# Layer Separation for Vessel Enhancement in Interventional X-ray Angiograms Using Morphological Filtering and Robust PCA

Hua Ma[1], Gerardo Dibildox[1], Jyotirmoy Banerjee[1], Wiro Niessen[1,2], Carl Schultz[3], Evelyn Regar[4], and Theo van Walsum[1]

[1] Biomedical Imaging Group Rotterdam, Departments of Radiology and Medical Informatics, Erasmus MC, Rotterdam, The Netherlands
h.ma@erasmusmc.nl
[2] Quantitative Imaging Group, Faculty of Applied Sciences, Delft University of Technology, Delft, The Netherlands
[3] Department of Cardiology, Royal Perth Hospital, Perth, Australia
[4] Department of Cardiology, Erasmus MC, Rotterdam, The Netherlands

**Abstract.** Automatic vessel extraction from X-ray angiograms (XA) for percutaneous coronary interventions is often hampered by low contrast and presence of background structures, e.g. diaphragm, guiding catheters, stitches. In this paper, we present a novel layer separation technique for vessel enhancement in XA to address this problem. The method uses morphological filtering and Robust PCA to separate interventional XA images into three layers, i.e. a large-scale breathing structure layer, a quasi-static background layer and a layer containing the vessel structures that could potentially improve the quality of vessel extraction from XA. The method is evaluated on several clinical XA sequences. The result shows that the proposed method significantly increases the visibility of vessels in XA and outperforms other background-removal methods.

## 1 Introduction

Percutaneous coronary intervention (PCI) is a minimally invasive procedure for treating patients with advanced coronary artery disease. It is usually performed under guidance of X-ray angiograms (XA) where coronary arteries are opacified with contrast agent. Automatic processing of XA images, e.g. vessel extraction of coronary arteries, may serve as a basis for further processing, such as coronary motion analysis [1] and pre/intra-operative information fusion [2].

Hessian-based vessel enhancement filtering, e.g. Frangi vesselness filter [3], is commonly used for extraction of vessels in medical images. Applying such filters directly on interventional XA, however, often also enhances non-vascular structures, such as catheter segments and vertebral contours, due to their tubular or curvilinear structural appearances.

Related works have reported on methods to remove non-vessel structures or improve the visibility of vessels in XA images. In [4], a method that subtracts the median frame was used for removing static structures in XA, such as vertebral bodies. Schneider et al. [5] proposed a post-processing technique on vesselness images that combines a local probability map with local directional vessel information for artifact reduction and catheter removal. Layer separation methods provide an alternative way of vessel enhancement. In [6], a multi-scale framework was developed to separate XA images into three layers based on different motion patterns such that coronary arteries are better visible in the fast motion layer. This method involves human-interactions to label corresponding control points in XA images for motion field estimation. In another study [7], a Bayesian framework was developed that combines dense motion estimation, uncertainty propagation and statistical fusion to achieve motion layer separation. Both layer separation methods require to compute motion field. Robust principal component analysis (Robust PCA) is a data decomposition technique that has e.g. been used for background modeling from surveillance video in [8]. In [9], Robust PCA was adopted for registration of DCE MR time series.

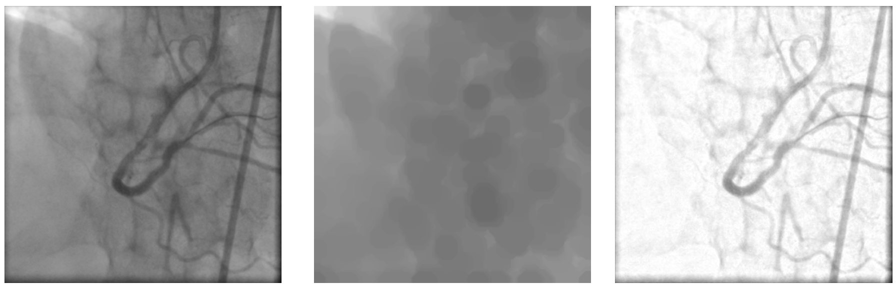
In this paper, we propose an automatic method to robustly separate foreground (contrast-enhanced vessels, guiding catheter tip) from (quasi) static background, such as vertebral bodies and guiding catheters in the aorta, while ignoring large-scale motion such as diaphragm movement. Our contributions are three folds: 1) the development of a Robust PCA based layer separation method that does not require computation of the motion field; 2) qualitative and quantitative evaluations on four clinical XA sequences; 3) comparison to other related background-removal approaches.

## 2 Method

The method enhances vessels in XA images by separating an image into three layers, i.e. a large-scale breathing layer, a quasi-static background layer and a foreground layer containing the vessels. To this end, our proposed method consists of two steps: first, separation and removal of large-scale breathing structures, such as diaphragm, from the original images, using morphological closing; second, separation of a quasi-static background from the moving structures using Robust PCA. In the remainder of this section, we describe both steps in more details, followed by the integrated layer separation.

### 2.1 Separation of breathing structures

To obtain a separate layer containing large-scale structures, we remove small objects from the original image, including guiding catheters, guide wires, stitches and vertebral bodies. Similar to the approach in [10], we apply morphological closing to the image with a circular structuring element of 8.5 $mm$ in diameter. Pilot experiments indicated that this size was adequate for a complete removal of vessels and guiding catheters from our images while not causing too much circular artifacts. An example of a resulting image is shown in Fig. 1(b). Compared to the original image, the guiding catheter and coronary arteries are removed and vertebral contours are blurred, while structures that presents respiratory motion, such as the diaphragm and lung tissue, remain in the image (white area in the upper left part of the image). The resulting image that contains large scale structures which exhibit respiratory motion is called the breathing layer, and will later be subtracted from the original image to obtain the difference image (DI, Fig. 1(c)) of an XA frame for further processing.



(a) (b) (c)

Fig. 1: Morphological closing operation on an XA image: (a) the original image, (b) image processed with morphological closing, (c) the difference image (DI) of (a) and (b).

### 2.2 Background separation using Robust PCA

Robust PCA decomposes a data matrix into two different sources: a low-rank matrix and a sparse matrix. Suppose that $M$ is an $m \times n$ matrix to be decomposed, which contains $n$ observations of $m$ dimensional data in its columns. Robust PCA is formulated as the following optimization problem [8]:

$$\begin{aligned} \text{minimize} \quad & \|L\|_* + \lambda \|S\|_1 \\ \text{subject to} \quad & L + S = M \end{aligned} \tag{1}$$

where $L$ is a low-rank matrix and $S$ is a sparse matrix of the same size as $M$. $\|L\|_*$ denotes the nuclear norm of $L$ and $\|S\|_1$ is the $L_1$ norm of $S$. $\lambda$ is the tuning parameter of regularization. Source decomposition is achieved by solving this optimization problem. In this work, we use inexact Augmented Lagrange Multiplier (ALM) method [11] to solve the problem.[1]

Robust PCA can be applied for separation of the background layer of DI from the vessel layer. The background of an XA sequence is an image series with small changes of pixel intensity containing (quasi) static structures, while the foreground, or the vessel layer, consists of moving objects. Thus, resizing the background image into a column vector and combining all these vectors from a

[1]The implementation is available at http://perception.csl.illinois.edu/matrix-rank/sample_code.html

background series together results in a low rank matrix. Likewise, the image series of vessel layer can be modeled as a sparse matrix, as either vessels or guiding catheters take up only a small part of the whole image content. Therefore, the background layer and vessel layer of DIs can be separated by solving the Robust PCA problem.

### 2.3 Image processing pipeline of XA layer separation

The proposed layer separation algorithm consists of the following steps. All steps are illustrated in Fig. 2.

1. Given an XA sequence, apply morphological closing on each frame of the series, as described in Section 2.1. For each frame, subtract the morphological-closed image from the original image to obtain the DI.
2. Rearrange the DIs of the XA sequence to construct a matrix whose columns represent the frames. This matrix is considered as the input matrix $M$ in Equation 1.
3. Solve the Robust PCA problem to obtain the background layer matrix $L$ and vessel layer matrix $S$. Resize $L$ and $S$ to get the background layer and vessel layer of the previous size for each frame of the sequence.

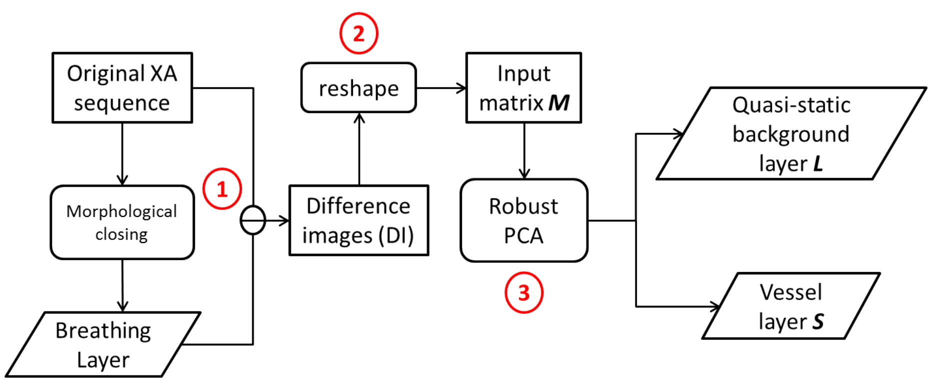



Fig. 2: The pipeline of the proposed layer separation method.

## 3 Experiments

Fully anonymized imaging data were used in our experiments. Four XA image series that were acquired with Siemens AXIOM-Artis biplane system were analyzed. The frame rate of all sequences is 15 frames per second. The number of frames per series ranges from 55 to 169. From our data, the image matrix is $512 \times 512$ pixels for one of the series and $600 \times 600$ for the other three, with resolution $0.216 \times 0.216$ and $0.184 \times 0.184$ $mm^2$, respectively.

To quantify the visibility of vessels in an image, the contrast-to-noise ratio (CNR) is used in the experiments. CNR is a measure of image quality based on contrast. Once the background and foreground of an image is defined, the definition of CNR can be formulated as:

$$CNR = \frac{|\mu_F - \mu_B|}{\sigma_B} \tag{2}$$

where $\mu_F$ and $\mu_B$ are the mean of foreground and background pixel values respectively, and $\sigma_B$ is the standard deviation of the background pixel values. This definition of CNR measures the contrast between the foreground and background pixel intensities in relation to the standard deviation of the background pixel intensities. Larger CNR values imply a better contrast.

Two different versions of CNR are computed, using two different masks for defining the foreground (vessel) and the background in XA images (Fig. 3). In mask 1, as shown in Fig. 3 column 1, a 4 *mm*-wide image area around the manually-labeled vessel centerline is defined as the foreground (the dark area inside white region); the background are its 3 *mm*-wide neighborhood area (white region surrounding the vessel). This mask can be used to assess the local contrast around vessels in XA. In mask 2, as shown in Fig. 3 column 3, everything outside the foreground is considered background, which thus also evaluates the removal of the diaphragm, guiding catheters, etc.. In our experiments, we randomly select 5 frames once from each sequence for the mask generation and compute the average CNR of the 5 frames.

We compare the performance of our approach to 3 other related methods. In [4], static background is eliminated by subtracting the median of the first 10 frames from each frame in the sequence. This method is referred to as *MedSubtract 1*. Second, we considered an advanced version of median subtraction by firstly removing the breathing layer using morphological closing and then subtracting the median. This is called *MedSubtract 2* in the experiments. Third, a conventional PCA technique is explored. The breathing layer is first removed to generate the difference image and the background layer is later reconstructed with the first principal component using PCA. This is referred to as *Normal PCA*.

For the parameter $\lambda$ in the formulation of Robust PCA, we use the value suggested in [8]. All experiments were implemented in MATLAB 2013b on an Intel Core i7-4800MQ 2.70 GHz computer with 16 GB RAM running Windows.

## 4 Results

Fig. 4 shows an example result of layer separation on one XA sequence. Note that in the original image (Fig. 4(a)), the presence of the diaphragm, the vertebral

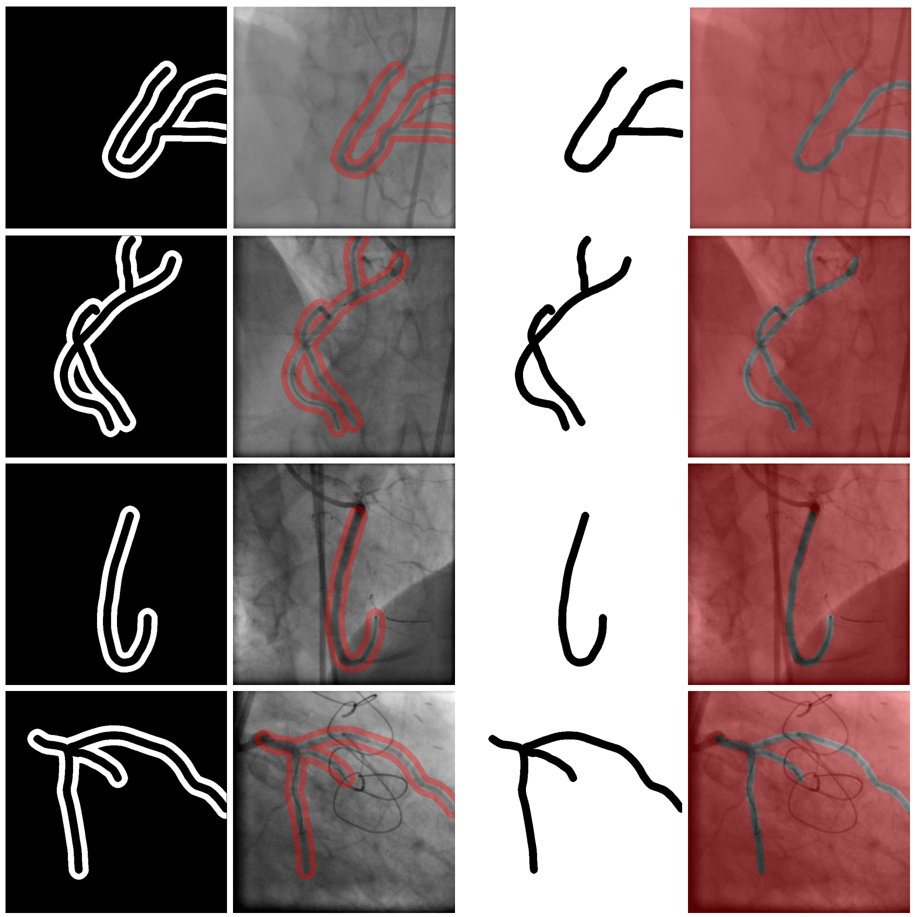
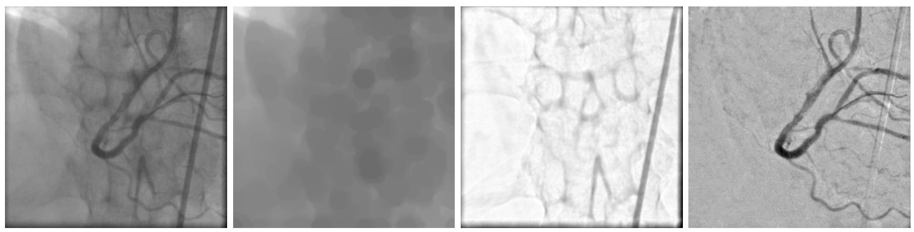


Fig. 3: Two types of mask images. Background is defined as the white image region, foreground is defined as the dark area within the white part: (Column 1) Mask 1 for one frame in the four XA sequences; (Column 2) Mask 1 overlaid on the corresponding XA frames; (Column 3) Mask 2 for one frame in the four XA sequences; (Column 4) Mask 2 overlaid on the corresponding XA frames.

structures and the long guiding catheter segment makes extracting the vessels challenging. In the vessel layer image (Fig. 4(d)), those structures are removed, and the contrast between vessels and their neighborhood pixels is larger than in the original image.

Fig. 5 presents the comparison of our proposed method (Row 5) to three



(a) (b) (c) (d)

Fig. 4: An example of layer separation: (a) the original image, (b) breathing layer, (c) quasi-static background layer, and (d) vessel layer.

other background-removal methods (Row 2-4) applied on four XA sequences. For each of the sequences, we selected a representative frame. It can be observed that all the four methods increase the visibility of vessels in XA with better contrast. However, the result of *MedSubtract 1* method (Row 2) still presents artifacts in the foreground due to the motion of diaphragm, whereas our method successfully removes the diaphragm using morphological closing. Compared to *MedSubtract 2* (Row 3) and *Normal PCA* methods (Row 4), the method based on Robust PCA performs better on removing quasi-static structures, such as the guiding catheter segment in aorta (column 1-3) and stitches (column 4).

The CNR values of XA sequences and vessel layers are illustrated in Fig. 6. Compared to the original XA, as shown in both Fig. 6(a) and Fig. 6(b), all methods improve the CNR values. For CNR 1, when only local contrast around vessels is measured, *Robust PCA* method performs better than the other approaches for patient 1 and 2, but has slightly lower CNR than *Normal PCA* for patient 3 and 4. In the case that the removal of diaphragm and guiding catheter is considered, as what CNR 2 indicates, *Robust PCA* is superior in all four patients.

## 5 Discussion and Conclusion

We have developed an automatic method for layer separation of interventional XA images, to enhance vessel visualization. The method separate XA images into a breathing layer, a quasi-static background layer and a vessel layer using morphological filtering and applying Robust PCA. The separation is evaluated on four XA sequences, demonstrating better separation of the coronary arteries

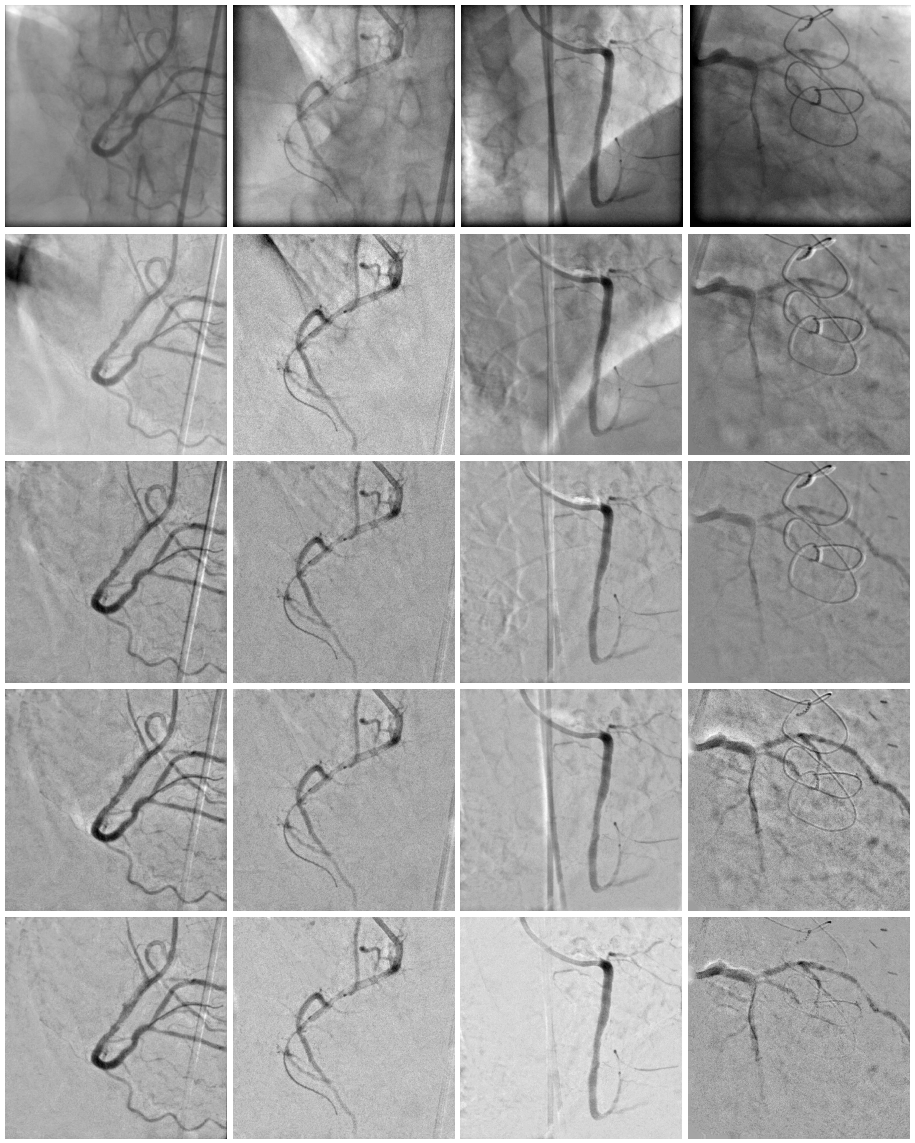
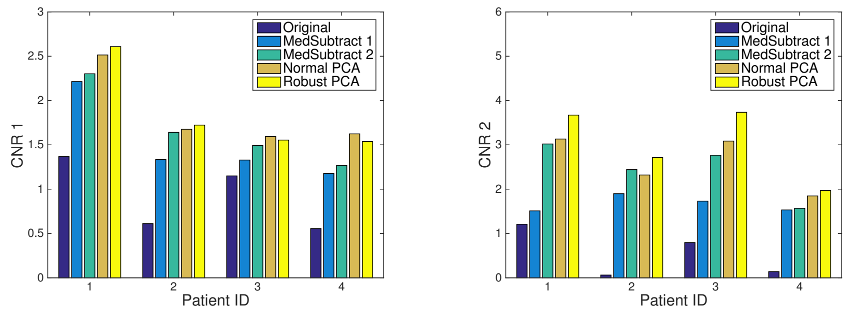


Fig. 5: Example frames of foreground images obtained by different background-removal techniques applied on four XA sequences: (Column 1-4) The four different XA sequences, (Row 1) The original image, (Row 2) *MedSubtract 1*, (Row 3) *MedSubtract 2*, (Row 4) *Normal PCA*, (Row 5) our method using Robust PCA.




(a) CNR 1 (b) CNR 2

Fig. 6: The average CNR over 5 randomly-chosen frames using two types of masks for the four XA sequences.

and reduced inclusion of breathing or quasi-static structures compared to other approaches.

Fig. 5 shows that the proposed method is able to improve the visibility of vessels and performs better on representative frames of the four XA sequences. Fig. 6(a) shows that the *Robust PCA* method is advantageous over the two median subtraction methods on improving the local contrast, and has similar performance with *Normal PCA*. Fig. 6(b), which displays the global CNR measure, shows that *Robust PCA* is superior on all four patients which indicates that the superiority of *Robust PCA* to other approaches is more on removing respiratory and quasi-static structures from XA to improve the contrast of vessels in the whole image. This advantage could potentially reduce the generation of spurious vessels when applying vessel extraction methods on XA.

Compared to original images, the *Robust PCA* method improves image quality in the vessel layer by removing breathing structures and background objects. Compared to the absolute-static background resulted from the median-subtraction-based methods, *Robust PCA* models a quasi-static background with small changes, which is more adaptive to the change of image content caused by coronary motion. *Normal PCA* also models a flexible background , which could be the reason why it has similar performance with *Robust PCA*. Compared to *Normal PCA*, *Robust PCA* produces less residuals of guiding catheter in the vessel layer after the removal of the background layer. The regularization parameter of *Robust PCA* enables better flexibility of balancing between moving objects and background in layer separation. Compared to other related techniques e.g. in [6][7], the main difference of the proposed method is that it does not rely on motion field, therefore, no motion field is required to extract before doing layer separation.

Several factors might have impact on CNR values. The masks defines the background and foreground, therefore the mask-related factors could directly influence the CNR values, e.g. the width of the foreground or background, whether or not including small vessels or the guiding catheter distal segment in the foreground. In addition, the number of the selected frames for mask generation from each XA sequence might also be an important factor. More in-depth analysis of these factors is part of the future work.

In conclusion, we proposed a novel layer separation method based on morphological operation and Robust PCA. We also demonstrated that the method improves the visibility of coronary arteries in XA and has advantages over several other related approaches. In the future, we will assess this technique in prospective settings and study its application in approaches that improve image guidance in XA guided cardiac interventions.

## References

1. Panayiotou, M., King, A.P., Housden, R.J., Ma, Y., Cooklin, M., O'Neill, M., Gill, J., Rinaldi, C.A., Rhode, K.S.: A statistical method for retrospective cardiac and respiratory motion gating of interventional cardiac x-ray images. Medical Physics, 41(7), 071901 (2014)
2. Baka, N., Metz, C.T., Schultz, C., Neefjes, L., van Geuns, R.J., Lelieveldt, B.P.F., Niessen, W.J., van Walsum, T., de Bruijne, M.: Statistical coronary motion models for 2D+ t/3D registration of X-ray coronary angiography and CTA. Medical Image Analysis, 17(6), 698-709 (2013).
3. Frangi, A., Niessen, W., Vincken, K., Viergever M.: Multiscale vessel enhancement filtering. Medical Image Computing and Computer-Assisted Interventation-MICCAI 98, Springer Berlin Heidelberg, 130-137 (1998)
4. Baka, N., Metz, C.T., Schultz, C.J., van Geuns, R.J., Niessen, W.J., van Walsum, T: Oriented Gaussian Mixture Models for Nonrigid 2D/3D Coronary Artery Registration. IEEE Transactions on Medical Imaging, 33(5), 1023-1034 (2014)
5. Schneider, M., Sundar, H.: Automatic global vessel segmentation and catheter removal using local geometry information and vector field integration. Biomedical Imaging: From Nano to Macro, 2010 IEEE International Symposium on., IEEE, 45-48 (2010)
6. Zhang, W., Ling, H., Prummer, S., Zhou, K. S., Ostermeier, M., Comaniciu, D.: Coronary tree extraction using motion layer separation. Medical Image Computing and Computer-Assisted Interventation-MICCAI 2009, Springer Berlin Heidelberg, 216-223 (2009)
7. Zhu, Y., Prummer, S., Wang, P., Chen, T., Comaniciu, D., Ostermeier, M.: Dynamic layer separation for coronary DSA and enhancement in fluoroscopic sequences. Medical Image Computing and Computer-Assisted Interventation-MICCAI 2009, Springer Berlin Heidelberg, 877-884 (2009)
8. Candes, E., Li, X., Ma, Y., Wright, J.: Robust Principal Component Analysis?. Journal of the ACM, 58(3), 11 (2011)
9. Hamy, V., Dikaios, N., Punwani, S., Melbourne, A., Latifoltojar, A., Makanyanga, J., Chouhan, M., Helbren, E., Menys, A., Taylor, S., Atkinson, D.: Respiratory motion correction in dynamic MRI using robust data decomposition registrationApplication to DCE-MRI. Medical Image Analysis, 18(2), 301-313 (2014)
10. Ma, H., Dibildox, G., Schultz, C., Regar, E., van Walsum, T.: PCA-derived respiratory motion surrogates from X-ray angiograms for percutaneous coronary interventions. International Journal of Computer-Assisted Radiology and Surgery, 10(6), 695-705 (2015)

11. Lin, Z., Liu, R., Su, Z.: Linearized alternating direction method with adaptive penalty for low-rank representation. Advances in Neural Information Processing Systems, 612-620 (2011)