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Toward Onboard Estimation of Physiological Phase for an Epicardial Crawling Robot

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Abstract

HeartLander is a miniature mobile robot which adheres to and crawls over the surface of the beating heart to provide therapies in a minimally invasive manner. Although HeartLander inherently provides a stable operating platform, the motion of the surface of the heart remains an important factor in the operation of the robot. The quasi-periodic motion of the heart due to physiological cycles, respiration and the heartbeat, affects the ability of the robot to move, as well as localize accurately. In order to improve locomotion efficiency, as well as register different locations on the heart in physiological phase, two methods of identifying physiological phases are presented: sliding-window-based and model-based. In the sliding-window-based approach a vector of previous measurements is compared to previously learned motion templates to determine the current physiological phases, while the model-based approach learns a Fourier series model of the motion, and uses this model to estimate the current physiological phases using an Extended Kalman Filter (EKF). The two methods, while differing in approach, produce similarly accurate results on data recorded from animal experiments *in vivo*.

I. Introduction

Minimally invasive cardiac therapy possesses the capability to improve patient outcomes. Standard cardiac surgeries which require invasive sternotomies or thoracotomies incur high associated morbidity. Minimally invasive techniques have been developed which access the heart using rigid endoscopic tools through multiple ports, yet these techniques still require lung deflation and stabilization to provide the surgeons a stable operating platform [1]. This has led to research to develop robotic systems to enable minimally-invasive beating-heart surgery without stabilization [2]–[4]. As an alternative approach to meeting these challenges, we have developed a dedicated epicardial crawling robot which minimizes the morbidity associated with accessing the treatment site and inherently provides a stable operating environment.

HeartLander, shown in Fig. 1, is a miniature mobile robot which navigates over the surface of the beating heart to enable therapies to be delivered to the epicardial surface. The robot is an inchworm-style robot which uses suction to adhere to the epicardial surface. Access to the heart is gained through a subxiphoid skin incision and a small incision in the pericardium, the sac which surrounds the heart. Locomotion is achieved by extending and retracting drive wires which control the distance between the two feet, and by alternating suction between the feet. Previous work has shown the ability of HeartLander to successfully access the pericardium, locomote over the surface of the heart, and to have sufficient targeting accuracy. Also, because of the dynamic and wet environment and the

lack of free space in situ, the locomotion efficiency of the robot has been shown to be as low as 40% [5].

Previous work has increased this efficiency by synchronizing the motion of HeartLander with the physiological cycles, respiration and heartbeat, to coincide with minimum intrapericardial pressure [6]. This work detected the end of expiration and start of systole, the contraction of the heart, using an accelerometer placed on the surface of the chest. These methods proved successful; however, they require external sensors and significant processing, complicating the system, and they only provide detection of discrete events, rather than continuous phase detection. More recent work provided continuous estimates of the physiological phase values by modeling the motion with Fourier series, then approximated the phase values using the first-order Fourier series parameters [7]. Although this work provided reasonable estimates of the phase values, the method is limited by the first-order approximation and the underconstrained formulation.

The goal of this work is to develop a method of detecting physiological phases continuously using the same tracker data already used for locomotion. The continuously detected physiological phases can then be used for synchronization, as well as for mapping of the surface of the heart.

II. Problem Definition

An example of the position measurements of HeartLander while on the surface of the beating heart in a porcine model *in vivo* is shown in Fig. 2(a). These measurements come from a 6-degree-of-freedom electromagnetic tracking sensor (microBIRD, Ascension Technology) embedded in the front foot of the robot. From data it is clear that there are two major modes of motion: a lower-frequency motion due to respiration, and a higher-frequency motion due to the heartbeat.

The corresponding ground-truth physiological phase values of the position data are shown in Fig. 2(b). These phase values are in the notation of Shechter et al. [8], where the respiration phase ranges from -1 to 0 during expiration and from 0 to 1 during inspiration, and the cardiac phase ranges from 0 to 0.42 during systole and from 0.42 to 1 during diastole. These ground-truth phase values were determined using offline supervised detection of the respiratory and cardiac events in accelerometer and ECG signals [6]. For respiration, the end-expiration events were detected from zero-phase-lag filtered data from an accelerometer placed on the surface of the porcine chest. End-systole events in the cardiac cycle were detected using the Pan-Tompkins detector to identify the QRS complex of each heartbeat [9].

The scope of this work is to learn a method which maps features composed of the current and past position measurements provided by the electromagnetic tracker to the ground truth cardiac and respiration phase values, ϕ_C and ϕ_R . It is important to note that no future measurements may be considered as the learned function will be applied in real time to provide an estimate of the current physiological phases.

III. Related Work

Considerable work has been done on modeling of the deformation of the surface of the heart. A large volume of this work comes from the medical imaging community and involves building models of the heart from Magnetic Resonance Imaging (MRI) or X-ray computed tomography (CT) data. Representative work in this area includes modeling the

heart using parametric spline representations [10], finite element models [11], and statistical shape models [12].

Other work is aimed towards developing vision-based systems which allow a surgeon to operate on the beating heart by providing a stable operating environment. Tracking, modeling, and predicting the motion of a region of the heart has been shown using physics-based models [13], parametric thin-plate spline models [14], and thin membrane models [15].

Due to the 6-DOF position measurements provided by the HeartLander system, the most relevant work involves modeling of cardiac motion to predict where a point of interest on the heart will be in the future to improve motion compensation [2], [3], [16]–[21]. While the proposed work aims to predict the current physiological phase and not predict future motion, the two goals are intertwined by the required approach. Existing approaches to modeling the motion of the heart can generally be grouped into two categories: sliding-window-based and model-based.

Sliding-window-based methods assume no functional form to the deformation and instead keep a vector of the previous N data points, X .

$$X = [x_t, x_{t-1}, \dots, x_{t-(N-1)}]^T \quad (1)$$

Using these vectors of previous data points, future motions are predicted in various ways. Ortmaier et al. compare the current sliding window with previous windows to find similar inner states. Future states are then predicted by combining the weighted average of previous similar time series [16]. Copies of the previous heartbeat cycle, identified by ECG signal, have also been used to predict future states [2]. Another method assumes a linear relationship between past and future windows,

$$VX = [x_{t+1}, x_{t+2}, \dots, x_{t+N}]^T, \quad (2)$$

and adaptively learns the relationship, V , using a least squares method [17]. An advantage of each of these methods is that they do not parameterize the motion, reducing the risk of not accurately characterizing the underlying dynamics. Where these approaches lack, though, is their reliance on external signals or assuming constant dynamics to make future predictions.

The second family of methods is those that assume a functional form to model the deformation of the heart. The models assumed in these methods are either splines or Fourier series. Cuvillon et al. use splines to model the respiratory component of motion, and a Linear Parameter Variant Finite Impulse Response (FIR) model combined with a spline to model the cardiac component of motion [3]. This model of cardiac motion accounts for the variation of the heartbeat with the lung volume.

Model-based methods which use Fourier series to model the motion of the heart are generally of the form:

$$x = x_0 + \sum_{n=1}^{H_r} a_n \sin(n\omega_r t) + b_n \cos(n\omega_r t) + \sum_{n=1}^{H_c} c_n \sin(n\omega_c t) + d_n \cos(n\omega_c t), \quad (3)$$

where x_0 is the mean position, ω_r and ω_c are the respiratory and cardiac frequencies, H_r and H_c are the number of respiratory and cardiac harmonics, and a_n , b_n , c_n , and d_n are the Fourier series parameters. Various methods are used to fit this model to data online including Fourier Linear Combiners (FLC) and Weighted Fourier Linear Combiners (WFLC) which use a least squares method to fit the model [18]. Other implementations use an Extended Kalman Filter (EKF) to fit the model [7], [19]–[21]. A major advantage of these methods is their ability to adapt to changes in the frequency of the physiological cycles directly by including them in the state vector.

Unlike the methods presented here, our purpose is to predict the current physiological phases and not to predict future motion; however, the approaches to these problems are similar. There currently does not appear to be any work attempting to solve this particular problem, likely due to the distinctive approach and hardware specific to the HeartLander robot.

IV. Methods

Two different methods are taken to solve the phase estimation problem. Because of the two distinct approaches, model-based and model-free, in the related work, two approaches based on these methods are compared here: one which uses sliding window vectors, and one which uses Fourier series to model the motion of the heart. In each case, though, the basis of the problem remains the same, in that the deformation of the heart consists of two sources: respiration and heartbeat. Thus the current location of the heart at respiration phase ϕ_R and cardiac phase ϕ_C , $x(\phi_R, \phi_C)$, is composed of a base location, x_0 , plus components due to respiration, $x_R(\phi_R)$, and cardiac motion, $x_C(\phi_C)$.

$$x(\phi_R, \phi_C) = x_0 + x_R(\phi_R) + x_C(\phi_C) \quad (4)$$

In order to learn each respective component to this form, the signal must be deconstructed into the two components, which are assumed to be independent. As previously mentioned, the respiration component of motion is the low-frequency disturbance, while the cardiac component is the higher-frequency disturbance. A frequency analysis of the deformation is shown in Fig. 3. In the power spectrum the first harmonic of the respiration motion occurs at 0.23 Hz, while the first harmonic of cardiac motion occurs at 1.31 Hz. Other peaks in the power spectrum correspond to higher harmonics of each motion. In order to separate and isolate each of the components, the respiration component is learned, then subtracted from the signal, leaving only the cardiac component.

In order to isolate the respiration component of motion, and due to the fact that in training we have access to future states, the raw signal is zero-phase-lag filtered using a second order Chebyshev low pass filter with a cutoff frequency of 0.8 Hz. This filter removes the high-frequency cardiac component, leaving only the respiration component. Using the ground truth labels for respiration phase at each point, each respiration cycle can be extracted from the raw time series, as shown in Fig. 4(a). From these cycles the respiration component of motion, $x_R(\phi_R)$, can be learned.

Using the previously learned respiration motion, $x_R(\phi_R)$, the motion due to the heartbeat can be isolated by subtracting the respiration motion from the raw signal. Then using the ground truth cardiac phase labels, each cardiac cycle can be extracted from the time series, as shown in Fig. 4(b). From these cycles the cardiac component of motion, $x_C(\phi_C)$, can be learned.

In the model-free approach the components of motion are represented using vectors, while in the model-based approach a functional form is assumed and fit to the extracted cycles. Because of the different representations, the ways in which they determine the current phases are different. The different approaches are described in the following sections.

A. Model-Free Method

In this method, no functional form is assumed for the deformation of the heart. Using the isolated components of motion templates for each of the signals take the form of vectors

$$T_R = [x_R(-1), x_R(-1 + \delta\varphi_R), \dots, x_R(1)]^T \quad (5a)$$

$$T_C = [x_C(0), x_C(\delta\varphi_C), \dots, x_C(1)]^T, \quad (5b)$$

where $\delta\varphi_R$ and $\delta\varphi_C$ are discretizations of the phase angles which control how dense each template is sampled. In the current implementation, the values in the templates, $x_R(\varphi_R)$ and $x_C(\varphi_C)$, are assumed to be the mean of all cycles seen in the training data. These templates then represent the mean respiration and cardiac motions over each of their respective phase.

With these templates we wish to label the current phases in real time. In order to do this the current location must be described using a sliding window of previously seen data. Like previously described, the vector describing the current timestep, X_t , is a sliding window of the previous data:

$$X_t = [x_t, x_{t-1}, \dots, x_{t-(N_R-1)}]^T, \quad (6)$$

where N_R is a parameter that must be chosen such that the vector, X_t , contains as close to a complete respiration cycle as possible. An example of extracting a sliding window vector is shown in Fig. 5. Points are sampled such that the length of the sliding window is the same length as the template.

In order to determine the current respiration phase, the current sliding window, X_t , is compared to the respiration template, T_R . The respiration template, as previously stated, corresponds to a respiration phase of 1. In order to span the entire phase range, the template is shifted by $\delta\varphi_R$ through the entire phase range, such that the template matrix, TM_R , is defined as:

$$TM_R = [T_R, T_R(\delta\varphi_R), \dots, T_R(n\delta\varphi_R)], \quad (7)$$

where each column is a shifted version of T_R corresponding to phase shifts of $\delta\varphi_R$ spanning the entire range of phases. The phase value of the current sliding window, X_t , is determined using 1-NN to the template matrix, TM_R . The distance metric, d , used to determine the nearest neighbor can be either cross-correlation, which takes the form:

$$d = TM_R^T X_t, \quad (8)$$

where the nearest neighbor is chosen by maximizing the distance metric, or, alternatively, Euclidean distance, given by:

$$d(i) = (TM_R(i) - X_t)^T (TM_R(i) - X_t), \quad (9)$$

where the nearest neighbor is determined by minimizing the distance metric. Both methods were investigated with similar results. After the current respiratory phase is determined the template corresponding to that phase is then subtracted from the current sliding window, leaving only the cardiac component.

In order to label the current cardiac phase, a second sliding window vector is then extracted from the previous sliding window vector, less the respiration component. Because the cardiac cycle is shorter than the respiration cycle, the sliding window vector, X_t , will contain multiple cardiac cycles. Labeling cardiac phase proceeds in a manner exactly the same as respiration phase labeling, using the cardiac motion template, T_C .

B. Model-Based Method

In this method, the respiration and cardiac motions are assumed to be Fourier series. The current location, x , is then a function of respiration motion, $x_R(\phi_R)$, and cardiac motion, $x_C(\phi_C)$,

$$x_R(\phi_R) = \sum_{n=1}^{H_R} a_n \cos(n\phi_R + \psi_{Rn}) \quad (10a)$$

$$x_C(\phi_C) = \sum_{n=1}^{H_C} b_n \cos(n\phi_C + \psi_{Cn}), \quad (10b)$$

where H_R is the number of respiration harmonics, H_C is the number of cardiac harmonics, and $a_n, \psi_{Rn}, b_n, \psi_{Cn}$ are the Fourier series parameters. The parameters of the model are learned from the extracted cardiac cycles using nonlinear regression. Similar to previous work, 2 harmonics are used for the respiration model, while 5 are used for the cardiac motion [7].

With the parameters of the models learned from training data, the models may be used to estimate the current phase in test data. An Extended Kalman Filter (EKF) is used to dynamically estimate the current respiration and cardiac phases. The states describing the model are given by:

$$\begin{bmatrix} \phi_{Rk+1} \\ \phi_{Ck+1} \\ \omega_{Rk+1} \\ \omega_{Ck+1} \\ x_{0k+1} \end{bmatrix} = \begin{bmatrix} \phi_{Rk} + \omega_{Rk} dt \\ \phi_{Ck} + \omega_{Ck} dt \\ \omega_{Rk} \\ \omega_{Ck} \\ x_{0k} \end{bmatrix} \quad (11)$$

The measurement model of this model is given by:

$$x_k = x_{0k} + \sum_{n=1}^{H_R} a_n \cos(n\phi_{Rk} + \psi_{Rn}) + \sum_{n=1}^{H_C} b_n \cos(n\phi_{Ck} + \psi_{Cn}) \quad (12)$$

Using the given motion model and measurement model the EKF recursively estimates the states of the system. Implicit in the EKF framework is that the noise in the system is Gaussian. Note that this framework is able to estimate the frequency of the system, making it robust to changes in frequency.

V. Experiments

Position data from live animal experiments were used for testing of the previously described methods. Position data of the robot placed on the anterior, posterior, and right and left lateral walls, each approximately 120 s in length and sampled at 100 Hz, were split into training and test data, with a continuous half of each series being used for training and the remainder for testing.

In training the cardiac and respiration cycles were extracted using the ground truth phase labels. Using all of the training cycles respiration and cardiac templates were learned for the model free approach, while Fourier series parameters were learned for the model based approach.

Using the model free approach the templates were then used to estimate the respective phases in both training in testing. The distance metrics used were Euclidean distance for respiration, and correlation for cardiac motion. Using the model-based method and EKF, the learned Fourier series parameter were used to estimate the respective phases in both training and testing. Representative results are shown in Fig. 6, while full results are shown in Table I. Inspection of the results shows that both methods are quite successful at estimating the physiological phase. The model based approach performs better in predicting cardiac phase than the model-free approach, while the inverse is true for respiration phase.

VI. Discussion

The model-free method uses a 1-Nearest Neighbor approach to estimate the phases, while the model-based approach uses an Extended Kalman Filter (EKF) to recursively estimate the current phase based on the current measurement. While these approaches are different, the results for the two methods are similar. They are both able to accurately estimate the current physiological phases.

Work is ongoing on the methods presented. A major motivation for the work is to use the phase estimation in mapping the surface of the heart. At this time not enough data is available to cover the entire the surface of the heart and to make this approach general to the entire heart. Collection of such data is of the utmost importance in order to learn how the parameters of the model-based approach change over the surface of the heart, or to generate enough templates such that the model-free approach generalizes.

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References

1. Falk V, Diegler A, Walther T, Autschbach R, Mohr FW. Developments in robotic cardiac surgery. *Curr Opin Cardiol.* Nov.2000 15:378–387. [PubMed: 11198619]
2. Bebek O, Cavusoglu M. Intelligent control algorithms for robotic-assisted beating heart surgery. *IEEE Trans Robot.* Jun; 2007 23(3):468–480.

3. Cuvillon L, Gangloff J, de Mathelin M, Forgione A. Toward robotized beating heart TECABG: Assessment of the heart dynamics using high-speed vision. *Comput Aided Surg. Sep; 2006* 11(5): 267–277. [PubMed: 17127652]
4. Yuen SG, Kettler DT, Novotny PM, Plowes RD, Howe RD. Robotic motion compensation for beating heart intracardiac surgery. *Int J Rob Res. Oct; 2009* 28(10):1355–1372. [PubMed: 20436927]
5. Patronik N, Ota T, Zenati M, Riviere C. A miniature mobile robot for navigation and positioning on the beating heart. *IEEE Trans Robot. Oct; 2009* 25(5):1109–1124. [PubMed: 20179783]
6. Patronik N, Ota T, Zenati M, Riviere C. Synchronization of epicardial crawling robot with heartbeat and respiration for improved safety and efficiency of locomotion. *Int J Med Robotics Comput Assist Surg.* in press.
7. Wood N, Moral del Agua D, Zenati M, Riviere C. Position estimation of an epicardial crawling robot on the beating heart by modeling of physiological motion. *IEEE/RSJ Int Conf on Intelligent Robots and Systems. Sep.2011* :4522–4527.
8. Shechter G, Resar J, McVeigh E. Displacement and velocity of the coronary arteries: cardiac and respiratory motion. *IEEE Trans Med Imag. 2006; 25(3):369–375.*
9. Pan J, Tompkins W. A real-time QRS detection algorithm. *IEEE Trans Biomed Eng. 1985; 3:230–236.* [PubMed: 3997178]
10. Chen SY, Guan Q. Parametric shape representation by a deformable NURBS model for cardiac functional measurements. *IEEE Trans Biomed Eng. Mar; 2011* 58(3):480–487. [PubMed: 20952325]
11. Park, K.; Metaxas, D.; Axel, L. *Int Conf Medical Image Computing and Computer Assisted Intervention*, ser *Lecture Notes in Computer Science*. Vol. 2878. Springer; Berlin/Heidelberg: 2003. A finite element model for functional analysis of 4d cardiac-tagged MR images; p. 491-498.
12. Suinesiaputra A, Frangi A, Kaandorp T, Lamb H, Bax J, Reiber J, Lelieveldt B. Automated detection of regional wall motion abnormalities based on a statistical model applied to multislice short-axis cardiac MR images. *IEEE Trans Med Imag. Apr; 2009* 28(4):595–607.
13. Bogatyrenko E, Pompey P, Hanebeck U. Efficient physics-based tracking of heart surface motion for beating heart surgery robotic systems. *J Comput Assisted Radiology and Surgery. 2011; 6:387–399.*
14. Richa R, Poignet P, Liu C. Deformable motion tracking of the heart surface. *IEEE/RSJ Int Conf on Intelligent Robots and Systems. Sep.2008* :3997–4003.
15. Bader T, Wiedemann A, Roberts K, Hanebeck U. Model-based motion estimation of elastic surfaces for minimally invasive cardiac surgery. *IEEE Int Conf on Robotics and Automation. Apr. 2007* :2261–2266.
16. Ortmaier T, Groger M, Boehm D, Falk V, Hirzinger G. Motion estimation in beating heart surgery. *IEEE Trans Biomed Eng. Oct; 2005* 52(10):1729–1740. [PubMed: 16235658]
17. Franke T, Bebek O, Cavusoglu M. Prediction of heartbeat motion with a generalized adaptive filter. *IEEE Int Conf on Robotics and Automation. May.2008* :2916–2921.
18. Thakral, A.; Wallace, J.; Tomlin, D.; Seth, N.; Thakor, N. *Int Conf Medical Image Computing and Computer Assisted Intervention*, ser *Lecture Notes in Computer Science*. Vol. 2208. Springer; Berlin/Heidelberg: 2001. Surgical motion adaptive robotic technology (S.M.A.R.T): Taking the motion out of physiological motion; p. 317-325.
19. Yuen S, Novotny P, Howe R. Quasiperiodic predictive filtering for robot-assisted beating heart surgery. *IEEE Int Conf on Robotics and Automation. May.2008* :3875–3880.
20. Richa R, Bo APL, Poignet P. Motion prediction for tracking the beating heart. *IEEE Int Conf Engineering in Medicine and Biology Society. Aug.2008* :3261–3264.
21. Richa R, Bo A, Poignet P. Beating heart motion prediction for robust visual tracking. *IEEE Int Conf on Robotics and Automation. May.2010* :4579–4584.

Fig. 1.
The HeartLander robot.

(a)

(b)

Fig. 2.
 (a) Position data of the HeartLander robot on the surface of the heart and (b) ground truth physiological phase values.

Fig. 3.
Frequency analysis of heart deformation.

Fig. 4.

Using the ground truth phase labels the respiration and cardiac motion may be isolated and separated.

Fig. 5.
Example of sliding window vector extraction.

Fig. 6.

Representative results of (a) model-free and (b) model-based results. Respiration phase is shown in the upper plots while cardiac phase is shown in the lower plots. The ground truth values are shown in blue and red respectively, while the predicted values are in green. Error is shown in black.

TABLE I

Error in physiological phase estimation¹

		Cardiac		Respiration	
		Mean	Std.	Mean	Std.
Model-Free	Training	-2.0	10.0	0.1	2.0
	Test	-1.0	10.0	-0.1	1.5
Model-Based	Training	-0.3	10.0	-3.0	5.0
	Test	0.7	7.0	3.0	3.5

¹ Units are percentage of a cycle.