Robust PCA Unrolling Network for Super-Resolution Vessel Extraction in X-Ray Coronary Angiography

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***Abstract*—Although robust PCA has been increasingly adopted to extract vessels from X-ray coronary angiography (XCA) images, challenging problems such as inefficient vessel-sparsity modelling, noisy and dynamic background artefacts, and high computational cost still remain unsolved. Therefore, we propose a novel robust PCA unrolling network with sparse feature selection for super-resolution XCA vessel imaging. Being embedded within a patch-wise spatiotemporal super-resolution framework that is built upon a pooling layer and a convolutional long short-term memory network, the proposed network can not only gradually prune complex vessel-like artefacts and noisy backgrounds in XCA during network training but also iteratively learn and select the high-level spatiotemporal semantic information of moving contrast agents flowing in the XCA-imaged vessels. The experimental results show that the proposed method significantly outperforms state-of-the-art methods, especially in the imaging of the vessel network and its distal vessels, by restoring the intensity and geometry profiles of heterogeneous vessels against complex and dynamic backgrounds. The source code is available at https://github.com/Binjie-Qin/RPCA-UNet**

***Index Terms*—Algorithm unrolling, RPCA unrolling network, X-ray coronary angiography, vessel extraction, sparse feature selection, super-resolution.**

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I. INTRODUCTION

II. Related Works

A. XCA Vessel Extraction

B. Unrolling Neural Network

h . : , , , h h . h . h . Th h - h 54 55 . h , h h . , 55 56 h h . h h h - h 57 , 58 . A h h h h h h h , h - h h h, h h . Th - , h h 59 h h h h h - h h h h h . B h h , h h h h h h h . T , h 60 - h h , - . , h CA- C A h h 1,2- . , h h h . Th , 61 h h h h- h h h h h . , h h 62 , 63 h . h h 48 , 64 h h h - , h h , h h . T h , h CA- h RPCA . - h , h h 65 , 66 .

III. Method

Th h h / CA- h . 1 RPCA

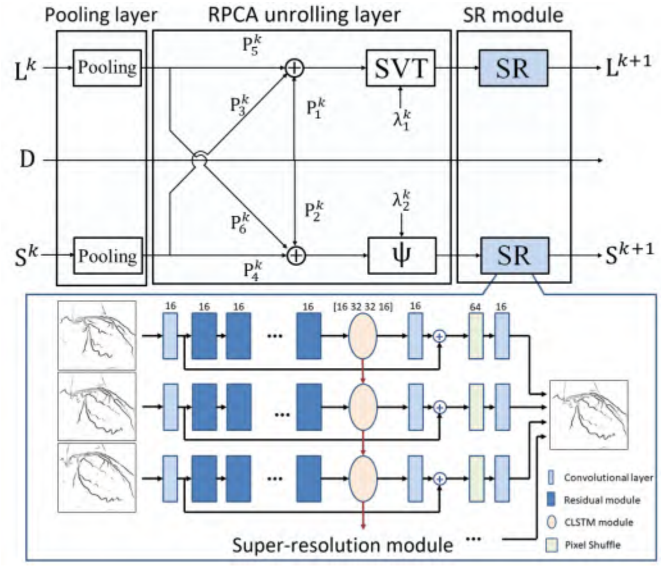

Fig. 1. The architecture of a single iteration/layer of RPCA-UNet for decomposing XCA data D into vessel (S) and background (L) components, which consists of a pooling layer, an RPCA unrolling layer, and an SR module. The SR module is mainly built upon the convolutional layer, residual module and CLSTM network.

D h ( ) ( ) . - h . h , h h CA- . , CA- h h h - - h h- h - , h h , C T .

A. RPCA Modelling

Th . Th , h - . Th , CA RPCA D :

$$\|\ \|_{*} + \lambda \|\ \|_1 \quad s.t. D = \ + \tag{1}$$

h h h , h h - , h , h h . h (h h h), $\|\ \|_1$ h 1- , λ h . Th CA h h h D 14 :

$$D = H_1 \ + H_2 \ + \tag{2}$$

h H_1 H_2 h , , h h h h h h .

(CA , $H_1 = H_2 =$), h . Th CA h :

$$\frac{1}{2} - H_1 - H_2 \;_F^2 + \lambda_1 + \lambda_2 \;_{1,2} \tag{3}$$

h $\cdot_{1,2}$ h $_{1,2}$- λ_1 λ_2 h , . Th $_{1,2}$- h h h h . h :

$$= [\;], \; _1 = \begin{bmatrix} \\ 0 \end{bmatrix}, \; _2 = \begin{bmatrix} 0 \\ \end{bmatrix}, A = \begin{bmatrix} H_1 \\ H_2 \end{bmatrix} \tag{4}$$

Th , E (3)

$$\frac{1}{2} D - A \;_F^2 + (\;) \tag{5}$$

h ( ) = $\lambda_1 \; _1 + \lambda_2 \; _2 \;_{1,2}$. Th , h (5) - , h h h - h / h h h , h h h . $^{+1}$ $^{+1}$ + 1 14

$$^{+1} = \;_{\lambda_1/} (- \frac{1}{} H_1^H H_1) - H_1^H H_2 + H_1^H D \tag{6}$$

$$^{+1} = \psi_{\lambda_2/} (- \frac{1}{} H_2^H H_2) - H_2^H H_1 + H_2^H D \tag{7}$$

h $_{\lambda_1/}$ h - h h , $\psi_{\lambda_2/}$ h - h h , h - h .

B. RPCA Unrolling Network

T h , h h h h h 15 . Th , h h h h h h . h , h H_1 H_2 (6) (7) h .

$_1, \; _2, \ldots, \; _6$ h H_1 H_2. C h h , h h h . Th , h h h :

$$^{+1} = \;_{\lambda_1} \; _5 + \; _3 + \; _1 D \tag{8}$$

$$^{+1} = \psi_{\lambda_2} \; _6 + \; _4 + \; _2 D \tag{9}$$

h . Th h h . 1. , h $_1, \ldots, \; _6$, - , λ_1 λ_2 h .

C. Patch-Wise Super-Resolution Module

CA CA h fi , h h h - CA h / . A h h h λ_1 λ_2 h h h , CA h - h h , h .

C h - h h h - 67 , h h ' . , h h h - h h h- 2 , 3 , h- h CA- .

Th h- h

$$t = t \circ t-1 + t \circ t \quad (\quad t + \quad t-1 + \quad)$$
$$t = \sigma(\quad t + \quad t-1 + \quad \circ t + \quad)$$
$$t = t \circ t \quad (t) \tag{10}$$

h * h ∘ h . Th t . Th h h , t, t, t, . Th t h h - h . Th , t h , h h h h h

, h C T h , h h h - , h h h h . h C T h h h h h h h h h . Th C T h h h h h- - CA- . , h h C T - , h h h h h h , h h CA .

D. Automatic Vessel Labelling

CA- h h CA , h h h CA- . Th , CA- - h h h - - BC h 9 , h h h h - h - . , BC CA- - . A h - h h h- . , - - h h h , . , h h CA .

IV. Experimental Results

A. Experimental Materials

43 CA h h T . Th h h 30 140 . h CA . h h . T 512 × 512 h 8 . h h h h h h , h CA- h h 800 Ah h h CA- h . Th , h h h .

B. Experiment Settings and RPCA-UNet Training

CA- 4 . Th = 5 h = 1, = 2 , h h = 3 h = 1, = 1 . h h ADA h 0.0001. h , h h - = 2 = 2 . Th h 2. CA- - - . T / h BC h 9 h 64 × 64 × 20 h h (50% h h). A 15 900 h h h 20000. Th , h - , , 0.6:0.2:0.2, . Th h h h h h h . Th h h h h / - h h / .

C. Comparison Methods

h BC 9 - - h - CA- h , h h A - CA 68 , - CA 69 , C - CA 6 C A 14 . , h h , - h h h h h , C 70 , t . 27 h h - - - 48 C 2- 71 . Th h h h h - .

D. Visual Evaluation on Experimental Results

h . 2, h h h CA- h - h (. 2( )-( )). , h h h . A h h C A (. 2( )), h h

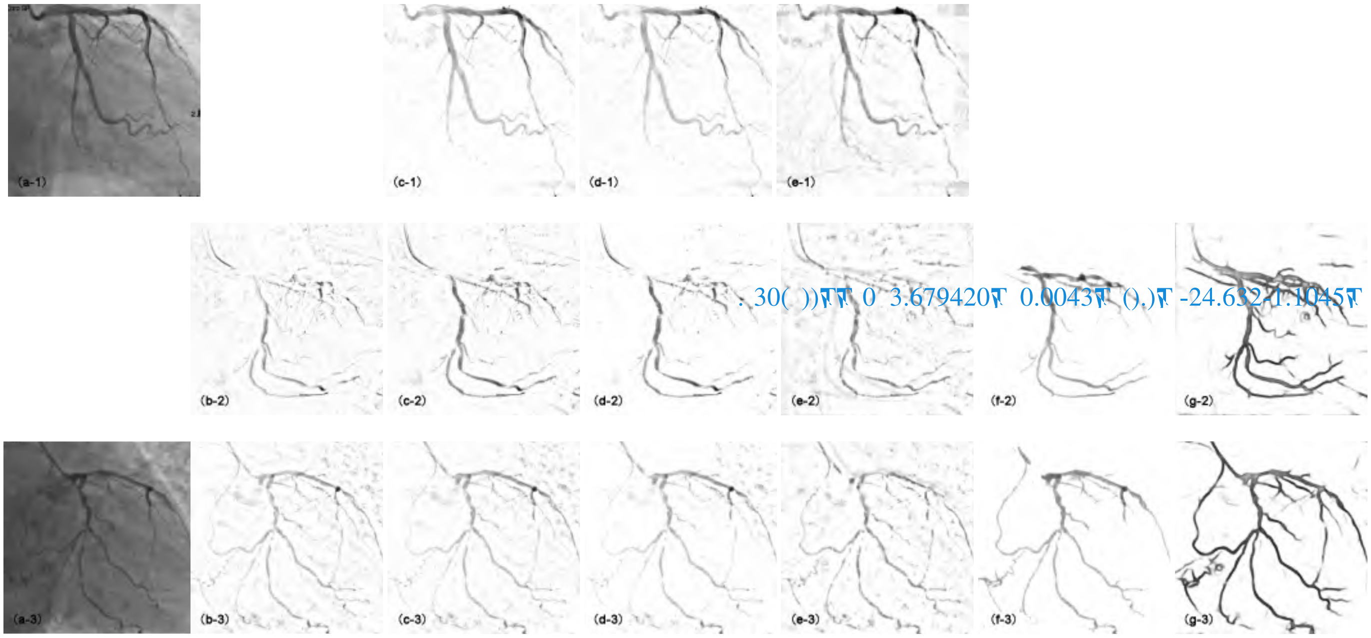

Fig. 2. XCA vessel extraction results. (a) Original XCA image; (b) ALF-RPCA; (c) MoG-RPCA; (d) MCR-RPCA [6]; (e) CORONA [14]; (f) VRBC [9]; (g) RPCA-UNet.

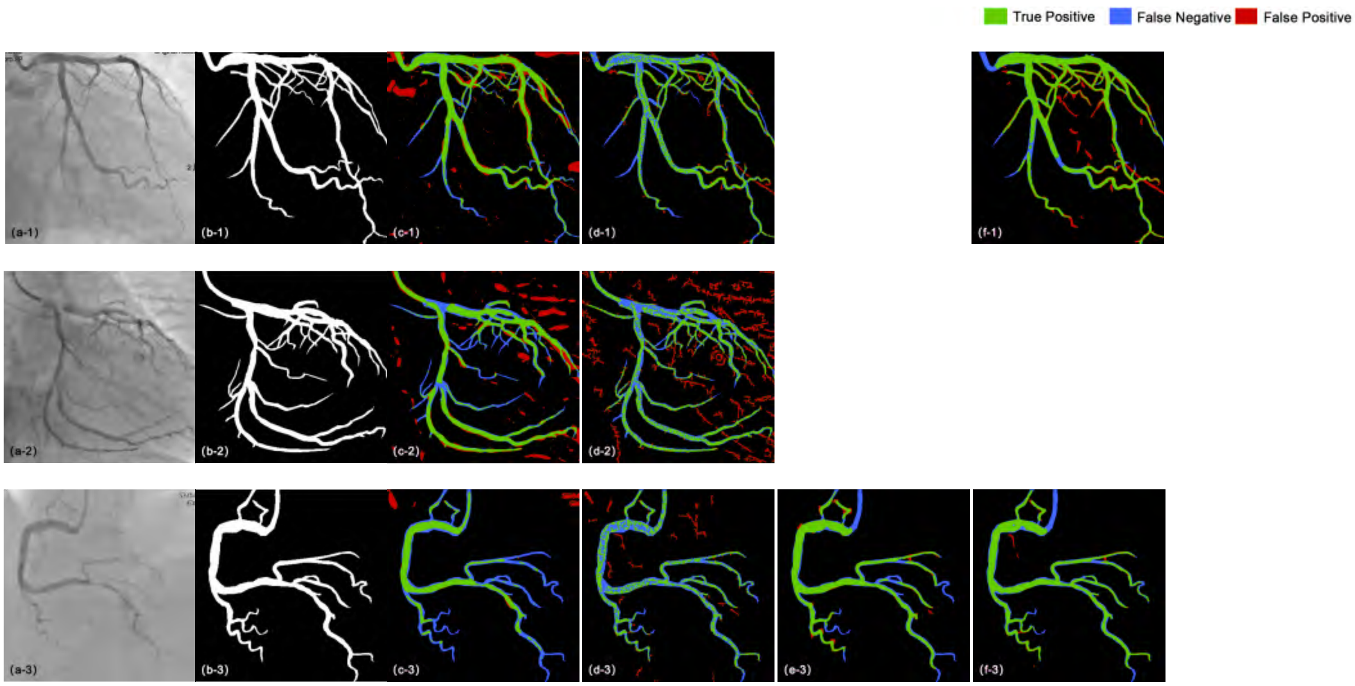

Fig. 3. XCA vessel segmentation results. Pixels labelled with green, blue, and red colours represent true positive pixels, false negative pixels, and false positive pixels, respectively. (a) Original XCA image; (b) Ground-truth vessel mask; (c) Frangi's; (d) Coye's; (e) SVS-net; (f) CS^2-Net; (g) RPCA-UNet.

TABLE I

PERFORMANCE OF DIFFERENT VESSEL EXTRACTION METHODS IN TERMS OF CNR VALUES (MEAN± STANDARD DEVIATION)

Fig. 6. The effect of coarse versus fine vessel label on the result of weakly supervised learning. The first row are the coarse and fine grey value labels automatically generated by the VRBC combined with different binary vessel mask segmentations, i.e. from left to right being original segmentation method in the VRBC, SVS-net with training data generated by the original segmentation method, SVS-net with training data by manual annotation; the second row of results are test cases of the corresponding networks trained with different grey value labels.

V. Conclusion and Discussion

Acknowledgment

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