Reducing the X-ray radiation exposure frequency in cardio-angiography via deep-learning based video interpolation

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Abstract—Cardiac coronary angiography is a major technology to assist doctors during cardiac interventional surgeries. Under the exposure of X-ray radiation, doctors inject contrast agents through catheters to determine the position and status of coronary vessels in real time. To get a coronary angiography video with a high frame rate, the doctor needs to increase the exposure frequency and intensity of the X-ray. This will inevitably increase the X-ray harm to both patients and surgeons. In this work, we innovatively utilize a deep-learning based video interpolation algorithm to interpolate coronary angiography videos. Moreover, we establish a new coronary angiography image dataset, which contains 95,039 triplets images to retrain the video interpolation network model. Using the retrained network we synthesize high frame rate coronary angiography video from the low frame rate coronary angiography video. The average peak signal to noise ratio (PSNR) of those synthesized video frames reaches 34dB. Extensive experiment results demonstrate the feasibility of using the video frame interpolation algorithm to synthesize continuous and clear high frame rate coronary angiography video. With the help of this technology, doctors can significantly reduce exposure frequency and intensity of the X-ray during coronary angiography.

Index Terms—Coronary angiography, contrast agent, video interpolation, deep learning

I. INTRODUCTION

Cardiac coronary angiography is a major technology to assist doctors during cardiac interventional surgeries. In Coronary angiography, a radiopaque contrast agent is injected into a blood vessel and X-rays are taken to produce detailed images of the blood vessel. Coronary angiography provides information about the coronary arteries, which supply the heart with oxygen-rich blood. During insertion, the doctor uses fluoroscopy (a continuous x-ray procedure) to observe the progress of the catheter as it is threaded into place. Side effects of radiopaque contrast agents include allergic reactions and kidney damage. To get a coronary angiography video with a high frame rate, the doctor needs to increase the exposure frequency and intensity of the X-ray. This will inevitably increase the X-ray harm to patients and surgeons. The video frame interpolation algorithm mainly includes the following steps: bidirectional motion estimation, motion interpolation, occlusion inference, and motion compensated frame interpolation. However, these methods introduce various disturbances, such as blur, ghost etc. In the past few years, deep-learning methods, especially deep convolutional network methods [2], [3], [7], [12]-[14] have been effectively applied and extended in the field of video frame interpolation. These methods use neural networks to extract kernel functions and optical flow features, and Apply adjacent frames to compose the middle frame. Although these methods have been greatly improved, the effect is still not very good when dealing with large object motion and occlusion.

The DAIN method [2] has good performance in the field of video frame interpolation. In the method, a variety of neural network structures are used to extract image context features, optical flow features, depth map features [4]-[6], and applies adaptive convolutional layers [3] to synthesize new video frames. This method can deal with the situation of adapting to strong motion and large object occlusion.

In this work, we apply video frame interpolation to coronary angiography video to increase the frame rate and generate slow motion videos. The video frame interpolation algorithm we choose is the DAIN method. Moreover, we establish a new dataset containing 95,039 triplets where each triplet contains 3 consecutive coronary angiographic frames to retrain the network model of DAIN. Then we utilize the trained network model to interpolate the coronary angiography videos and analyze the results of interpolation frames. Finally, we compare the performance of different frame interpolation algorithms in different periods of the cardiac cycle.

We make the following contributions in this work:
1. We innovatively apply deep learning-based video frame interpolation algorithms to coronary angiography videos.
2. We make a new coronary angiography dataset for video interpolation algorithm.
II. RELATED WORK

Recently deep learning and specifically convolutional neural networks (CNNs) have been successfully applied in computer vision areas, which inspired various deep learning based frame interpolation methods. The early works on CNN-based video frame interpolation[1] proposed an CNN architecture that takes two input frames and directly estimate the intermediate frame. However, these typical approaches often lead to blurred outputs.

The later methods, instead of directly computing the output pixels, mainly focused on where to find the pixel from input frames and estimated spatially-adaptive interpolation kernels to synthesize pixels from a large neighborhood. In the AdaConv method[13], the adaptive filter is convolved with adjacent input frame images to synthesize the data of the middle frame. But this method can only deal with moving objects within a size of 41x41 pixels at most which can not meet the situation of strenuous exercise and occlusion. A separable neural network calculation method is applied in the SepConv[12] method, which can greatly save the use of physical memory during the frame insertion process and shorten the time used to train the network.

In the SuperSlomo method[7], a CNN is used for bidirectional motion estimate, then a simplified motion interpolation method is applied, and at the end a second CNN performs motion estimate refinement and occlusion reasoning. This work achieved overwhelming quality when applied on videos taken at high frame-rates. However, it seems that they do not aim at covering a wide range of motions.

The adaptive deformable neural network[19] is defined in creative deformable convolution. This method trains a weight kernel at each pixel value position, and then each kernel weight corresponds to a pixel value with an offset. Any positive number, so the bi-linear interpolation method is used to synthesize the pixel value at any position. It performs better under intense movement and occlusion.

In the DAIN method[2], a pretrained model is used to extract the context feature map[14], depth features map[8], [9], frame interpolation kernel, and optical flow feature map[11] of the two adjacent frames, and the adaptive convolution layer is used to synthesize any frame data between two adjacent frames. The DAIN method can synthesize video frames at arbitrary positions and has a good performance in dealing with the situation of strong motion and occlusion of objects.

III. METHOD

In this section, we rely on the DAIN method proposed by Bao, w et al.[2]. We first introduce the DAIN method and describe the main architecture of the network. And then we redefine the loss function and introduce the implementation details.

A. Depth-Aware Video Interpolation

The main architecture of the DAIN model is shown in Fig.1. Given two input images I₀ and I₁ and a time t ∈ (0, 1), the goal is to predict the interpolate image \( \hat{I}_t \) at time \( T = t \). The DAIN model consists of the following submodules: the flow estimation, depth estimation, context extraction, kernel estimation, and frame synthesis networks. The DAIN algorithm uses the proposed depth-aware flow projection layer to obtain intermediate flows and then warps the input frames, depth maps, and contextual features within the adaptive warping layer. Finally, the frame synthesis network generates the output frame with residual learning.

The DAIN model utilizes the pretrained PWC-Net[11] as the optical flow estimation network. \( F_{0→1} \) and \( F_{1→0} \) are the estimated optical flows by the flow estimation network. \( F_{0→1} \) and \( F_{1→0} \) denote the optical flow from I₀ to I₁ and I₁ to I₀, respectively. The depth estimation network uses the hourglass architecture[9], [16]. \( D₀ \) and \( D₁ \) are the estimated depth map of I₀ and I₁. The DAIN method contains a depth-aware flow projection[2] which combine the optical flow and the depth map to get the projected flow at time \( T = t \). The projected flow \( F_{t→0} \) can be obtained from the flow \( F_{0→1} \) and the depth map \( D₀ \). The projected flow \( F_{t→1} \) can be obtained from the flow \( F_{1→0} \) and the depth map \( D₁ \).

The projected flow \( F_{t→1} \) is defined by:

\[
F_{t→1}(x) = -(1-t) \cdot \frac{1}{\sum_{y \in S(x)} D₀(y)} \cdot F_{0→1}(y) \quad (1)
\]

\( S(x) = \{ y : \text{round}(y + (1 - t) F_{0→1}(y)) = x, \forall y \in [H, W] \} \)

Where \( S(x) \) indicates the set of pixels that pass through the position \( x \) at time \( t \). The projected flow \( F_{t→0} \) is defined by:

\[
F_{t→0}(x) = -t \cdot \frac{1}{\sum_{y \in S(x)} D₁(y)} \cdot F_{1→0}(y) \quad (3)
\]

\( S(x) = \{ y : \text{round}(y + t F_{0→1}(y)) = x, \forall y \in [H, W] \} \quad (4)\)

The context extraction model consists a pretrained ResNet[17]. The contextual features \( C₀ \) and \( C₁ \) are extracted from the input frames I₀ and I₁. The interpolation kernels \( K₀ \) and \( K₁ \) are estimated by a U-Net architecture[15] network. With the interpolation kernels \( (K₀ \) and \( K₁) \) and interpolated flows \( F_{t→0} \) and \( F_{t→1} \) generated from the depth-aware flow projection layer, using the adaptive warping layer[3] to warp the input frames(I₀ and I₁), depth maps(D₀ and D₁), contextual features(C₀ and C₁), to generate the output frame \( \hat{I}_t \), the algorithm utilizes a frame synthesis network, which consists of 3 residual blocks. The algorithm concatenates projected flows(\( \hat{F}_{t→0} \) and \( \hat{F}_{t→1} \)) and interpolation kernels(\( K₀ \) and \( K₁)\), the warped input frames(I₀ and I₁), warped depth maps(D₀ and D₁), warped contextual features(C₀ and C₁) as the input to the frame synthesis network. In addition, the algorithm linearly blend the two warped frames(I₀ and I₁) and enforce the network to predict the residuals between the ground-truth frame and the blended frame.

B. Implementation Details

Loss Function. We denote the synthesized frame by \( \hat{I}_t \) and the ground-truth frame by I₁. We retrain the DIAN model by optimizing the following loss function:
Fig. 1. Architecture of DAIN model[2]. The model consists of the following submodules: the flow estimation, depth estimation, context extraction, kernel estimation, Depth-ware flow projection layer, adaptive warping layer, and frame synthesis networks.

\[ L = \lambda_1 l_1 + \lambda_2 l_2 \]

where \( \lambda_1 = 0.95 \) and \( \lambda_2 = 0.05 \).

The loss \( l_1 \) models how good the reconstruction for the intermediate frame is:

\[ l_1 = \sum_x \rho(||\hat{I}_t(x) - I_t(x)||_1) \]

where \( \rho(x) = \sqrt{x^2 + \epsilon^2} \) is the Charbonnier Function. We set the constant \( \epsilon \) to \( 1e^{-4} \).

The purpose of coronary angiography video frame interpolation is to obtain a clearer coronary artery structure. So we define the structure loss \( l_2 \) as

\[ l_2 = \sum_x \rho(||\phi\hat{I}_t(x) - \phi I_t(x)||_1) \]

where \( \phi \) denote the conv4\(_x\) features of a pretrained ResNet[17].

Training Dataset. In order to train a better network model conforming to coronary angiography scene we create a new training dataset. The dataset contains 950,399 triplets of consecutive frames with a resolution of 480x360. The triplets are extracted from 31 coronary angiography videos the total duration of which is about 25 hours. The videos are produced by recording screen images during cardiac intervention. We processed these videos and selected suitable coronary angiography fragments as the data set. The image frame rate of coronary angiography is 7-15fps, but the frame rate used for recording screen images is 25fps, so we preprocess the recorded videos to remove duplicate video frames. Coronary angiography images contain some patient’s information, so we occlude and remove these information to ensure that the patient’s privacy is not leaked. Also we augment the training data by horizontal and vertical flipping.

Training strategy. Every triplet in the dataset contains 3 consecutive video frames, which are the previous frame, the middle frame, and the next frame. We train the network to predict the middle frame that serves as ground truth. We use a pre-trained model as the initial model for training. The learning rate is initially 0.0001 and decays half every 20 epochs. The batch size is 4 and the the network is trained for 100 epochs. We train the network on an NVIDIA 2080Ti GPU card, which takes about 30 hours.

IV. EXPERIMENTS AND RESULTS

In this section, we first introduce the testing datasets. Second, we compare the output of the pretrained model with the retrained DAIN model. Then we compare our results with state-of-the-art frame interpolation approaches and analyze the performance of different frame interpolation methods in different cardiac cycles. Finally we discuss how to further improve the current results.

A. Testing Dataset

We randomly selected 1,000 triplets from the coronary angiography dataset as one test dataset which is represented by D1000. At the same time, we extracted four coronary angiography video clips, each of which contained 30-45 continuously frames, and each video clip includes the process of injection, diffusion, and disappearance of the contrast agent. We use VC1, VC2, VC3, VC4 to represent these four video clips. For these four clips, we use odd frames to predict even frame, and then use even frames to predict odd frame, so we can compare all the predicted frames with the original frames. We utilize the PSNR and SSIM values as the evaluation criteria for the two-frame image error.

B. Results

We use the testing dataset to compare the results of the pretrained DAIN model with the retrained model. Fig.2 shows the inputs of two original frames, the original middle frame
| Test data | D1000  | VC1   | VC2   |
|-----------|--------|-------|-------|
| DAIN-Pre  | 0.961  | 40.142| 0.902 | 33.839 | 0.900 | 34.368 |
| DAIN-Re   | 0.962  | 40.523| 0.904 | 34.068 | 0.902 | 34.754 |

Table I: The experiments results of different datasets.

Fig. 2. Comparison of the output of the retrained model and the pretrained model. The $I_{t=0.5}^{Re}$ is the predicted video frame of pretrained model and the $I_{t=0.5}^{Pre}$ is the predicted video frame of retrained model.

Fig. 3. PSNR of interpolation frame changes with frame index, the test data is VC4

C. Comparison and Discussion

We compare our results with several stat-of-the-art algorithms including SepConv-l1[12], SepConv-lf[12], Super-Slomo[7]. In order to exclude the influence of the training dataset, we use the coronary angiography dataset to retrain these several network models respectively. Then we use these retrained models to process the testing datasets.

In Table II, it shows the comparisons of different methods on the coronary angiography testing datasets. The tables summarizes the average PSNR and SSIM of these experiments. The average PSNR of DAIN method is 0.2dB-1.6dB higher than the other methods.

In Fig.4, it shows the interpolation frames of several video interpolation methods in the case of occlusion and large object movement. As shown in the figure, the DAIN method performs well in both aspects. The image edges of the interpolated frames are clearer and sharper.

In Fig.5, we plot the PSNR curves of several frame interpolation algorithms on two coronary angiography video clips. First, the overall PSNR curve of DAIN is higher than other methods. Second, all the PSNR curves has a periodic change. When the systolic and diastolic phases are switched in the cardiac cycle, lower PSNR values appear. We analyze the reason for this result is that when the phase of the cardiac cycle is switched, the optical flow characteristics between two adjacent frames are not obvious enough, and the possible motion vectors of the coronary arteries cannot be accurately predicted. At the same time, we can see that the PSNR value decreases with the index of the frame. The reason for this problem is that the vascular motion area of the coronary angiography image continues to expand with the diffusion of the contrast agent in the coronary arteries. As shown in Figure 5 (b), after the contrast agent has diffused to the end of the coronary artery, the PSNR no longer changes significantly between the 35th and 45th frames.

In order to further improve the quality of coronary angiography interpolation frame, we can use the trained coronary artery segmentation [18]network model to extract the coronary artery segmentation results from the synthetic frame and the original frame, respectively. We take the error of coronary artery segmentation in two frames as part of the loss function. This method may also improve the problem that the interpolation frames have lower PSNR values when the cardiac cycle phase switched.
Ground truth  SepConv-l1  SepConv-lf  SuperSlomo  DAIN

Fig. 4. The interpolation Frame of DAIN, SepConv-l1, SepConv-lf, SuperSlomo. It mainly shows the performance of several methods in the case of occlusion and large object movement. As can be seen from the figure, the DAIN method performs better in both aspects.

| Test data | VC1 SSIM, PSNR | VC2 SSIM, PSNR | VC3 SSIM, PSNR | VC4 SSIM, PSNR | D1000 SSIM, PSNR |
|-----------|----------------|----------------|----------------|----------------|-----------------|
| SepConv-l1| 0.901 33.657   | 0.901 34.672   | 0.904 33.649   | 0.902 33.745   | 0.962 39.823    |
| SepConv-lf| 0.878 32.768   | 0.883 34.039   | 0.883 33.003   | 0.883 32.872   | 0.956 39.741    |
| SuperSlomo| 0.901 33.838   | 0.898 34.468   | 0.902 33.768   | 0.901 33.704   | 0.958 38.868    |
| DAIN      | 0.904 34.068   | 0.902 34.754   | 0.908 33.977   | 0.908 34.205   | 0.962 40.523    |

V. CONCLUSION

In this paper, we innovatively apply the deep learning-based video frame interpolation algorithm to coronary angiography. We establish a new coronary angiography dataset to retrain the network of DAIN method. The retrained model has a better performance in the application scenarios of coronary angiography. Moreover, we retrain several other deep learning-based algorithms and compare the results of these frame interpolation algorithms. The retained DAIN model has better performance than other methods in the case of occlusion and large object movement. Extensive experiment results demonstrate the feasibility of using the video frame interpolation algorithm to synthesize continuous and clear high frame rate coronary angiography video. With the help of this technology, doctors can significantly reduce exposure frequency and intensity of the X-ray during coronary angiography.

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Fig. 5. The PSNR curves of several frame interpolation algorithms on two continuous coronary angiography clips. (a) shows the results of VC2 and (b) shows the results of VC3. The vertical red line indicates the beginning of systole and the vertical black line indicates the beginning of diastole.

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