ECG signal in ARMC algorithm improved the reference signal estimation.

Besides ECG, additional biological signals may enhance the tracking performance. Using the blood pressure signals, noise robustness can be improved and unexpected rhythm abnormalities and arrhythmias can be detected.

In addition to sonometric sensors in sensing motion of the POI, more mechanical position sensors can be introduced. Merging the sensor data from multiple sources would increase the accuracy of motion detection and improve tracking results.

Weighting parameters of the MPC algorithm were hard to tune during experiments. Although the weighting parameters were tuned to get minimum RMS error values, a more comprehensive study can be conducted to find optimum values. During parameter tuning experiments, significant noise due to the coupling of the axes were observed. Some high frequency noise was introduced to the system due to the inertial coupling of the upper two axes of the PHANToM robot. One of the next steps of the research will be focusing on to the elimination of such noises from the system by better modeling of the axes.

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References

[1] M. K. Newman et al. "Longitudinal assessment of neurocognitive function after coronary-artery bypass surgery" in *New England Journal of Medicine*, vol. 344, no. 6, pp. 395-402, February 2001.

[2] J. D. Puskas, C. E. Wright, R. S. Ronson, W. M. Brown, J. P. Gott, R. A. Guyton, "Off-pump multi-vessel coronary bypass via sternotomy is safe and effective", *Annals of Thoracic Surgery*, vol. 66, no. 3, pp. 1068-72, September 1998.

[3] M. C. Cavusoglu, J. Rotella, W. S. Newman, S. Choi, J. Ustin, S. S. Sastry, "Control Algorithms for Active Relative Motion Cancelling for Robotic Assisted Off-Pump Coronary Artery Bypass Graft Surgery" in *Proceedings of the 12th International Conference on Advanced Robotics (ICAR 2005)*, Seattle, WA, USA, July 18th-20th, 2005.

[4] M. C. Cavusoglu, W. Williams, F. Tendick, S. S. Sastry, "Robotics for Telesurgery: Second Generation Berkeley/UCSF Laparoscopic Telesurgical Workstation and Looking towards the Future Applications" in *Proceedings of the 39th Allerton Conference on Communication, Control and Computing*, Monticello, IL, October 3-5, 2001.

[5] J. Rotella, "Predictive Tracking of Quasi Periodic Signals for Active Relative Motion Cancellation in Robotic Assisted Coronary Artery Bypass Graft Surgery", M.S. Thesis, Case Western Reserve University, August 2004.

[6] K. Sharma, W. S. Newman, M. Weinhous, G. Glosser, R. Macklis, "Experimental evaluation of a robotic image-directed radiation therapy system" in *Procedings of IEEE International Conference on Robotics and Automation ICRA '00*, vol. 3, pp. 2913-2918, 2000.

[7] A. Schweikard, G. Glosser, M. Bodduluri, M. J. Murphy, J. R. Adler, "Robotic motion compensation for respiratory movement during radiosurgery", *Computer Aided Surgery*, vol. 5, no. 4, pp. 263-77, 2000.

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

[9] A. L. Trejos, S. E. Salcudean, F. Sassani, S. Lichtenstein, "On the Feasibility of a Moving Support for Surgery on the Beating Heart" in *Proc. Medical Image Computing and Computer-Assisted Interventions (MICCAI99)*, pp. 1088-1097, 1999.

[10] Y. Nakamura, K. Kishi, H. Kawakami, "Heartbeat synchronization for robotic cardiac surgery" in *Proceedings of IEEE International Conference on Robotics and Automation, 2001. ICRA'01*, vol. 2, pp. 2014-2019, 2001.

[11] A. Thakral, J. Wallace, D. Tomlin, N. Seth, N. V. Thakor, "Surgical motion adaptive robotic technology (S.M.A.R.T): Taking the motion out of physiological motion" in *Proceedings of the 4th International Conference In Medical Image Computing and Computer-Assisted Intervention - MICCAI 2001*, Utrecht, The Netherlands, October 14-17, 2001, vol. 2208 of Lecture Notes in Computer Science, pp. 317-325, Springer, 2001.

[12] T. Ortmaier, "Motion Compensation in Minimally Invasive Robotic Surgery", Doctoral Thesis, Technical University of Munich, April 2003.

[13] R. Ginhoux, J. A. Gangloff, M. F. de Mathelin, L. Soler, J. Leroy, J. Marescaux, "A 500 Hz predictive visual servoing scheme to mechanically filter complex repetitive organ motions in robotized surgery" in *Proceedings of International Conference on Intelligent Robots and Systems 2003 IEEE/RSJ (IROS 2003)*, vol. 4, pp. 3361-3366, 2003.

[14] R. Ginhoux, J. A. Gangloff, M. F. de Mathelin, L. Soler, J. Leroy, M. M. A. Sanchez, J. Marescaux, "Active filtering of physiological motion in robotized surgery using predictive control" in *IEEE Transactions on Robotics*, volume 21, no. 1, pp. 67-79, February 2005.

[15] C. E. Garcia, D. M. Prett, M. Morari, "Model predictive control: Theory and practice-A survey", *Automatica*, vol. 25, no. 3, pp. 335-348, 1989.

[16] E. F. Camacho, C. Bordons, *Model Predictive Control*, Springer, 1999.

[17] B. D. O. Anderson, J. B. Moore, *Optimal Control Linear Quadratic Methods*, Prentice Hall, 1990.

[18] American Heart Association Web page, http://www.americanheart.org, 2005.

[19] J. Malmivuo, R. Plonsey, *Bioelectromagnetism - Principles and Applications of Bioelectric and Biomagnetic Fields*, Oxford University Press, New York, 1995.

[20] R. M. Berne, M. N. Levy, *Cardiovascular Physiology*, 8th Edition. Mosby Inc, St. Louis, 2001.

[21] R. M. Berne, M. N. Levy, *Principles of Physiology*, 3rd Edition. Mosby Inc, St. Louis, 2000.

[22] M. B. Ratcliffe, K. B. Gupta, J. T. Streicher, E. B. Savage, D. K. Bogen, Jr L. H. Edmunds, "Use of sonomicrometry and multidimensional scaling to determine the threedimensional coordinates of multiple cardiac locations: Feasibility and initial implementation" in *IEEE Transactions on Biomedical Engineering*, vol. 46, no. 6, pp. 587-598, June 1995.

[23] R. Poli, S. Cagnoni, G. Valli, "Generic design of optimum linear and nonlinear QRS detection" in *IEEE Trans on Biomed Eng*, vol. 42, pp. 1137-1141, 1995.

[24] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, S. Luo, "ECG beat detection using filter banks" in *Trans Biomed Eng*, vol. 46, no. 2, pp. 192-201, 1999.

[25] I. Dotsinsky, T. Stoyanov, "Ventricular beat detection in single channel electrocardiograms" in *BioMedical Engineering OnLine*, vol. 3, no. 3, 2004.

[26] C. Li, C. Zheng, C. Tai, "Detection of ECG characteristic points using wavelet transforms" in *IEEE Trans on BioMedical Engineering*, vol. 42, pp. 21-28, 1995.

[27] I. Chirstov, "Real time electrocardiogram QRS detection using combined adaptive threshold" in *BioMedical Engineering OnLine*, vol.3, no. 28, 2004.

[28] M. Bahoura, M. Hassani, M. Hubin, "DSP implementation of wavelet transform for real wave forms detection and heart rate analysis", *Computer Methods and Programs in Biomedicine*, vol. 52, pp. 35-44, 1997.

[29] M. C. Cavusoglu, D. Feygin, F. Tendick, "A Critical Study of the Mechanical and Electrical Properties of the PHANToM™ Haptic Interface and Improvements for High Performance Control", *In Presence*, vol. 11, no. 6, pp. 555-568, December 2002.