FAST TRACKING OF CATHETERS IN 2D FLUOROSCOPIC IMAGES USING AN INTEGRATED CPU-GPU FRAMEWORK

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ABSTRACT

Catheter tracking has become more important in recent interventional applications for atrial fibrillation (AF) ablation procedures. It can provide real-time guidance for the physicians and be used for motion compensation by overlaying a 3D left atrium model on live 2D fluoroscopic images. To achieve that, this paper has two main contributions. We first propose a new approach to generate tracking hypotheses based on catheter electrode detection. The novelly-designed tracking hypotheses are evaluated by a Bayesian-framework that fuses learning-based detection and template matching. The second contribution is a novel integrated framework that efficiently distributes computation between a GPU (graphics processing unit) and a CPU. Our framework implements Probabilistic Boosting-Tree (PBT)-based [7] classification for object detection in 2D data on the GPU. Quantitative evaluation has been conducted on a databases of 1073 clinical fluoroscopic sequences. The new framework achieves robust performance with the median error at 0.5mm and the 95^{th} percentile error at 1.0mm. The speed of tracking the coronary sinus (CS) catheter reaches more than 30 frames-per-second (fps) on most evaluation data. The achieved speed is faster than most real-time fluoroscopy frame rates.

Index Terms— catheter localization, object tracking, GPU, atrial fibrillation, ablation procedure

1. INTRODUCTION

Atrial fibrillation (AF) is a rapid, highly irregular heartbeat caused by abnormalities in the electrical signals generated by the atria of the heart. AF is one of the most common cardiac arrhythmia and involves the two upper chambers of the heart. Surgical and catheter-based therapies have become common AF treatments throughout the world [4]. Catheter ablation modifies the electrical pathways of the heart in order to treat the disease and the procedures have recently attracted research [5, 8, 3]. To measure electrical signals in the heart and assist the operation, three catheters including ablation, coronary sinus (CS) and circumferential mapping catheters, are inserted and guided to the heart. The entire operation is usually monitored with real-time fluoroscopic images. The integration of static tomographic volume renderings into 3D catheter tracking systems has introduced an increased need for mapping accuracy for the AF procedures. The ability to update the 3D model in real time enables catheter navigation. Current technologies concentrate on gating catheter position to a fixed point in time within the cardiac cycle. Accurate and fast tracking of catheters during the AF ablation procedures may lead to accurate model overlay by compensating respiratory motion. In this paper, we proposes a new tracking hypothesis generation method in a novel integrated CPU-GPU framework and focus its application to fast tracking of the CS catheter electrodes in 2D fluoroscopic images. Figure 1 illustrates examples of catheters commonly used in AF ablation procedures in fluoroscopic images.

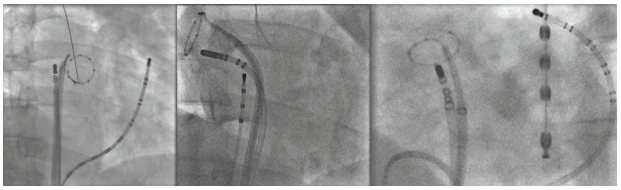


Fig. 1. Examples of catheters used in AF ablation procedures in fluoroscopic images.

2. CATHETER ELECTRODE TRACKING

Our approach represents the CS catheter as an ordered set of electrodes starting from the tip. Z denotes image observation, C denotes a catheter model, and T_C denotes a set of coordinates and associated image intensity values, called the catheter template. Subscript t denotes t-th frame. Assume E electrodes on the catheter, $\{e^i, i = 1, ..., E\}$. Figure 2 illustrates the proposed framework. The CS catheter is manually initialized in the first frame. In the *Model building* step the catheter template, T_C, is initialized using the clicked electrodes and catheter shape. *Tracking at each frame* consists of four steps: learning-based catheter tip and electrode detection, a new pair-of-electrodes-based hypothesis generation, hypothesis evaluation by a Bayesian formula, non-rigid model deformation using the Powell's method [6]. The pro-

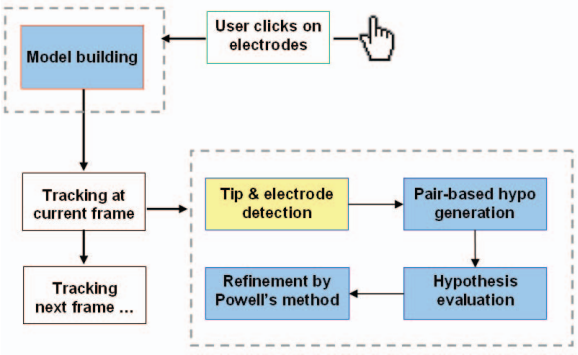


Fig. 2. The proposed catheter tracking framework.

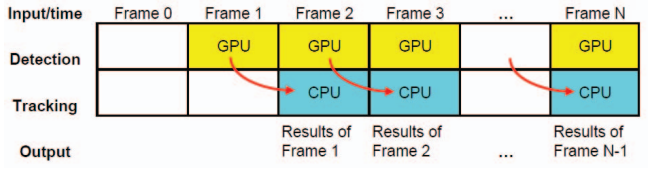


Fig. 3. The proposed integrated CPU-GPU computation framework.

posed framework is different from our previous method [8] in two aspects: 1) a new hypothesis generation method and 2) a novel CPU-GPU tracking framework. We describe the first aspect in the following and the second one in Section 3 and 4.

During tracking, our method first applies Probabilistic Boosting-Tree (PBT)-based [7] catheter tip and electrode detectors on the image. Our method obtains K electrode candidate positions, $\{d_k, k = 1, ..., K\}$, after non-max suppression. The proposed hypothesis generation works as follows. For each unique pair of detected electrodes, d_{kl}, our approach generates E hypotheses by translating the i-th electrode to d_k. For each hypothesized combination, it computes the affine parameters (scale and rotation) which best fit d_{kl} and e^{ij}. The procedure is as follows. For the i-th electrode, it finds another electrode, j-th, so that the vector, e^{ij}, has an acute angle and minimum length difference from d_{kl}. It then computes the rotation angle, θ_{kl}^{ij}, between d_{kl} and e^{ij} and applies θ_{kl}^{ij} rotation transformation of e^{ij} to obtain the rotated electrode vector e_R^{ij}. It next computes the scale parameters S_x^h, S_y^h from e_R^{ij} to d_{kl}. Using the set of computed θ_{kl}^{ij} and S_x^h, S_y^h our method applies affine transformation on T_C to generate the tracking hypotheses.

The above hypothesis generation is novel and different from our previous method [8], which generates the tracking hypotheses by translating each e^i to each d_k and then applying affine transformation to generate the hypotheses. Here we give a comparison of two hypothesis generation schemes. Assume the previous method manipulates rotation and skew only, and rotation parameters have R candidate values and skew parameters have S candidate values. The previous method generates $E \cdot K \cdot R \cdot S$ hypotheses. For instance, to search from -45 to 45 degree rotation at 2 degree step size, we have $R = 46$. And to search the skew from -0.2 to 0.2 at 0.1 step size, we have $S = 5$. There are $E{\cdot}K{\cdot}230$ hypotheses. In contrast, the proposed approach generates $E \cdot K \cdot (K-1)$ hypotheses. The actual number of hypotheses is even smaller than this since some hypotheses in which electrodes are too far away or close to each other are removed. Assume $K = 9$, the number of hypotheses generated by the new approach is $E \cdot K \cdot 8$, which is 29 times less than the number of hypotheses generated by the previous method. The decrease of hypothesis number gives much increased tracking speed. The new method would miss the ground truth hypothesis when only one or none electrode on the catheter was detected. The probability of this happening is significantly low given robustness of PBT-based electrode detectors [8]. The spirit of using a subset of detected electrode candidates to generate tracking hypotheses applies to using triplets or other numbers of electrode candidates.

An effective tracking hypothesis evaluation method is necessary to determine the exact position and shape of the CS catheter. We apply a Bayesian framework to evaluate catheter tracking hypotheses. The overall goal for evaluating a tracking hypothesis is to maximize the posterior probability such as $\hat{C}_t = \arg\max_{C_t} P(C_t|Z_{0...t})$. By assuming a Markovian representation of catheter motion the formula is expanded as: $\hat{C}_t = \arg\max_{C_t} P(Z_t|C_t)P(C_t|C_{t-1})P(C_{t-1}|Z_{0...t-1})$. The formula combines two elements: the likelihood term, $P(Z_t|C_t)$, which is computed as combination of detection probability and template matching score, and the prediction term, $P(C_t|C_{t-1})$, which captures the catheter motion. To maximize tracking robustness, the likelihood term $P(Z_t|C_t)$ is estimated by combining tip and electrode detection and catheter body template matching as follows:$P(Z_t|C_t) = P(E_t^*|C_t) \cdot P(T_C|C_t)$ and E_t^* is estimated probability measure about electrodes and tips at t-th frame. The detection term $P(E_t^*|C_t)$ is defined in terms of a part model by combining the detection score at the catheter tip and other electrodes. $P(T_C|C_t)$ is the intensity cross-correlation between the catheter template and C_t.

To refine tracking results locally, we apply Powell's method [6] to find the hypothesis with the locally maximum confidence score. The method maximizes the catheter model's probability score by a bi-directional search along each affine parameter search direction in turn. The algorithm iterates a number of times until no more improvement are possible. Similar to [8], the catheter template, T_C, is updated online and for catheters which have more than 8 electrodes, a multi-part tracking method is applied.

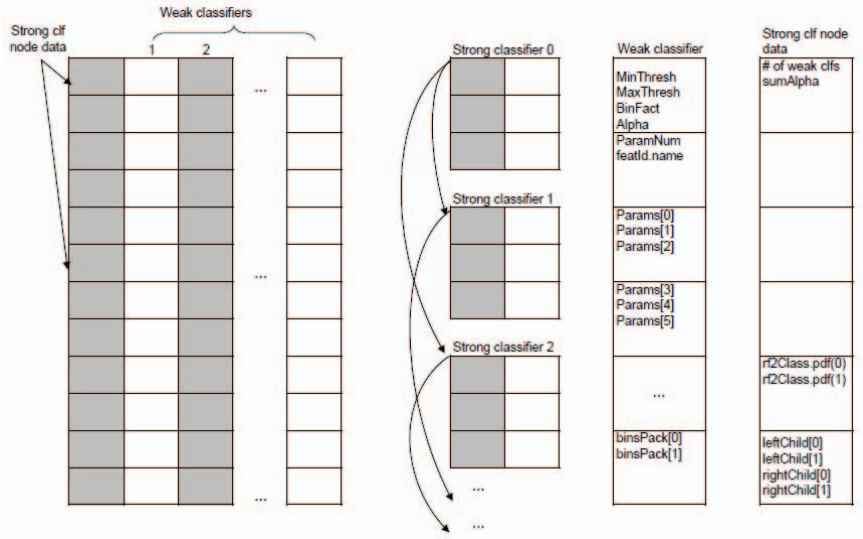


Fig. 4. Implementation of the PBT classification for 2D data on a GPU.

3. A CPU-GPU TRACKING FRAMEWORK

The use of one or many GPUs to perform general purpose scientific and engineering computing has been demonstrated in numerous applications. In our application, we focus on a real-time online tracking system, in which at each time (the interval depends on the fluoroscopy frame rate) our system receives a new fluoroscopic image or two in a biplane system. The scenario of one-frame fluoroscopic data arriving from the X-ray machine at each time is challenging to fully take advantage of the GPU's many-core computation capability because of lack-of-large-amount-of-data. To address the issue, we propose a novel integrated CPU-GPU computation framework, illustrated in Figure 3, to maximize the computation distribution among the CPU and the GPU. In the figure, the red arrows depict the data flow between frames. At the k-th frame, the framework assigns the GPU to perform catheter tip and electrode detection, and the CPU to perform catheter electrode tracking using the detection results of the $(k-1)$-th frame. By doing this, the framework keeps both the CPU and the GPU occupied at any time. The approach delays the output of tracking results by one-frame interval. For example, in a 7.5 fps biplane acquisition mode, the delay is 133ms, which can usually be accepted in clinical settings. Figure 2 shows the computation distribution in the tracking framework, where the yellow block indicates catheter tip and electrode detection by the GPU and the blue blocks indicate computation done by the CPU.

4. ELECTRODE DETECTION ON A GPU

Learning-based methods have demonstrated their strong capabilities to effectively explore object content and context in numerous applications such as segmentation, detection and tracking. The catheter tips and electrodes are detected as points (x, y), which are parameterized by their position, using trained PBT classifier [7]. The classifiers use Haar features in a centered window of size $H \times H$. Each classifier outputs a probability. During classifier training, we apply the bootstrapping strategy to effectively remove the false alarms. There are two stages for individual electrode detection. The first stage is trained with target electrodes against randomly selected negative samples. The second stage is trained with the target electrodes against the false positives predicted by the first stage detector.

Figure 4 illustrates the implementation of the PBT classifier in the GPU texture memory, which include the strong classifier node data and the weak classifier data. During detection, the PBT kernel is launched and executed on the GPU device by many thousands of threads, each of which takes one candidate image position as input. The GPU texture memory spaces reside in GPU device memory and are cached in texture cache, so a texture fetch or surface read costs one memory read from device memory only on a cache miss, otherwise it just costs one read from texture cache. The texture cache is optimized for 2D spatial locality, so threads of the same warp that read texture or surface addresses that are close together in 2D will achieve best performance [1]. Reading device memory through texture, which is advantage of our implementation of the PBT classifier on the GPU, thus becomes an advantageous alternative to reading device memory from global or constant memory. Birkbeck et al. recently proposed PBT implementation for classification, pose detection and boundary detection on a GPU [2] and we have applied it with 2D feature extraction for catheter electrode detection on the GPU.

5. RESULTS

A database of 1073 fluoroscopic sequences, which were collected from electrophysiology AF ablation procedures with many different catheter tracking scenarios, is used for evaluation. The image resolutions are 1024×1024 with pixel spacing 0.1725 or 0.183 mm/pixel. The CS catheter electrode and tip detectors are trained from 5103 frames annotated manually. For all evaluation sequences, we have annotated the catheter electrodes in the first frame and a number of randomly selected frames. The annotation in the first frame is regarded as the user initialization. The algorithm tracks the catheter in the remaining frames. Tracking errors are computed as the average 2D Euclidean distance in millimeter(mm) from the ground truth electrode locations to the results in each frame.

Table 1 summarizes the tracking performance by the previous method on the CPU [8] and the proposed CPU-GPU framework using the new hypothesis generation method. The table reports the frame errors at the median, the 75^{th} (p75), 80^{th} (p80), 85^{th} (p85), 90^{th} (p90) and 95^{th} (p95) percentiles. The table shows two clear observation: 1) both methods achieve robust performance with the median error at 0.5mm and the 95^{th} percentile error at 1.0mm; 2) the proposed CPU-GPU framework obtains consistent tracking accuracy as the CPU-based tracking method [8]. The tracking speed of the proposed CPU-GPU framework with the new hypothesis generation method reaches faster than 30fps on most CS catheter data on a workstation with dual processor (Intel(R) Xeon(R) CPU E5440) and an NVIDIA Quadro FX 5600. The speed is much faster than most fluoroscopy real-time frame rates and the speed improvement is significant compared to [8]. Our proposed framework gives great potential to real-time tracking of multiple catheters for AF ablation procedures in live fluoroscopic images.

6. CONCLUSION

Tracking catheters in the fluoroscopic data is a challenging task due to constant cardiac and respiratory motion and data variation. However, the task is very relevant to clinical procedures since it can provide useful and real-time motion information which can enable many clinical applications. This paper presents a new hypothesis generation method in a novel integrated CPU-GPU framework to track catheters and its application to CS catheter tracking in AF ablation fluoroscopic data. The novelty and superior results of the proposed framework differentiates itself from existing approaches and the proposed framework is also generic and can be applied to track other kinds of devices.

	median	p75	p80	p85	p90	p95
CPU	0.5	0.6	0.7	0.7	0.8	1.0
CPU-GPU	0.5	0.7	0.7	0.8	0.8	1.0

Table 1. Summary of the CS catheter tracking performance. Frame errors (mm) are at the median, the 75^{th}, 80^{th}, 85^{th}, 90^{th} and 95^{th} percentiles.

7. ACKNOWLEDGEMENT

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8. REFERENCES

[1] NVIDIA CUDA C Programming Guide, Version 3.2. 2010.

[2] N. Birkbeck, M. Sofka, and S. Zhou. Fast boosting trees for classification, pose detection, and boundary detection on a gpu. In *CVPR Workshops, Seventh IEEE Workshop on Embedded Computer Vision*, 2011.

[3] A. Brost, W. Wu, M. Koch, A. Wimmer, T. Chen, R. Liao, J. Hornegger, and N. Strobel. Combined cardiac and respiratory motion compensation for atrial fibrillation ablation procedures. In *MICCAI*, 2011.

[4] H. Calkins and et al. HRS/EHRA/ECAS expert consensus statement on catheter and surgical ablation of atrial fibrillation: recommendations for personnel, policy, procedures and follow-up. a report of the heart rhythm society (hrs) task force on catheter and surgical ablation of atrial fibrillation. *Heart Rhythm*, 4, 2007.

[5] Y. Ma, A. King, N. Gogin, C. Rinaldi, J. Gill, R. Razavi, and K. Rhode. Real-time respiratory motion correction for cardiac electrophysiology procedures using image-based coronary sinus catheter tracking. In *MICCAI*, 2010.

[6] M. Powell. An efficient method for finding the minimum of a function of several variables without calculating derivatives. *Computer Journal*, 1964.

[7] Z. Tu. Probabilistic boosting-tree: Learning discriminative models for classification, recognition, and clustering. In *ICCV*, 2005.

[8] W. Wu, T. Chen, A. Barbu, P. Wang, N. Strobel, S. Zhou, and D. Comaniciu. Learning-based hypothesis fusion for robust catheter tracking in 2D X-ray fluoroscopy. In *CVPR*, 2011.