

Sensor Guided Ablation Procedure of Left Atrial Endocardium

Hua Zhong¹, Takeo Kanade¹, and David Schwartzman²

¹ Computer Science Department, Carnegie Mellon University, USA

² University of Pittsburgh Medical Center, USA

Abstract. In this paper, we present a sensor guided ablation procedure of highly motile left atrium. It uses a system which automatically registers the 4D heart model with the position sensor on the catheter, and visualizes the heart model and the position of the catheter together in real time. With this system clinicians can easily map the motile left atrium shape and see where the catheter is inside it, therefore greatly improve the efficiency of the ablation operation.

1 Introduction

Recent years have witnessed an expanding need for percutaneous, endocardium-based cardiac interventions, including ablation, injection, and device deployment. These interventions are generally not focal, but rather involve a broad region of endocardial anatomy. This anatomy is complex topographically, as well as motile. Current modalities for real-time intraoperative endocardial imaging and navigation are highly inaccurate, which has been the cause of procedure inefficacy and complications. In the present paper, we will focus on catheter ablation of left atrial endocardium. This procedure is performed in an attempt to cure atrial fibrillation, a common heart rhythm disorder. The left atrium has the attributes noted above - complex topography and motility. At present, the ablation procedure is performed by attempting to "register" preoperative four-dimensional imaging data (derived from computed tomography) with two-dimensional intraoperative imaging data (derived from intracardiac echocardiography and fluoroscopy) using the mind's eye. This is laborious, highly operator-dependent (which prohibits dissemination) and inaccurate. To the clinician, the optimal situation would be one in he/she were "injected" into the operative environment with automatic registration, such that endocardial intervention would be akin to painting a wall (left atrial endocardium) with a brush (ablation catheter). When painting a wall, complex topographical hurdles (eg. molding on the wall, windows, light switches) are not a problem, because of real-time feedback provided by direct visualization of the paint target. Motion of the room could be easily overcome by registering the motion of the room with that of the painter.

To realize such a goal, the system should be able to visualize the dynamic shape of left atrium and together with real time updated catheter position. Currently GE's Litespeed CT scanner can provide up to 10 3D CT scan of

heart during one cardiac cycle. Assuming the changes in shape of left atrium repeat from one cardiac cycle to another, this one cycle heart scan is sufficient to capture the dynamic shape of left atrium. With such CT scan (3D + time), we can reconstruct a 4D heart shape model. Besides, currently available magnetic tracking systems (CARTO and NOGA from Biosense) can track position of catheter tip in real time synchronized with ECG signals. However the heart model and magnetic tracking systems are working independently now. Our task is to automatically register the magnetic tracking system with the 4D heart model, and visualize the result to facilitate the ablation procedure.

In [1] a registration system (HipNav) of position sensors and CT/MRI scans for bones has been introduced. In [2] 3D MRI models are built to navigate in hearts. In our case we have to use a 4D model to represent motile heart shape. Our registration problem then becomes 4D as well. [3] introduced a 4D registration method for two MR image sequences. Our problem is also a 4D registration but for 4D points and 4D surface models. In section 2 we will show how to do a space time registration and in section 3 we will show experiment results which validate our system’s correctness. Also we will discuss how we can take advantage of this 4D property of both model and points to make the registration even easier and more robust than 3D shape registration.

2 Sensor Guided Ablation Procedure

To register the heart model with the magnetic position sensor, we first need to collect some points which are on the inner heart wall of left atrium with magnetic tracking system. We call these points ”*constraint point set*”. Then our system will find a transformation function F which aligns these points to the 4D heart model so that all the points are on the inner heart wall of the model. We also need to align the time axis. Next we will describe our method step by step.

2.1 4D Heart Model Reconstruction from CT

CT scan is proceeded one day before the operation assuming the heart shape won’t change within one day. We use GE’s CT scanner which can generate a 3D heart scan at every 10% of a cardiac cycle, and totally 10 3D CT scans for one cardiac cycle. Left atrium is then segmented out manually. We extract the surface model from the segmented CT data using Marching Cube(MC) algorithm. The extracted surface should represent the inner heart wall. We remove the small floating parts by discarding all triangles except those in the largest connecting group of the model. Then we smooth the model based on geometry cues with an implicit integration method [4].

Each 3D surface model extracted from CT data corresponds to a time $t \in [0, 1)$ (suppose $t = 0$ is at the beginning of a cardiac cycle and $t = 1$ is at the end of a cardiac cycle) in a cardiac cycle when the CT was scanned. In the rest of the paper, we use $C = \{C_0, C_1, \dots, C_{n-1}\}$ to represent the 4D heart model, n is the number of 3D models for one cardiac cycle. In our example we capture a 3D CT scan at every 10% of a cardiac cycle, we can extract $n = 10$ surface

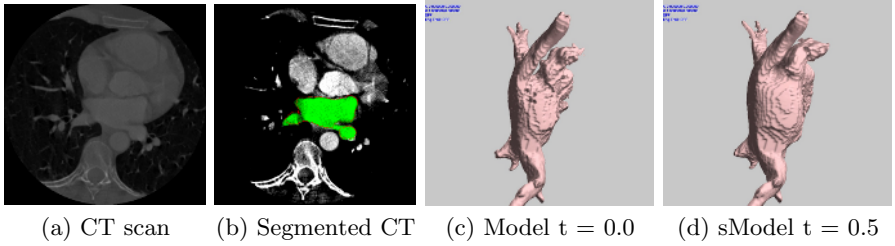


Fig. 1. CT scan and 4D Heart Model of a patient. It contains 10 3D models for one cardiac cycle.

models $C = \{C_0, C_1, \dots, C_9\}$ where each model C_i represents the heart shape at time $t = i/10, i = 0, 1, \dots, 9$. This process is shown in Figure 1.

2.2 Constraint Point Set Collection

At the beginning of the operation, the clinician needs to capture 20-30 points spread on the inner heart wall with magnetic position sensor (Figure 2(b)). During this step, another catheter with intracardiac echocardiography sensor, which can generate 2D ultrasound images as shown in Figure 2(a) in real time, is used to verify the touching of ablation catheter tip on the inner heart wall. The magnetic tracking system can be setup to capture points at 10 evenly distributed time spots within a cardiac cycle as the CT scan, so each captured point will have a time coordinate of $t = 0, 0.1, \dots, 0.9$. We group those points with same time coordinates together (though they may be captured in different cardiac cycles). Then all the recorded points can be organized into 10 groups: $P = \{P_0, P_1, \dots, P_9\}$. P can be thought as a 4D point set.

2.3 Registration

Initial Registration. Space initial registration can be done in a coarse-to-fine scheme. First a rough alignment can be found based on the orientation of

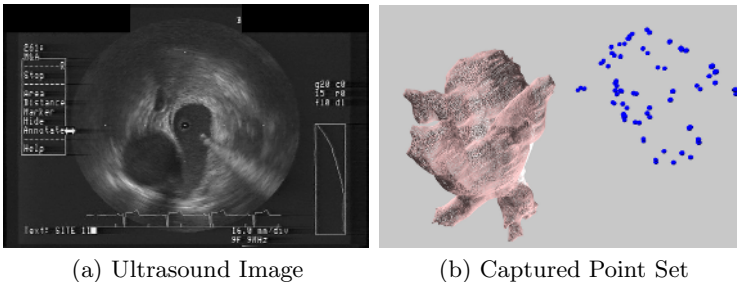


Fig. 2. Constraint Point Set. (a) Ultrasound image with the ablation catheter tip visible in it. Clinicians can verify if the ablation catheter tip is touching the heart wall. (b) A set of captured points (blue dots) at $t = 0.0$. They are not aligned with the heart model yet.

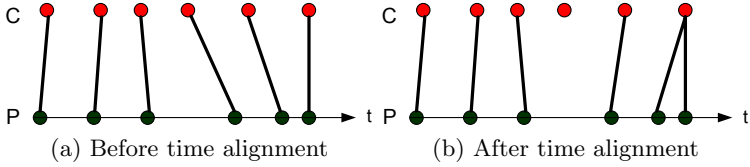


Fig. 3. Time Alignment. Upper row represents models, lower row represents point sets. x axis represents time. (a) Initial time alignment, we assume it’s simple one-on-one correspondence. (b) The best correspondence scheme will be found after time alignment.

the patient on the bed. This rough alignment can be further refined by some points captured on some designated regions of the heart. These regions should be easy to locate solely from ultrasound images, such as the entrance region of pulmonary veins. Then we find an alignment so that these points are near the same regions in the heart model as where we know they are captured. Other information such as where the catheter enter the left atrium and some inside points can also help to eliminate global alignment ambiguities. If we define the registration error as the average distance from the real positions of constraint points from their calculated positions, the initial alignment should be able to reduce this error to approximate 10-20mm.

Time registration equals to a correspondence scheme S which tells for any point set P_i in P which C_j in C is its correspondence according to time. We know that we captured heart model $C = \{C_0, C_1, \dots, C_9\}$ and points $P = \{P_0, P_1, \dots, P_9\}$ both at $t = 0, 0.1, \dots, 0.9$. Ideally the time registration should be P_i corresponds to C_i for any i . In reality, the heart model is synchronized to ECG signal one day before the operation during CT scan, while the magnetic tracking system is synchronized to ECG signal during the operation, and under the operation conditions, sometimes the patient’s heart beat rate is not stable, then this one-on-one correspondence of C_i with P_i may not be true. This problem will be more noticeable if we have more CT scans in one cardiac cycle in the future, for example 100 3D models instead of 10. So time alignment is necessary (Figure 3). For initial time registration, we just use the correspondence scheme of P_i to C_i for any $i \in [0, 9]$.

Space Registration. Under a given correspondence scheme S , the space registration is to find a transform function F (rotation and translation) for P so that the average distance from each point in each transformed point set $F(P_i)$ to its corresponding model C_j is minimized. We use a modified Iterative Closest Points [5] algorithm for space registration. Different from original ICP, here during each iteration, when we try to find each constraint point’s nearest point on the model, for any P_i , we only find nearest points from its corresponding model C_j , called P_{i_near} . And then we use $P = \bigcup_i P_i$ and its nearest point sets $P_{near} = \bigcup_i P_{i_near}$ to find the transformation function for that iteration.

To accelerate, we use K-D tree structure for nearest neighbor searching. And we add random perturbation of the registration result use it as a new initializa-

tion and run the ICP again for multiple times to avoid local minimum. To reduce side effects of outlier points, we use a trimmed ICP with 95% of the points [6].

Space Time Registration. Under a given space registration F , the correspondence scheme can be decided by: for any P_i, C_j which has the least average distance from all the points in $F(P_i)$ to C_j is its corresponding model. But now we fall into a dilemma: to register time, we need to know the space registration; to register space, we need to know time registration (correspondence scheme).

To solve this problem, an EM algorithm is proposed assuming errors have a gaussian distribution. We take the correspondence scheme S as a hidden variable. The EM algorithm finds a space transformation function F and a time correspondence scheme S that maximize the expectation of log likelihood of $p(F(P)|S, C)$. The probability $p(F(P)|S, C)$ can be defined as

$$p(F(P)|S, C) = \prod_i p(F(P_i)|C_{si}) = \prod_i (\exp(-||F(P_i), C_{si}||)) \quad (1)$$

Here C_{si} is the corresponding model for P_i defined by scheme S . Each $p(F(P_i)|C_{si})$ can be defined as an exponential function of the average distance from every point in $F(P_i)$ to model C_{si} , which is written as $||F(P_i), C_{si}||$. With this definition, the EM algorithm is:

Initial Alignment: We first use simple correspondence scheme of P_i to C_i , and calculate a space registration based on this initial time registration (with the help of other initial registration methods described before). This is our initial space registration F^0 .

E step: At iteration k , given the spatial registration of iteration $k - 1$: F^{k-1} , the probability of each possible correspondence scheme S can be calculated using the following formula:

$$p(S|F^{k-1}) = a^{-1}p(F^{k-1}(P)|S, C)prior(S) \quad (2)$$

where a^{-1} is a normalization constant. $p(F^{k-1}(P)|S, C)$ is similar as the probability in Equation 1. $prior(S)$ is the prior probability of each scheme S . We set $prior(S)$ to be very low or zero for schemes S that map P_i to a C_j where $||i - j||$ is large. From now we use term $p(S)$ to represent the probability in Equation 2.

M step: With $p(S)$ known, we can find a F^k that maximizes the expectation of log likelihood:

$$\arg \max_{F^k} \sum_S p(F^k(P)|C, S)p(S) \quad (3)$$

Maximizing Equation 3 equals to minimizing a weighted distance function

$$\arg \min_{F^k} \sum_S \sum_{i=1}^{m=10} ||F^k(P_i) - C_{si}||p(S).$$

This distance function can be minimized similarly with our modified ICP algorithm. Only difference is here we need to combine the P and its nearest point set P_{near} under different correspondence scheme S with weight $p(S)$.

EM stops: when the registration improvement from F^k to F^{k-1} is less than a given threshold or a certain number of iterations has been reached whichever becomes true first. Time registration S is then computed based on the final space registration F^k .

2.4 Visualization of Ablation Procedure

After registration, the heart model and catheter position can be displayed together in real time: input catheter position in magnetic tracking system coordinate (x, y, z, t) will be transformed to model’s coordinate $(F(x, y, z), S(t))$. The “beating” rate of the heart model is also synchronized with ECG signal from patient. Clinicians can setup a virtual camera anywhere in the space to monitor the whole ablation procedure. The procedure therefore is like a simple “painting the room” job (Figure 4).

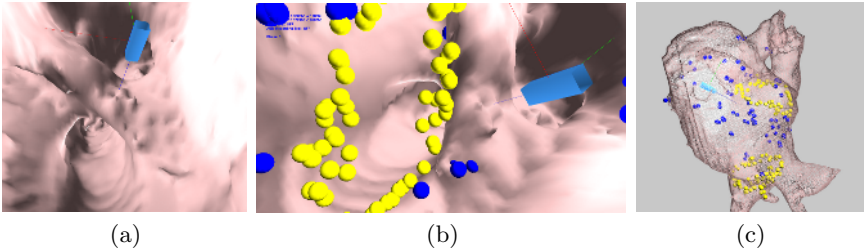


Fig. 4. Visualization (a) view of the catheter from inside left atrium. (b) view of ablation sites(yellow) together with constraint points(blue). (c) view from outside the left atrium.

3 Results and Discussion

3.1 Patient Data Test

To validate our system, we test it with a real patient’s data. The CT scan’s resolution is $512 \times 512 \times 116 \times 10$ (X×Y×Z×time). Voxel size is X: 0.48mm per voxel, Y: 0.48mm per voxel, Z: 0.625mm (or 1.25mm) per voxel, time: 10% of a cardiac cycle(Figure 1). We use CARTO system by Biosense to track the catheter position (1mm average error). CARTO can capture position at the beginning of each cardia cycle. So here the points we have is $P = P_0$ (Figure 2(b)). We collect 76 constraint points to do the registration: for every location, we recorded two points both at $t = 0$. Then the clinician proceeded the ablation procedure *without* our system’s help and recorded all the ablation sites. Our system then mapped where those ablation sites are based on registration. The correctness of registration is verified by the clinician who knows where those

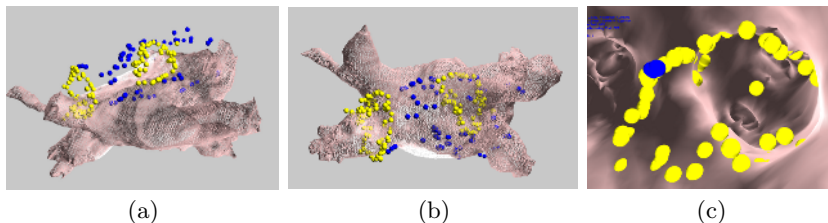


Fig. 5. Patient data test (a) Initial alignment (intentionally deteriorated to test robustness). (b) Outside view of the registration result. Yellow points are ablation sites. They are correctly mapped to the pulmonary veins entrance regions. (c) Inside view, these points are right on the surface.

ablation sites should be mapped to. The registration error is: 1.6347mm. This result may vary from case to case because of different heart shape and CT scan quality. Results are shown in Figure 5.

3.2 4D Registration Versus 3D Registration

To fully exploit the information of a 4D heart model, we record constraint points in such a way: we move the catheter to touch the heart wall, stay on the wall for a cardiac cycle, and record all 10 positions $p = \{p_0, \dots, p_9\}$ at time $t = 0, 0.1, \dots, 0.9$, generally $p_i \neq p_j$ if $i \neq j$ because the heart is beating. We can call p a 4D point. After we record one 4D point, we actually add one 3D point to each point set P_i , $i = 1$ to 10. No extra efforts are necessary to capture one 4D point than a 3D point. To demonstrate how 4D points can improve registration performance, we did the following experiments. For a 4D heart model of a patient, we simulate the collection of constraint points, both 4D points and 3D points (3D points are all recorded on model C_0). And we use a random transformation F_r to transform the points away from the heart model. F_r has 0–30 degree of rotation and 0–20mm of translation. Then we use our algorithm to find registration transformation F which maps points back to the surface model. We define the error as the average of $\|v - F(F_r(v))\|$ for every vertex v of the heart model. The result is shown in Figure 6. As we can see, 4D point registration achieves same registration accuracy with fewer constraint points than 3D point registration in our test. The spatial distribution of constraint point set is random but same for 3D and 4D points.

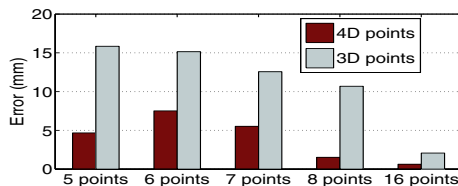


Fig. 6. Constraint point number vs registration error. For each item, we run the registration test for several times and the average error is shown here.

3.3 Speed Performance

Usually 15-30 seconds are needed for clinicians to record one constraint point, 2 minutes or less are needed for registration. With the automatic registration and visualization system, the whole procedure time can be greatly reduced.

4 Conclusion

In this paper, we described a new left atrial endocardium ablation procedure with automatic 4D registration and visualization. Registration for static objects (bones) can be thought as a subset of our registration problem. Promising results have been shown. Although the registration problem is far from totally solved, we believe 4D registration is the way we should go. In the future, we will focus on more lab animal tests to further verify and quantify the accuracy of 4D registration. Then more real patient tests will be done.

References

1. Gioia, D., etc.: Hipnav: Pre-operative planning and intra-operative navigational guidance for acetabular implant placement in total hip replacement surgery. In: Computer Assisted Orthopaedic Surgery Symposium. (1995)
2. Lardo, A., etc.: Mr guided radiofrequency ablation: Creation and visualization of atrial lesions. In: presented at International Society for Magnetic Resonance in Medicine, Sixth Scientific Meeting. (1998)
3. Dimitrios Perperidis, R.M., Rueckert, D.: Spatio-temporal free-form registration of cardiac mr image sequences. In: MICCAI. (2004)
4. Desbrun, M., Meyer, M., Schröder, P., Barr, A.H.: Implicit fairing of irregular meshes using diffusion and curvature flow. *Computer Graphics* **33** (1999) 317–324
5. Besl, P.J., McKay, N.D.: A method for registration of 3-d shapes. In: *IEEE Trans. Pattern Analysis and Machine Intelligence*. (1992) 14:239–256
6. Chetverikov, D., Stepanov, D.: Robust euclidean alignment of 3d point sets. In: *First Hungarian Conference on Computer Graphics and Geometry*. (2002) 70–75