Guide-wire Detecting Using a Modified Cascade Classifier in Interventional Radiology

Li Wang, Xiao-Liang Xie, Zhan-Jie Gao, Gui-Bin Bian and Zeng-Guang Hou

Abstract— **Endovascular surgery is becoming a widespread procedure to treat cardiovascular diseases (CVDs) such as abdominal aortic aneurysm and peripheral artery disease. The guide-wire is a crucial surgical instrument inserted into vessels to offer guidance to physicians during the surgery. There are some approaches for tracking the guide-wire, most algorithms consist of two phases, namely, the initialization phase and the tracking phase. In the initialization phase, most algorithms use B-splines for modeling the guide-wire which requires manually annotated data. In the tracking phase, the guide-wire motion is non-linearity because it is deforming and changing its shape and size as a result of patients' respiration, some algorithms decompose the non-linearity motion into rigid motion and non-rigid motion, while the computational complexity is high especially for the non-rigid motion. This paper mainly presents an approach to detect the guide-wire. The algorithm has two main advantages. First, without modeling the guide-wire, this approach uses a cascade classifier which can detect the guide-wire under arbitrary motion automatically. Second, by taking the guide-wire motion direction into consideration, the detection accuracy improves significantly. The presented work has been validated on a test set of 349 frames, and the mean tracking accuracy achieves more than 95% which proves the effectiveness of the proposed method.**

I. INTRODUCTION

Cardiovascular diseases (CVDs) such as abdominal aortic aneurysm and peripheral artery diseases are worldwide killers especially to the old, endovascular surgery is a widely used method to treat the diseases instead of long-recovery-time open-heart surgery. The main task of the surgery is to thread medical tools to the intervention situs [1]. During the surgery, physicians rely on their 3-D knowledge of anatomical structures with the guidance of haptic feedback, and the visual feedback using imaging modalities such as X-ray images. The X-ray images offer instant visual feedback when the tools are maneuvered through the patient's body towards the desired situs. So the navigation, namely detecting and tracking the medical tools to get their positions in X-ray images, is crucial for a successful surgery [2]. However, there are many challenges in reducing surgery time and improving the safety because of the regular exposure to radiation, lack of automatic tracking of the medical tools and so on. The navigation especially the guide-wire detection becomes a challenging task. Firstly, as a consequence of low energy of X-ray used during the surgery to reduce patients' X-ray radiation, the signal-to-noise ratio (SNR) of the images is low, so the guide-wire can be hardly distinguished from the cluttered backgrounds with the influence of bone and organ interfaces. Furthermore, the guide-wire is thin and 1-D structure, it deforms and changes its shape and size with patients' motion and the interaction of physicians, the motion of the guide-wire is non-linearity [3]. It is challenge to detect the guide-wire. Here is a review of some approaches for detecting and tracking the guide-wire. (a) Frame difference method [4], the disadvantage of the method is that when the displacement of the guide-wire in two adjacent frames is too small or the interval time between two adjacent frames is too short, it can only get some discrete points of the guide-wire and cannot extract the full guide-wire; (b) Kalman filtering method, the drawback is that it assumes a stationary patient without breathing in order to be able to establish the background estimation, while it is not consistent with the actual conditions; (c) Background subtraction method [5], it depends on the background model which needs to be real-time updated, while the scene is complex and unpredictable, so it is difficult to achieve the motivation. The detection accuracies of above methods are showed in Fig. 2. In comparison, this paper proposes a detecting method which is based on a modified cascade classifier. It needs to train a cascade classifier using LBP feature firstly, then adopt the classifier in [6] to detect the guide-wire. Based on one simple assumption that the motion direction of guide-wire is steady, the algorithm gets a robust result with detection speed achieves 8 frames per second and the mean detection accuracy achieves 95%. While the detecting speed remains need to improve.The remainder of the paper is organized as follows. Section II gives a brief introduction about the cascade classifier and the detailed description of the improved approach. Section III gives a through show of the detection results. Section IV is a conclusion of the proposed approach.

II. THE METHOD

A. LBP feature

Local Binary Pattern (LBP) [7] [8] operator is used to describe the local image texture feature. The LBP value of a pixel reflects the relationship between the pixel and its surrounding pixels. The original LBP operator is defined in a 3 by 3 window, setting the center pixel value as the threshold, then comparing it with its neighbors' pixel value, if the neighbor' pixel value is greater, marking the corresponding

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neighbor value as 1, otherwise 0. Thus, the eight neighbors' value makes up a binary, then converting the binary into a decimal number which is considered as the LBP value of the center pixel. The LBP feature has significant advantages such as rotation invariance and gray invariance. It is a widely used feature to describe the differences between the target and the background.

B. AdaBoost algorithm

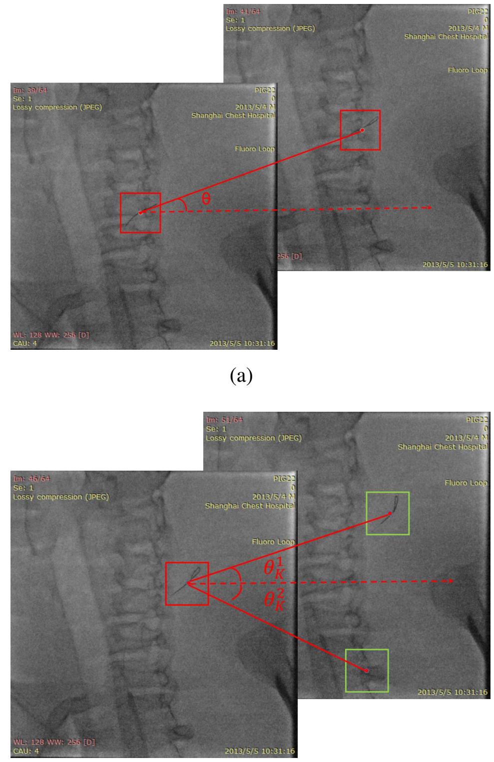
Adaptive Boosting (AdaBoost) is an iterative algorithm which is derived from Boosting [9]. It is focused on those samples which are difficult to be classified correctly. A new weak classifier is added each round until the detection accuracy reaches the required. It solves two main problems: (a) How to process samples; (b) How to combine weak classifiers together. It is a very efficient and flexible learning method which is easy to be trained and can avoid over-fitting phenomenon. Please follow [10] for more details.

C. Cascade structure

In an image, the target is considered as the positive sample and the background is considered as negative sample. In the cascade structure [11], amount of classifier is in series, when detecting the samples, only the ones detected by the previous levels of classifiers and those be considered as the positive samples will be detected by the next level classifier, otherwise considering them as the negative samples. The previous levels can accurately reject majority negative samples which have big differences with the target. Actually, a large number of samples are negative samples, so most samples will be rejected by previous levels of classifiers, only a small amount of samples need to go through all classifiers. So the cascade structure can greatly reduce the computation cost and shorten the computation time.

D. Improved algorithm

- Improved algorithm
  By using the cascade classifier, some noises can be rejected, but some structures which have high similarity with the guide-wire are not so easy to be rejected. An improved algorithm is proposed based on a simple assumption that the motion direction of the guide-wire is stable in each sequence. Relaying on the motion direction, the modified classifier can reject these structures which are highly similar to the guide-wire and move off the guide-wire motion direction can obtain robust detection result with great computational efficiency. The principle is showed in details in Fig. 1.
- Pseudo-code
  The pseudo-code is showed in **Algorithm 1**. The guide-wire motion direction angle is defined as the angle between the center line of the correct rectangles in the initial two frames and the horizontal direction



(a)

(b)

Fig. 1. The improved algorithm principle.(a) is the 1th and 2th frames,(b) is the kth and $(k+1)$th frames. The red rectangles are annotated manually, the green ones are the detection results.

III. RESULTS

The experimental platform is OpenCV [12]. The proposed method is evaluated on totally 349 X-ray images obtained by GE C-arm during animal (pig) testing of our developed in interventional robot in [13]. The frame size of each sequence is 512 by 512. The test sequences cover a variety of guide-wire shapes and motion conditions. The detecting results consist of three phases. The experiment in Phase 1 is only on the original images. The experiment in Phase 2 is on the images with pre-processing. The Phase 3 is the improvement on the Phase 2 by considering the guide-wire motion direction. For the purpose of obtaining the guide-wire motion direction in each sequence, it needs to annotate guide-wire in the initial two frames. To evaluate the performance of the guide-wire detection method comprehensively and quantitatively, the paper adopts the detection accuracy as the evaluation standard. To get the accuracy of each phase, it needs to annotate the correct guide-wire position in all the frames. The accuracies of three phases are showed in Fig. 2.

- Phase 1
  This phase is on the original images, due to the low SNR of the images and the noises influence, the detection accuracy showed in Fig. 2 labeled Phase 1 is very low.
- Phase 2
  This phase is on the images with pre-processing which aims to reduce the influence of noises. The paper mainly uses the erosion and dilation pre-processing method [14]. TABLE I shows the detection time comparison of Phases 1 and 2. It can be concluded that the detection

Algorithm 1: Supposing there are N frames in a sequence and all the images include a guide-wire. The rectangle presents the position of the guide-wire. The correct positions of the guide-wire is annotated in the first two frames.

Computing the motion direction angle

(a) Getting the guide-wire position, namely the rectangles' coordinates of first two frames are (X_i, Y_i, W_i, H_i), and the rectangle' centers are (x_i, y_i);

(b) Computing the motion direction angle θ

$$\theta = arctan\frac{|y_2 - y_1|}{|x_2 - x_1|},$$

$$x_i = X_i + \frac{W_i}{2}, y_i = Y_i + \frac{H_i}{2}, i = 1, 2;$$

Rejecting the error rectangles

for k = 1 to N

(a) Supposing the coordinate of the rectangle which presents the correct guide-wire position in the kth frame is: (X_k, Y_k, W_k, H_k), and the center is (x_k, y_k), after detecting the $(k+1)$th frame, there are two rectangles: $(X_{k+1}^j, Y_{k+1}^j, W_{k+1}^j, H_{k+1}^j)$, and the center coordinate is: $(x_{k+1}^j, y_{k+1}^j), j = 1, 2$;

(b) Computing the angle $\theta_{k+1}^j = arctan\frac{|y_{k+1}^j - y_k|}{|x_{k+1}^j - x_k|}$,

$$x_{k+1}^j = X_{k+1}^j + \frac{W_{k+1}^j}{2}, y_{k+1}^j = Y_{k+1}^j + \frac{H_{k+1}^j}{2}, j = 1, 2;$$

(c) Analyzing the angles

if $|\theta_{k+1}^j - \theta| \geq 5°$: the rectangle is error;

if $|\theta_{k+1}^j - \theta| < 5°$: the rectangle is correct;

Marking the correct detection results

TABLE I

DETECTION TIME COMPARISON OF PHASE 1 AND 2

Time(s)	Image Sequences			
	Sequence 1	*Sequence 2*	*Sequence 3*	*Sequence 4*
Phase 1	10.463	9.456	6.986	8.201
Phase 2	7.1910	6.710	4.884	5.771
Time(s)	**Image Sequences**			
	Sequence 5	*Sequence 6*	*Sequence 7*	*Sequence 8*
Phase 1	7.645	10.001	5.889	6.002
Phase 2	5.459	6.665	4.183	3.987

time is significantly reduced after the pre-processing mainly because when using the cascade classifier to detect, pre-processing can improve the contrast ratio between the guide-wire and the backgrounds, namely, it enhances the differences of the positive samples and the negative samples. So the pre-processing can reduce the detection time and improve the detection accuracy showed in Fig. 2 labeled Phase 2.

- Phase 3

  This phase is based on the result of Phase 2. Considered an simple assumption that the guide-wire motion direction is almost stable, so the motion direction is an essential difference, the guide-wire can be distinguished with other wire-like structures. Most of the wire-like structures off the direction can be rejected automatically. The detection accuracy improves lot. The result of Phase 3 is showed in Fig. 5 and the accuracy is showed in Fig. 2 labeled as Phase 3 .

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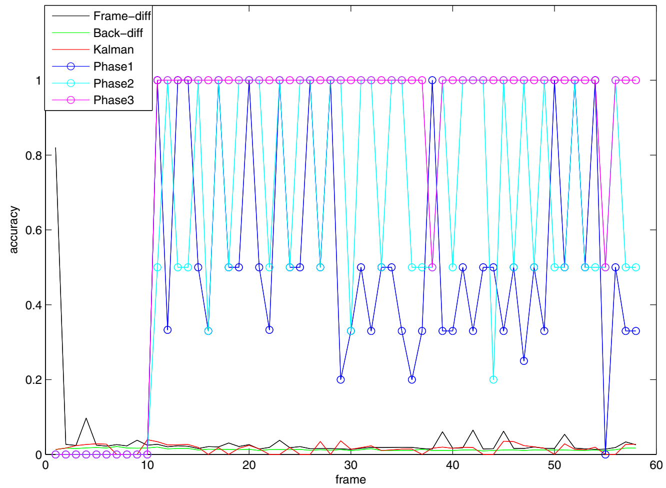

Fig. 2. The evaluation of guide-wire detectors on our datasets [?]. The approaches are ranked according to the accuracy, namely, the area overlap rate. The area overlap rate is defined as follows: after detection, if there is only one detection rectangle, then make sure whether the detection rectangle has overlap with the annotated rectangle. If it is true, then compute the overlap rate defined accuracy which $accuracy = \frac{s_i}{S_i}$, s_i is the area of the detection rectangle and S_i is the area of the annotated rectangle, if it is false, then $accuracy = 0$. While if there is more than one detection rectangle, supposing there are N detection rectangles, first, following the above method and compute the overlap rate of each detection rectangle defines acc_k, then compute the average overlap rate which $accuracy = \frac{1}{N}\sum_{k=1}^{N} acc_k$, finally considered the accuracy as the each frame detection accuracy.

IV. CONCLUSION

This paper presents a modified cascade classifier for guide-wire detection. The method can detect guide-wire under arbitrary motion automatically. and it can reject large amount of the wire-like structures by taking the guide-wire motion direction into consideration. The validation on a test set of 349 X-ray images demonstrates that the method can provide a robust detection result. It can be concluded from Fig. 2 that compared with the detection accuracy in Phase 1, the mean accuracy of Phase 2 improves from 35% to 56%. Relaying on the guide-wire motion direction, the mean accuracy of Phase 3 improves significantly and achieves 95% which demonstrates the efficiency of the proposed approach. The mentioned method is on the whole image, while the guide-wire is only in a small region, so it costs much time on the regions without the guide-wire, the next work will target on the image patches [15], then compare the detection accuracy and detection time.

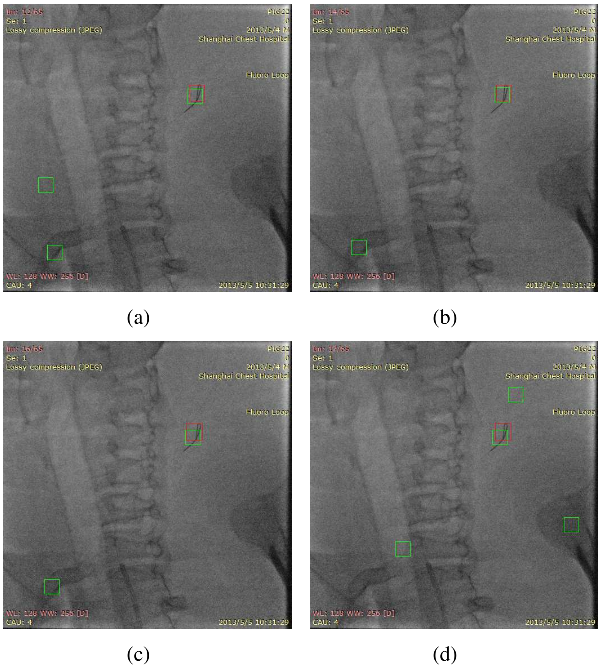

Fig. 3. Phase 1 detection result. (a)-(d) are the 12th, 14th, 16th and 17th frames. The red rectangles are annotated manually, the green ones represent detection result.

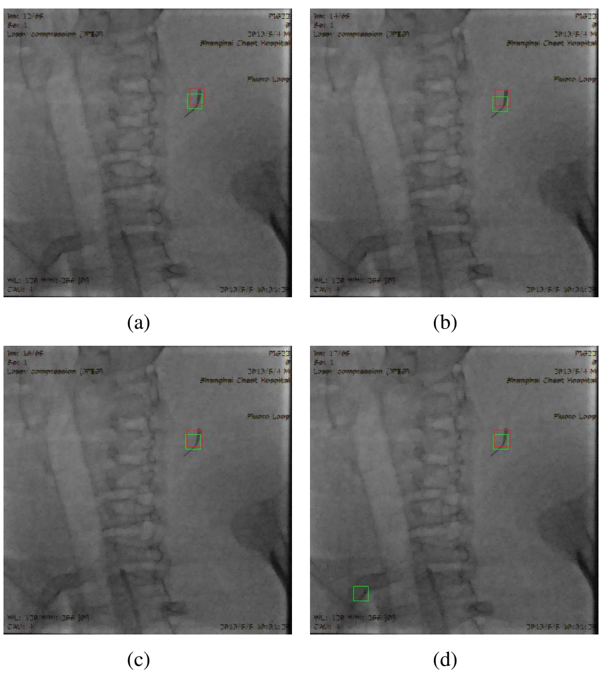

Fig. 4. Phase 2 detection result. The images are with pre-processing. (a)-(d) are the 12th, 14th, 16th and 17th frames. The red rectangles are annotated manually, the green ones represent detection result.

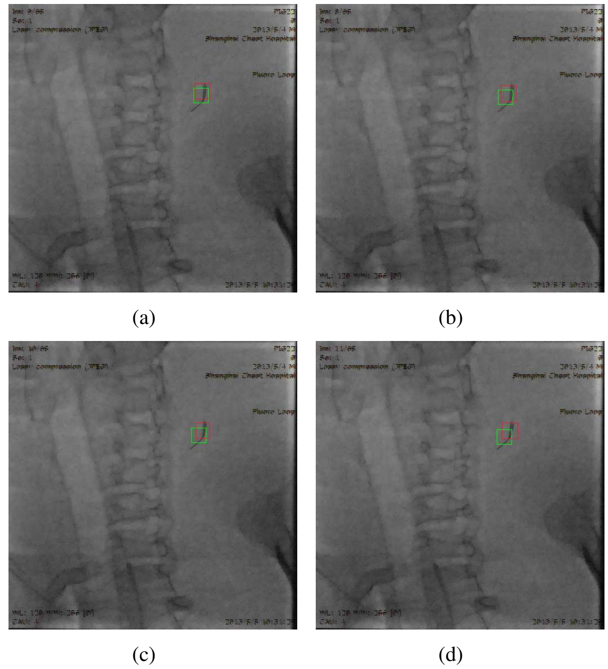

Fig. 5. Phase 3 detection. The detecting method considers the guide-wire motion direction. (a)-(d) are the 12th, 14th, 16th and 17th frames. The red rectangles are annotated manually, the green ones represent detection result.

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