2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

Prediction of Heartbeat Motion with a Generalized Adaptive Filter

Timothy J. Franke, Ozkan Bebek, M. Cenk Cavusoglu
Department of Electrical Engineering and Computer Science
Case Western Reserve University, Cleveland, Ohio, 44106-7221, USA
E-mail: tjf6@case.edu, ozkan@case.edu, cavusoglu@case.edu

Abstract— **In order to perform coronary artery bypass graft surgery, a stationary heart is necessary. A human cannot achieve manual tracking of the complex heartbeat motion. Robotics technology can overcome such limitations. In the robotic-assisted beating heart surgery, the robot actively cancels heart motion by closely following a point of interest on the heart surface—a process called Active Relative Motion Canceling. As a result, surgeon can operate on the beating heart as if it is stationary. In this paper, a generalized estimation algorithm, that uses an adaptive filter to generate future position estimates is studied. The predictor is parameterized on-line and adaptively to minimize the prediction error in the mean-square sense. The predictor is evaluated using a 3-degree-of-freedom test-bed system and prerecorded heart motion data.**

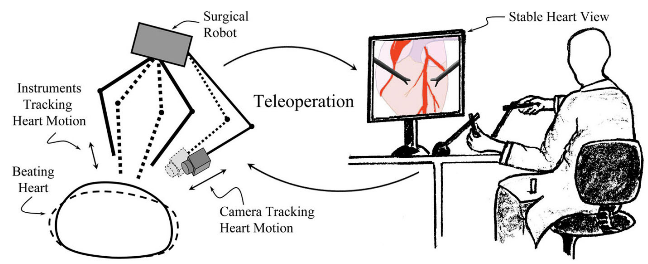

Fig. 1. System concept for Robotic Telesurgical System for Off-Pump CABG Surgery with Active Relative Motion Canceling (ARMC). Left: Surgical instruments and camera mounted on a robot actively tracking heart motion. Right: Surgeon operating on a stabilized view of the heart, and teleoperatively controlling robotic surgical instruments to perform the surgery.

I. INTRODUCTION

Robotic-assisted beating heart surgery has been proposed as an alternative for types of heart surgery that involve stopping or physically restraining the heart. Trejos [1] noted that the arteries on the heart surface moved too quickly to effectively be tracked by hand and that robotic tracking could solve this problem. A surgical robot can be used to track a point on the heart surface, moving with the heart and cancel the relative motion, allowing a surgeon to operate as if the heart were stationary.

Current techniques to compensate for the biological motion during coronary artery bypass graft (CABG) surgery is either to stop the heart and use a cardio-pulmonary bypass machine or to passively restrain the heart with stabilizers. Stopping the heart can cause significant complications during or after the surgery, resulting from the use of cardio-pulmonary bypass machine. These complications can include long term cognitive loss [2], and increased hospitalization time and cost [3].

Robotic-assisted surgery replaces conventional surgical tools with robotic instruments which are under the direct control of the surgeon through teleoperation, as shown in Figure 1. The surgeon views the surgical site through a camera mounted on a robotic arm that follows the heart motion, showing the surgeon a stabilized view. The robotic surgical instruments also track the heart motion, canceling the relative motion between the surgical site and the instruments. As a result, the surgeon operates on the heart as if the heart were still. This is in contrast to traditional off-pump CABG surgery where the heart is passively constrained to dampen the beating motion. The robotic approach is called "Active Relative Motion Canceling (ARMC)" to emphasize this difference [4]. Since this method does not rely on passively constraining the heart, it would be possible to operate on the side and back surfaces of the heart as well as the front surface using millimeter scale robotic manipulators that can fit into spaces the surgeon could not otherwise reach.

Tracking a point-of-interest (POI) on the heart surface during surgery requires high accuracy, especially when performing off-pump CABG surgery. The surgeon is required to operate on blood vessels that are small in diameter, ranging from 0.5-2.0 mm, and moving at a quasiperidic frequency range of 1-2 Hz. In order to operate on these vessels, accurate position tracking in the order of 100-250 μm root-mean-square (RMS) position error is required [5]. Error feedback control alone was found to be unable to reduce the tracking error sufficiently. A predictive controller in the feedforward path was found to be necessary [5]. The controller implements a receeding horizon model predictive controller (RHMPC) and is described in Rotella [6].

The primary goal of this research has been to improve the tracking performance of a surgical robot prototype as proof of concept that the degree of necessary tracking can be achieved. To this end, the tracking performance research has primarily been focused on developing estimation methods for use with a receding horizon model predictive controller (Details of the control algorithm, which can be found in [4], will not be discussed here because of space restrictions).

In this paper, a generalized adaptive filter based predictor is proposed to parameterize linear predictors for points throughout the horizon independently. The prediction scheme is implemented and its effectiveness is studied by simulation and on a 3-degree-of-freedom (DOF) hardware robotic system using previously recorded heart motion data, as the reference. Section II discusses how predictions were generated on similar projects. Section III formally formulates the prediction problem and introduces the prediction method. In Section IV, the 3-DOF robotic test-bed and experimental procedures are described, and the results are compared with earlier works in literature. Finally, conclusions and possible extensions to the predictor are presented.

II. Related Work in Literature

There are several research groups that have studied the problem of ARMC for beating heart surgery. Nakamura *et al.* [7] performed experiments to track the heart motion with a 4-DOF robot using high-speed visual servoing. The tracking error due to the camera feedback system was too large to perform beating heart surgery (error on the order of few millimeters in the normal direction). Ortmaier [8] used Takens Theorem—a statistical method for detecting chaotic attractors—to develop a robust prediction algorithm, anticipating periods of lost data when a tool obscured the visual tracking system. Ginhoux *et al.* [9] separated breathing motion from heart motion in the prediction algorithm. The breathing motion was treated as perfectly periodic, since the patient would be on a breathing machine. The heart motion was predicted by estimating the fundamental frequency, as well as the amplitude and phase of the first 5 harmonics. The predicted heart motion was used to estimate disturbance which was corrected by the controller. Rotella [6] used the previous cycle of heart motion data as an estimate of future behavior. The estimate was used along with a model predictive controller to achieve high precision tracking of the heart motion on a 1-DOF test-bed system. Using the previous cycle as a future estimate lead to problems since the heart motion was not perfectly periodic. Bebek *et al.* [4] improved upon this prediction scheme by synchronizing heart periods using ECG data and separated heart and breathing motion, predicting only heart motion.

Franke *et al.* [10] proposed a new estimation algorithm for the controller presented by Bebek *et al.* [4]. A recursive least squares based adaptive filter algorithm was used for parameterizing a linear system to predict the heart motion. The linear predictor was parameterized by a least squares algorithm, and was inherently robust to noise. The predictor only used observations close to and including the present observation making it less susceptible to differences between heart periods than the estimation algorithm of Bebek *et al.* [4]. Also, no assumptions were made towards periodicity of the system *a priori*. Rather the predictor was unconstrained so that it could best mimic the motion of the POI.

This paper extends and generalizes the work presented in [10] by generalizing the prediction method. The generalized method does not assume that the horizon can be generated through recursive implementation of a one-step predictor; instead, estimators for samples throughout the horizon are independently parameterized. In this way, there is no presumed linear dynamics governing the POI motion, in contrast to the recursive application of a one-step predictor which is

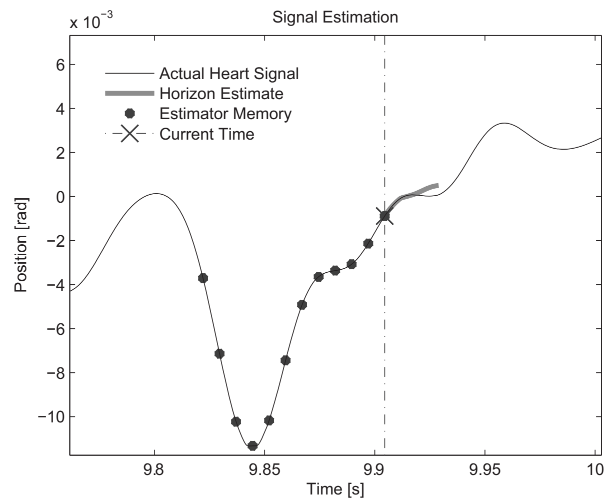

Fig. 2. A schematic of the prediction problem. The circles represent past observations, now in memory, the 'X' is the current observation, and the curve originating from there is the horizon estimate. The predictor takes the past observations and produces the horizon estimate from only those points.

a linear time-invariant model. A predictor that has horizon estimates related by a linear system is a special case of a model which presumes no such dependencies and therefore the former predictor is more general.

III. Horizon Estimator

First, allow the introduction of some notation. Let x_i represent an observation. In this case, x_i is a three dimensional column vector representing the location of the POI in Cartesian coordinates. The observation x_0 is the location of the heart at the current sample. The observation x_{-1} is the observation immediately prior to the current one. The older observations will be referenced by decreasing subscript index (e.g., x_{-5} would have been the current observation five samples ago). Likewise, x_1 represents the next observation. This observation has not occurred, and will not be known until it becomes the present value. So, the estimate for the next observation is introduced as $\hat{x}_1$.

With this notation, the prediction problem can be posed: given the N-dimensional vector of present and past observations, $[x_0, x_{-1}, \ldots, x_{-N+1}]^T$, find the best estimate of the M-dimensional horizon, $[x_1, x_2, \ldots, x_M]^T$ (see Figure 2). The 'best estimate' will be the one that minimizes the square of the estimation error, where the estimation error is the difference between the prediction and the observed value at that time.

A. Recursive Least Squares Estimation Scheme

In the recursive least squares estimation scheme (details were given in [10]), two assumptions were made. First, predictor, $\mathbf{W}: [x_0, \ldots, x_{-N+1}]^T \rightarrow \hat{x}_1$, is linear and therefore can be represented by matrix multiplication. Second, that estimates further in the the prediction horizon can be generated by recursively applying the single step predictor. Since the predictor is linear, it can be represented by matrix multiplication as:

$$\mathbf{W}\begin{bmatrix} x_0 \\ x_{-1} \\ \vdots \\ x_{-N+1} \end{bmatrix} = \hat{x}_1 \quad (1)$$

In order to have an online, adaptive method for determining $\mathbf{W}$, the recursive least squares (RLS) algorithm was employed. The updating of $\mathbf{W}$ was done through an adaptive filter which used the collection of observations from the previous sample as input and the current observation as the desired output [11]. Since $\mathbf{W}$ is updated at every time step, the estimator is able to adapt to slowly changing heart behavior.

This recursive relationship can be written explicitly. If $\mathbf{W}$ is factored as $\mathbf{W} = \mathbf{C}\mathbf{\Phi}_{0,1}$ where

$$\mathbf{\Phi}_{0,1} : [x_0, \ldots, x_{-N+1}]^T \rightarrow [\hat{x}_1, x_0, \ldots, x_{-N+2}]^T$$

$$\mathbf{C} : [x_0, \ldots, x_{-N+1}]^T \rightarrow x_0; \quad C = [I \;\; 0 \;\; \cdots \;\; 0],$$

then it is possible to define a matrix $\mathbf{U}$ such that it maps the memory of past observations to the expected horizon. In this case,

$$\mathbf{U} = \begin{bmatrix} \mathbf{C}\mathbf{\Phi}_{0,1} \\ \mathbf{C}\mathbf{\Phi}_{0,1}^2 \\ \vdots \\ \mathbf{C}\mathbf{\Phi}_{0,1}^M \end{bmatrix} \quad (2)$$

$$\mathbf{U} : (x_0, x_{-1}, \ldots, x_{-N+1}) \rightarrow (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_M).$$

B. Generalized Linear Prediction

In Section III-A, the optimal (in the sense of prediction error magnitude) linear one step predictor was formulated and used recursively to generate predictions. This method approximates the heart dynamics as being a linear discrete time system and leads to sub-ideal predictions, as the POI motion has nonlinear dynamics. In the generalized prediction method that is proposed in this paper, the assumption of a linear system relation between consecutive time samples is abandoned. Instead, a linear estimator for each point in the horizon is independently estimated. This is done by extending (1) as follows:

$$\mathbf{V}\begin{bmatrix} x_0 \\ x_{-1} \\ \vdots \\ x_{-N+1} \end{bmatrix} = \begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \vdots \\ \hat{x}_M \end{bmatrix} \quad (3)$$

Where $\mathbf{V}$ is the estimation matrix that maps from the collection of observations to the expected horizon. In the same way as $\mathbf{W}$ was parameterized, RLS is used to determine $\mathbf{V}$ online and adaptively. However, since (3) contains the estimated values that are being solved for, it is unsuitable for implementation via RLS as is. This can be solved by assuming POI statistics to be stationary, or at least slowly varying, which makes $\mathbf{V}$ approximately constant. The assumption of time invariance of the heart statistics is utilized to introduce M delays so that all quantities have been observed when solving for $\mathbf{V}$.

$$\mathbf{V}\begin{bmatrix} x_{-M} \\ x_{-M-1} \\ \vdots \\ x_{-N-M+1} \end{bmatrix} = \begin{bmatrix} x_{-M+1} \\ x_{-M+2} \\ \vdots \\ x_0 \end{bmatrix} \quad (4)$$

The analogy can be made between (4) and an adaptive filter. The right hand side is the desired output and the observation vector on the left hand side is the input. Further, introducing the estimation matrices

$$\mathbf{\Phi}_{0,i} : [x_0, \ldots, x_{-N+1}]^T \rightarrow [\hat{x}_i, \hat{x}_{i+1}, \ldots, \hat{x}_{-N+i}]^T$$

for $1 \leq i \leq M$, then $\mathbf{V}$ can be decomposed similar to $\mathbf{U}$ in (2) as

$$\mathbf{V} = \begin{bmatrix} \mathbf{C}\mathbf{\Phi}_{0,1} \\ \mathbf{C}\mathbf{\Phi}_{0,2} \\ \vdots \\ \mathbf{C}\mathbf{\Phi}_{0,M} \end{bmatrix} \quad (5)$$

The generalization of this prediction method results from the fact that, unlike in (2), $\mathbf{\Phi}_{0,i}$ are parameterized independently and not, in general, equal to $\mathbf{\Phi}_{0,1}^i$. The removal of this constraint allows for the nonlinear dynamics throughout the prediction horizon to be better predicted by a linear estimator.

The predictor is implemented in a similar way to the previous vector RLS adaptive filter, see [10]. The adaptive filter is formulated to solve the delayed prediction equation 4. This is equivalent to using a bank of n-step predictors, but is more computationally efficient. The largest cost in the RLS algorithm involves updataing the inverse covariance matrix of the inputs. Since each estimate is using the same input vector, the updating only needs to be done once, providing a dramatic reduction in computational complexity when predictions are being made at many points throughout the horizon.

IV. Experiments and Results

A. Heart Motion Data

The motion of the heart surface is quasi-periodic in nature. The motion of the POI on the heart is primarily the superposition of two effects: motion due to the heart beating and motion due to breathing. Each of these signals closely resemble periodic signals. Measurement of heart motion with high precision and high confidence is required for precise motion canceling performance. Also, redundant sensing systems are desirable for safety reasons. Sensors that are planned to be used to collect heart motion data include sonomicrometric sensors, a whisker sensor, a multi-camera vision system and a laser sensor [12]. The prerecorded data used in this study was collected from an adult porcine using a Sonomicrometry system by Cavusoglu *et al.* [5]. Fourier analysis of the heart signal data reveals how this periodic nature is prevalent (see Figure 3). Lung motion has the

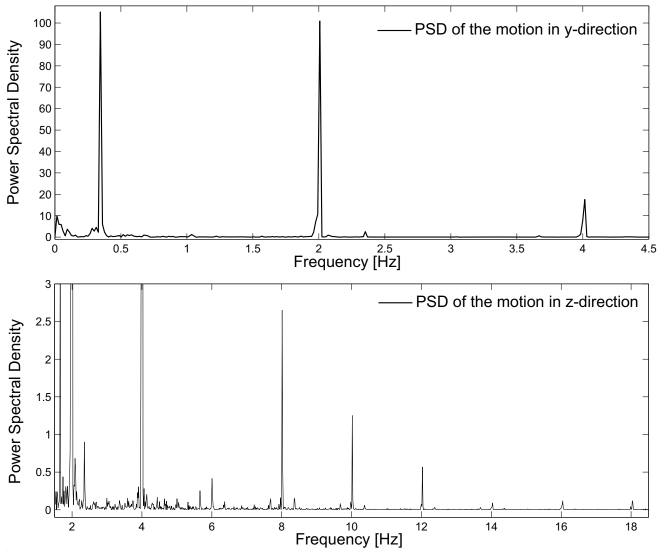

Fig. 3. Power Spectral Density of the heart motion in the y and z directions. Tall, narrow peaks with the absence of intermittent frequencies indicate largely periodic motion of the heart.

lower frequency with a fundamental period of approximately 0.4 Hz with only the primary harmonic appearing significant. The heart motion itself has a fundamental frequency of 2 Hz, corresponding to 120 bpm, with the first five harmonics being considered significant. The sharpness of these peaks indicate that the harmonics decay very little in time, meaning that the overall motion of the POI is similar to a superposition of periodic signals. The first 10 seconds of the 56-second-long prerecorded data was used to tune the controller parameters. Then the validation experiments were carried out using the complete 56-s-long heart motion data.

B. 3-DOF Robotic Test Bed

The proposed estimation algorithm was tested on a PHANToM Premium 1.5A haptic device, which is a 3-DOF robotic system. The nonlinearities of the system (i.e., gravitational effects, joint frictions, and Coriolis and centrifugal forces) were canceled independently from the controller. In order to maintain the accuracy of the experiments, the manipulator was brought to a selected home position, in this case its zero configuration, before every experiment. A schematic of the degrees of freedom and the zero configuration of the manipulator is shown in Figure 4.

The controller from [4] was modified to include the new prediction algorithm. The trials used the same prerecorded heart motion data described above. The robot was made to follow the combined motion of heartbeat and breathing. The system was run using prerecorded data points in place of online measurements. The controller was implemented in Simulink for xPC Target and ran in real time with a sampling time of 0.5 ms on a 2.6 GHz Pentium 4 PC. The linearized robot model was controlled using a receding horizon model predictive controller (RHMPC). The RHMPC was formulated to track the horizon estimate weighted by a quadratic objective function. The encoder positions on the PHANToM

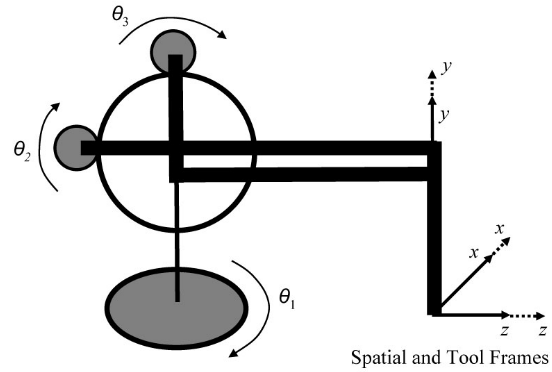

Fig. 4. Zero Configuration of the PHANToM manipulator, also showing the axes movements and spatial and tool frames.

were recorded and these positions were transformed into end effector positions. The reported RMS errors are calculated from the difference between the prerecorded target point and the actual end effector position.

C. Simulation and Experimental Results

The same control method and reference data were used while running simulations and experiments. During the trials, an estimator that made use of the past 10 observations predicted 4 different future points in the 25 ms horizon and quadratic interpolation was accounted for the intermittent points. The predictor was downsampled by a factor of 15, processing observations that were 7.5 ms apart. The experiments were carried out using the 56-s long heartbeat data which is explained in Section IV-A. Experiments were run ten times with the estimation algorithm and again with the actual heart motion data as future signal reference for the prediction horizon. The later case represents a ‘perfect’ estimation, providing a performance base of the robotic system’s capability. The end-effector RMS position errors in millimeters along with maximum end-effector position errors are reported in Table I. The three axes mean of the RMS control efforts are also tabulated. Tracking results with the generalized adaptive filter estimation is shown in Figure 5. In the figure magnitude of the end effector position error superimposed with the reference signal for the x-axis is shown. We believe that, the maximum error values are affected from the noise in the data collected by Sonomicrometry sensor as it is unlikely that the POI on the heart is capable of moving 5 mm in a few milliseconds. The data has been kept as-is without applying any filtering to eliminate these jumps in the sensor measurement data as currently we do not have an independent set of sensor measurements (such as from a vision sensor) that would confirm this conjecture.

As can be seen from Table I, in the simulation the estimator and the exact heart signal performed almost equally. The maximum error and control effort were slightly smaller with the estimated horizon. In the experiments, the controller with estimator outperformed the controller with exact heart signal reference. The maximum error and control effort were also slightly smaller, similar to the simulation results. However,

TABLE I

SIMULATION AND EXPERIMENT RESULTS: END-EFFECTOR RMS POSITION ERROR, MAX POSITION ERROR AND RMS CONTROL EFFORT VALUES FOR THE CONTROL ALGORITHMS USED WITH 56-S HEART MOTION DATA.

End-effector Tracking Results	RMS Position Error [mm]		Max Position Error [mm]		Control Effort [mNm]	
	Simulation	PHANToM	Simulation	PHANToM	Simulation	PHANToM
Receding Horizon Model Predictive Controller with Exact Reference Information	0.295	0.312	1.732	1.993	14.8	45.2
Receding Horizon Model Predictive Controller with Generalized Adaptive Filter Estimation	0.295	0.305	1.680	1.813	14.6	45.6

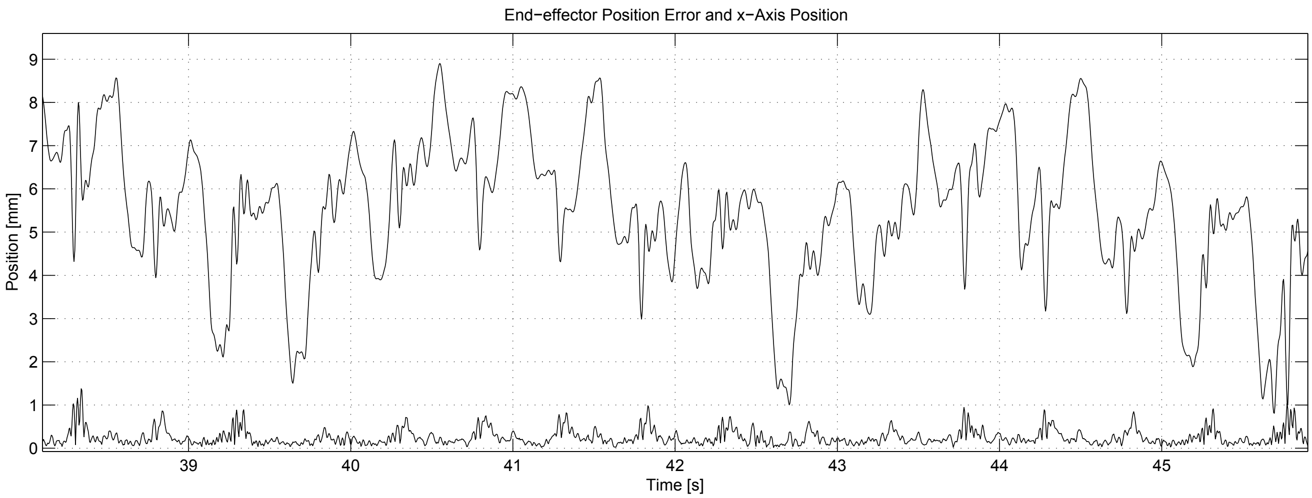

Fig. 5. Tracking results with Receding Horizon Model Predictive Controller with Generalized Adaptive Filter Estimation. Magnitude of the end effector error (below) superimposed with the reference signal for the x-axis.

the control effort of the new predictor was slightly larger in the hardware trials, indicating that though the tracking performance increased, it did so at a tradeoff.

At this point, it would be informative to compare the presented tracking results with the previously reported values in the literature.

Ginhoux *et al.* [9] used motion canceling through prediction of future heart motion using high-speed visual servoing with a model predictive controller. Their results indicated a tracking error variance on the order of 6-7 pixels (approximately 1.5-1.75 mm calculated from the 40 pixel/cm resolution reported in [9]) in each direction of a 3-DOF tracking task. Although it yielded better results than earlier studies using vision systems, the error was still very large to perform heart surgery.

Bebek *et al.* used the past heartbeat cycle motion data, synchronized with the ECG data, in their estimation algorithms. They achieved 0.682 mm RMS end-effector position error on a 3-DOF robotic test-bed system [4].

Franke *et al.* used a recursive least squares based adaptive filter algorithm for parameterizing a linear system to predict the heart motion. The predictor was used with the model predictive controller presented by Bebek *et al.* [4]. They reported 0.449 mm RMS end-effector position tracking results in [10].

The generalized predictor proposed in this paper represent the best results reported in the literature. These results show that the model predictive controller with the proposed generalized estimator and the exact reference data performed equally well, which indicates that the main cause of error is no longer the prediction but the performance limitations of the robot and controller. It is important to note that the results also need to be validated *in vivo*, which was the case in [9].

V. CONCLUSION AND FUTURE WORK

In this paper, a generalized estimator for predicting the horizon estimate for the model predictive controller is presented. The experimental RMS error of 0.295 mm obtained using the generalized estimator described in this paper represents a significant improvement in prediction performance compared to earlier studies. These results show that the estimation of future POI motion is no longer the bottleneck in the heartbeat motion tracking.

Initially, RHMPC was concluded to be capable of out performing causal controllers [6]; However, since predictions have become increasingly reliable, it is possible to consider controllers that use the horizon estimate in their control law. It remains as future work to implement such controllers to either improve upon the current setup or to demonstrate its effectiveness.

Another way to improve tracking quality is to incorporate other types of data into the estimation scheme. One such possibility is to include the electrocardiogram (ECG) signal into the observations. In this way, the predictor is able to use the electrical signals that activate heart contraction in order to improve the prediction. This may improve performance during heart contractions, when rapid POI motion occurs.

ACKNOWLEDGMENT

The authors would like to thank Dr. Mark Ratcliffe for his help during collection of the experimental data.

This work was supported in part by National Science Foundation under grants CISE IIS-0222743, EIA-0329811, and CNS-0423253, US DoC under grant TOP-39-60-04003, and Case Western Reserve University with a Support of Undergraduate Research and Creative Endeavors (SOURCE) award.

REFERENCES

[1] A. Trejos, S. Salcudean, F. Sassani, and S. Lichtenstein, "On the feasibility of a moving support for surgery on the beating heart," in *Proc. of Medical Image Computing and Computer-Assisted Interventions (MICCAI)*, 1999, pp. 1088–1097.

[2] M. F. Newman, J. L. Kirchner, B. Phillips-Bute, V. Gaver, H. Grocott, R. H. Jones, *et al.*, "Longitudinal assessment of neurocognitive function after coronary-artery bypass surgery," *New England Journal of Medicine*, vol. 344, no. 6, pp. 395–402, February 2001.

[3] J. D. Puskas, C. E. Wright, R. S. Ronson, W. M. Brown, J. P. Gott, and R. A. Guyton, "Off-pump multi-vessel coronary bypass via sternotomy is safe and effective," *Annals of Thoracic Surgery*, vol. 66, no. 3, pp. 1068–1072, September 1998.

[4] O. Bebek and M. C. Cavusoglu, "Intelligent control algorithms for robotic assisted beating heart surgery," *IEEE Trans. Robotics*, vol. 23, no. 3, pp. 468–480, June 2007.

[5] M. C. Cavusoglu, J. Rotella, W. S. Newman, S. Choi, J. Ustin, and S. S. Sastry, "Control algorithms for active relative motion cancelling for robotic assisted off-pump coronary artery bypass graft surgery," in *Proc. of the 12th International Conference on Advanced Robotics (ICAR)*, Seattle, WA, USA, July 2005, pp. 431–436.

[6] 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, Cleveland, OH, USA, August 2004. [Online]. Available: http://robotics.case.edu/publications.html#thesis

[7] Y. Nakamura, K. Kishi, and H. Kawakami, "Heartbeat synchronization for robotic cardiac surgery," in *Proc. of IEEE International Conference on Robotics and Automation (ICRA)*, vol. 2, 2001, pp. 2014–2019.

[8] T. Ortmaier, "Motion compensation in minimally invasive robotic surgery," Doctoral Thesis, Technical University of Munich, Germany, April 2003.

[9] R. Ginhoux, J. A. Gangloff, M. F. DeMathelin, L. Soler, J. Leroy, M. M. A. Sanchez, and J. Marescaux, "Active filtering of physiological motion in robotized surgery using predictive control," *IEEE Trans. Robotics*, vol. 21, no. 1, pp. 67–79, February 2005.

[10] T. Franke, O. Bebek, and M. C. Cavusoglu, "Improved prediction of heart motion using an adaptive filter for robot assisted beating heart surgery," in *Proc. of the International Conference on Inteligent Robots and Systems (IROS)*, San Diego, CA, USA, October-November 2007, pp. 509–515.

[11] S. Haykin, *Adaptive Filter Theory*, 4th ed. Upper Saddle River, New Jersey: Prentice Hall, 2001.

[12] O. Bebek, "Robotic-assisted beating heart surgery," Doctoral Thesis, Case Western Reserve University, USA, May 2008. [Online]. Available: http://robotics.case.edu/publications.html#thesis